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ÚSTAV TELEKOMUNIKACÍ

RESEARCH OF ADVANCED ONLINE HANDWRITING ANALYSIS METHODS WITH A SPECIAL FOCUS ON ASSESSMENT OF GRAPHOMOTOR DISABILITIES IN SCHOOL-AGED CHILDREN

VÝZKUM POKROČILÝCH METOD ANALÝZY ONLINE PÍSMA SE ZAMĚŘENÍM NA HODNOCENÍ GRAFOMOTORICKÝCH OBTÍŽÍ U DĚTÍ ŠKOLNÍHO VĚKU

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ABSTRACT

Graphomotor abilities (GA) represent a set of psychomotor activities that are executed during drawing and writing. The GA are prerequisites for mastering of elementary school skills, particularly writing. Children in 1 st and 2 nd grade can experience difficulties in execution of simple graphomotor tasks (GD) and later in 3 rd and 4 th grade even in handwriting tasks (HD). The disruption of processes involved in handwriting is generally called Developmental Dysgraphia (DD). The prevalence of DD in the Czech Republic is 3–5 %. To this day the DD is evaluated subjectively by teams of psychologists and special educationalist. Currently, an objective measuring tool that asses the properties of GD or HD is missing in practice. Consequently, this thesis is aiming to identify symptoms associated with graphomotor disabilities in school-aged children and design new parameters quantifying them. For this purpose, a new complex GA protocol was proposed (36 tasks), which represents an environment, where the identified symptoms can be manifested (24 symptoms). Moreover, 76 quantifying features were introduced. A new graphomotor difficulties rating scale (GDRS) was designed based on computerised analysis of handwriting. Finally, new online handwriting parameters based on advanced signal processing techniques were designed and tested, which can assess poor dexterity or unspecified motor clumsiness. The GDRS represents a novel and modern objective measurement tool, that is not yet available in the Czech Republic or in other countries. Its utilization will help in the modernization of DD diagnosis and in the remediation process. With proper research, it could be adapted into other languages as well. Moreover, the methodology can be used and optimized for other diseases, which affects GA, such as Autism, Attention Deficit Coordination Disorder (ADHD) or Developmental Coordination Disorder (DCD).

KEYWORDS

Developmental dysgraphia, handwriting difficulties, graphomotor abilities, graphomotor difficulties, online handwriting, in–air/on–surface movement, quantitative analysis, objective evaluation, machine learning, advanced parametrization techniques, Tunable Q Factor Wavelet Transform.

ABSTRAKT

Grafomotorické dovednosti (GA) představují skupinu psychomotorických procesů, které se zapojují během kreslení a psaní. GA jsou nutnou prerekvizitou pro zvládání základních školních schopností, konkrétně psaní. Děti v první a druhé třídě mohou mít potíže s prováděním jednoduchých grafomotorických úkolů (GD) a později ve třetí a čtvrté třídě také se samotným psaním (HD). Narušení procesů spojených se psaním je obecně nazýváno jako vývojová dysgrafie (DD). Prevalence DD v České republice se pohybuje kolem 3–5 %. V současné době je DD hodnocena subjektivně týmem psychologů a speciálních pedagogů. V praxi stále chybí objektivní měřicí nástroj, který by umožňoval hodnocení GD a HD. Z tohoto důvodu se tato disertační práce zabývá identifikováním symptomů spojených s grafomotorickou neobratností u dětí školního věku a vývojem nových parametrů, které je budou kvantifikovat. Byl vytvořen komplexní GA protokol (36 úloh), který představuje prostředí, ve kterém se mohou projevit různé symptomy spojené s GD a HD. K těmto symptomům bylo přiřazeno 76 kvantifikujících parametrů. Dále byla navrhnuta nová škála grafomotorických obtíží (GDRS) založena na automatizovaném zpracování online píma. Nakonec byla prezentována a otestována nová sada parametrizačních technik založených na Tunable Q Factor Wavelet Transform (TQWT). Parametry TQWT dokážou kvantifikovat grafomotorickou obratnost nebo nedostatečný projev v jemné motorice. GDRS přestavuje nový, moderní a objektivní měřící nástroj, který doposud chyběl jak v České republice, tak v zahraničí. Použití škály by pomohlo modernizovat jak diagnostiku DD, tak reedukační/remediační proces. Další výzkum by tento nástroj mohl adaptovat i do jiných jazyků. Navíc, tato metodologie může být použita a optimalizována pro diagnostiku dalších nemocí a poruch, které ovlivňují grafomotorické dovednosti, například pro autismus, poruchu pozornosti s hyperaktivitou (ADHD) nebo dyspraxii (DCD).

KLÍČOVÁ SLOVA

Vývojová dysgrafie, obtíže se psaním, grafomotorické dovednosti, grafomotorická neobratnost, online písmo, kvantitativní analýza, objektivní hodnocení, strojové učení, pokročilé parametrizační techniky, Tunable Q Factor Wavelet Transform.

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DECLARATION

I declare that I have written the Doctoral Thesis titled "Research of Advanced Online Handwriting Analysis Methods with a Special Focus on Assessment of Graphomotor Disabilities in School-aged Children." independently, under the guidance of the advisor and using exclusively the technical references and other sources of information cited in the thesis and listed in the comprehensive bibliography at the end of the thesis.

As the author I furthermore declare that, with respect to the creation of this Doctoral Thesis, I have not infringed any copyright or violated anyone's personal and/or ownership rights. In this context, I am fully aware of the consequences of breaking Regulation § 11 of the Copyright Act No. 121/2000 Coll. of the Czech Republic, as amended, and of any breach of rights related to intellectual property or introduced within amendments to relevant Acts such as the Intellectual Property Act or the Criminal Code, Act No. 40/2009 Coll., Section 2, Head VI, Part 4.

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Introduction

Handwriting is a complex skill, which includes cohesion of sensory, motor and cognitive processes. The process involves several muscles that act in various directions. Also, it is a relatively challenging cognitive activity, that is highly demanding in attention, planning, memory, and self–regulation. Moreover, it can be categorized as one of multitasking skills, that is challenging particularly for the working memory. Children with fully automated handwriting and spelling have their working memory freed for more complex cognitive procedures, such as composition or grammar. The automation level of handwriting is increasing as the child matures and it is also very individual. Even in the current digital era, the handwriting skills are still observed as a sign of school readiness and later their level is in relationship with child's grades. From child with handwriting difficulties, teachers may have an impression, that she/he is unmotivated, bored, or even less intelligent individual. This status can influence the child's frustration, motivation or can negatively impact her/his school performance and wellbeing.

Currently, the definition of Developmental Dysgraphia (DD) by the manuals DSM–V, ICD 10 (or the Czech translation MKN 10) is specified as a lack of ability to acquire proficient handwriting, or inadequate effort to attain it. The lack of consensus on the definition at expert level is having a negative effect on the community, where experts may not always be in agreement with each other on the diagnosis of DD, or on the degree of it. Even scientific literature is concerned, that the disease is not researched enough. The prevalence in the Czech Republic is around 3–5 %. The DD can negatively influence several aspects of handwriting and the natural development of the automatization process. It negatively affects the handwritten product, which has than a disproportionate size, inappropriate shape of letters, abnormal spacing, unsteady writing trace, etc. Also, it disturbs the process of handwriting, such as speed and duration, fine motor tremor, hesitation, and pen tip pressure. To clear up definitions, handwriting and drawing are defined to be part of graphomotor abilities (GA). The Graphomotor Difficulties (GD) are identified as problems with execution of basic graphomotor elements (starting in 1 st or 2 nd grade of primary school). Handwriting Difficulties (HD) are identified in 3 rd and 4 th grade, where the children are starting to write cursive letters.

The diagnosis and rating of DD is a complex task and in the Czech Republic it mostly relies on experience of psychologists (PS) and special educationalists (SE). Teams of PS and SE work together on anamnesis, testing memory and intelligence. Further diagnosis of DD is carried out by SE. Moreover, the DD diagnosis is based upon family anamnesis, school overall status, determination of intellect, working memory and visual–spatial ability. Generally, there is no standardized tool for DD diagnosis. It is up to the teams of PS and SE which tool will be a part of their test battery. Also, the validation criteria are mainly derived either from questionnaires or from analytic scales, that are either subjective or they measure the handwriting product/process manually and consequently inadequately. Moreover, the evaluation process is highly dependent on the physical state of the sight of the evaluator, as she/he is observing/counting specific properties of handwriting.

The identified limitation of the current state of DD diagnosis revealed a research gap. For this reason, the individual aims of this dissertation thesis are:

1. To identify symptoms associated with GD in school–aged children and design new parameters quantifying them.
2. To design new graphomotor disabilities rating scale based on computerized analysis of handwriting.
3. To design new online handwriting parameters based on advanced signal processing techniques.

The thesis is structured as follows. Chapter 1 provides detailed description of physiological and psychological mechanisms engaged during handwriting. Next, it introduces the DD and other related diseases, that affect the developmental handwriting. The symptoms linked with DD are listed. The summary is provided, where the graphomotor abilities (GA), graphomotor disabilities (GD) and handwriting difficulties (HD) are specified. Also, the DD diagnosis in the Czech Republic and its limitations are identified. The online handwriting is briefly described and consequent thorough review of the state of the art of GD analysis is reported. Chapter 2 introduces new graphomotor ability protocol. Next, symptoms related to the product and process are listed. Moreover, for each symptom several quantifying features are provided. Chapter 3 refers to the design of new graphomotor difficulties rating scale. Firstly, the methodology design is described. Afterwards, a preliminary analysis of the designed features is provided. Chapter 4 introduces a new advanced parametrization technique based on the Tunable Q Factor Wavelet Transform (TQWT). The TQWT features are tested in terms of ability to discriminate HD and GD from a proficient performance. The results from both analyses are discussed in detail. Chapter 5 provides a detailed discussion of the outcomes of this work, and finally Chapter 6 summarizes the thesis.

1 Handwriting difficulties in school-aged children and approaches of its diagnosis

1.1 Handwriting and difficulties

Handwriting is a complex skill, which expresses itself in a cohesion of sensory, motor and cognitive processes [138, 179]. The fact, that handwriting in not just a product of the motor mechanism, can be observed in children, that can write well, but have difficulties with drawing and vice versa [17].

Although in the global population of children is a prevalence of Developmental Dysgraphia (around 7–30 %), it is still a not widely researched topic and its underlying principle is still not clearly understood [39, 67]. The prevalence of DD in the Czech Republic is 3–5 % [77]. DD is a relatively neglected science field in the comparison with the developmental dyslexia [39] and the numbers of the prevalence are highly language dependent (i.e. orthographic depth, grammar etc.). The early detection of DD is crucial for successful intervention and therapy [72].

In current digital era, the need of handwritten text in elementary school teaching is slowly disappearing [50, 91]. Nevertheless, handwriting skills are still observed by experts to establish school readiness [115, 149]. The level of handwriting skills is in relationship with children's school grades [48, 80]. Children with poor handwriting can make an impression on teachers that he/she is an unmotivated, bored or even less intelligent individual [32, 92]. This bias can lead to frustration, demotivation or low self–esteem, which all can negatively impact children's school performance [92].

1.1.1 Mechanisms related to the handwriting

In the process of handwriting several muscles and even forces operate, that act in various directions [84]. In literature, the topic of mature pencil grasp was extensively researched [6, 84, 130, 136, 147, 149]. To summarize the theory of pencil grasp, the mature grasp is characterized by the usage of inner muscles of the hand for the pencil movement. On the contrary in the immature grasp, even if the children are holding the pen with fingers, the motor movement is carried out mainly by outer muscles of the hand [149, 152]. Many studies have suggested that the variation in grasp during handwriting does not influence legibility or speed of writing [61].

Handwriting is a relatively challenging cognitive activity, that is highly demanding on attention, planning, memory and self–regulation [78]. With handwriting there are connected meta–cognitive processes, such as revising, translation (transfer from thought to written product), spacing and orientation of letters on paper [66, 122, 131]. It can be viewed as an example of one of our multitasking skills, that is particularly challenging for working memory [78, 85, 94]. The children with fully automated handwriting and spelling have their working memory freed for more complex cognitive procedures, such as composition or grammar [75, 85, 92, 94]. Finally, with fully automated handwriting in adulthood, attention is focused on linguistic and semantic aspects of writing instead of motor processes [112, 166]. The level of automaticity of handwriting is changing as children mature and it is also very individual [85, 93, 95, 116, 165, 174].

1.1.2 Origin of Developmental dysgraphia

Various authors have different opinions on the etiology of the DD. One view is, that DD is the consequence of underdeveloped areas of the language, such as phonetics, phonology, morphology, or syntax [179]. It was also discovered that DD co–occurs more frequently with other diseases, such as Attention Deficit Hyperactivity Disorder (ADHD), Developmental Coordination Disorder (DCD), or autism [18, 110]. Similar brain activity was observed in children with DD and ADHD only [19, 127].

DD is generally described by the DSM–V [5] as a Specific Learning Disorder (SLD) with impairment in written expression, that is lacking in spelling accuracy, grammar and punctuation accuracy and organization or clarity of written expression. In the ICD–10 [175] DD is described as a Specific Developmental Disorder of Scholastic Skills with Specific Spelling Disorder, where the ability to spell orally and to write out words correctly are both affected (the Czech translation of ICD–10 is called MKN–10 [176]). Children with DD are not identified as having neurological problems or mental retardation [144]. DD is a subtype of SLD.

Overall, we can sum up that DD manifests itself in the lack of ability to acquire proficient handwriting, or with inadequate effort to attain it. As can be seen from previous taxonomies, DD is not specifically mentioned and defined. Even various authors are concerned, that this disorder isn't researched enough [30, 39, 93]. This led the authors to call Dysgraphia by different names, such as: poor handwriting, handwriting difficulties (HD), or even having special learning disorder SLD or disability (which is in agreement with ICD–10 and DSM–IV).

The diagnosis and rating of DD is a complex task and mostly relies on experience of teachers, psychologists and occupational therapists [144].

1.1.3 Symptoms of Developmental dysgraphia

The DD negatively influences one or several aspects (see Section 1.1.1) of handwriting. In the majority of cases, DD exhibits itself in lower speed of writing and legibility, which than limits the individual in school performance [92, 115, 140, 149, 152].

DD can also slow down natural development of automatization of handwriting, which can lead children to be less self–sufficient, less conscientious and more stressed writers [45, 72]. Also, the influence of DD can severely impact the graphomotor aspect of handwriting, where children are experiencing exhaustion [84]. The underlying mechanism behind DD is still unknown [39, 49, 93]. DD manifests itself generally in two domains: in the handwritten product and in the process of handwriting.

Symptoms in handwritten product

- Disproportionate size of letters: the letters are too big or too small or even are perpetually changing size [130, 132, 133].
- Shape of letters: children are drawing curves, that are less curved and more pointy [141, 157].
- Abnormal spacing: too wide, too narrow or high variability of spacing between letters or words [8, 134].
- Nonlinear vector of writing: children are unable to follow straight path during writing [45, 133].
- Text content error: low level of grammatical development corresponding to the age, similar letter confusion, excessive correction of handwritten text [39, 45, 74, 130, 133].

Symptoms affecting process of handwriting

- Speed and duration of writing: children with poor handwriting need more time to complete the given task due to additional effort, error correcting and poor planning [114]. Also, they have lower average speed of the strokes [79], but at the same time they have larger differences of speed between each stroke [9]. This disturbed fluency of handwriting can be also quantified by the time segments between strokes or differences of speed within each stroke [74, 110, 123, 174].
- Motor tremor: handwritten product can be affected by high level of fine-motor tremor [8].
- Hesitation: children with handwriting difficulties tent to stay longer with the pencil in trajectories hovering above the surface [8, 96, 133].
- Pen tip pressure: children with handwriting difficulties have more variability in the level of the pen tip pressure [79, 133].

1.1.4 Diagnosis of Developmental dysgraphia

Several approaches of DD diagnosis can be identified [45, 47, 140]. We can see a progress, that can be defined as a transition from the subjective evaluation by the examiner to the objective evaluation executed on the basis of quantitative analysis of handwriting signals [115, 141]. Abroad DD diagnosis is in the hands of occupational therapists (OT), who are responsible for assessment, diagnosis and remediation.

In the Czech Republic (CZR) the process of diagnosis is distributed among teams of psychologists (PS) and special educationists (SE). PS and SE work together on anamnesis, testing memory and intelligence. The further diagnosis (SLD such as dyslexia, dysgraphia etc.), are diagnosed by SE. The DD diagnosis is based on several diagnostic tools and the following information: family anamnesis, school overall status (grades, handwriting evaluation based on exercises or homeworks, behavior) and determining intellect, working memory and visual–spatial ability. Another part of the diagnostic process is an examination of laterality and handwriting process [73]. But generally, there is no standardized tool for DD diagnosis and it is up to the occupational therapist or psychologist which tools will be part of hers/his test battery [167].

Nowadays, the primary aim of DD researchers is to develop a standardised evaluation tool. For this purpose, Rosenblum et. all [140] outlined the following evaluation types: product evaluation and process evaluation. Product evaluation, executed by the experts, is based on two scales - global and analytic. The global scale is evaluated with the goal to describe global legibility. The analytic tests are tools, that are scoring handwriting in the terms of shape of letters, spacing, speed etc. In practice, there are lots of these analytic tests. Unfortunately, high percentage of them are lacking psychometric qualities [20, 47, 142].

The process evaluation is a new approach, that started with the advent of technology and particularly with the accessibility of digitizers. This approach is the next step after the product evaluation process. It offers precise measurements techniques (see Figure 1.2), that the human sight can't comprehend (stroke differentiation, fine tremor, pressure, in–air movement etc.). For this reason, quantitative analysis is regarded as more precise and objective.

The last evaluation type is an evaluation using questionnaires, where the children evaluate themselves or are assessed by others (teachers, occupational therapists etc). Several handwriting protocols exist [20], such as Concise Evaluation Scale for Children's Handwriting (BHK) [65], The Minnesota Handwriting Assessment (TMHA) [125], Handwriting Proficiency Questionnaire for Children (HPSQ-C) [135], Handwriting Proficiency Questionnaire (HPSQ) [129] and Drawing Proficiency Screening Questionnaire (DPSQ) [156]. In the BHK children are required to copy a text, which is evaluated with two scores by the therapist. The scores are related to the speed of the writing and to the legibility of the product. TMHA requires the children to copy a sentence in which all the letters from the alphabet are used. The task of the therapist is to determine the speed and quality score (legibility, form, alignment, size, spacing). HPSQ–C is ten–item questionnaire, where children are asked to evaluate themselves on the 5–point Likert scale. The HPSQ–C is designed to describe three factors of handwriting: performance time, legibility and well-being. The maximum (the worst) score that children can achieve is 40 points. HPSQ is the original questionnaire, from which HPSQ–C was derived. It has a similar structure of items. The difference is in the design, where the child related questions are evaluated by the teacher. Finally, DPSQ follows the item structure of HPSQ/HPSQ–C. It was designed to evaluate possible difficulties with drawing of children between 4-7 years of age. The assessment in this questionnaire is done by the occupational therapist or the teacher.

1.1.5 Summary of Developmental dysgraphia analysis

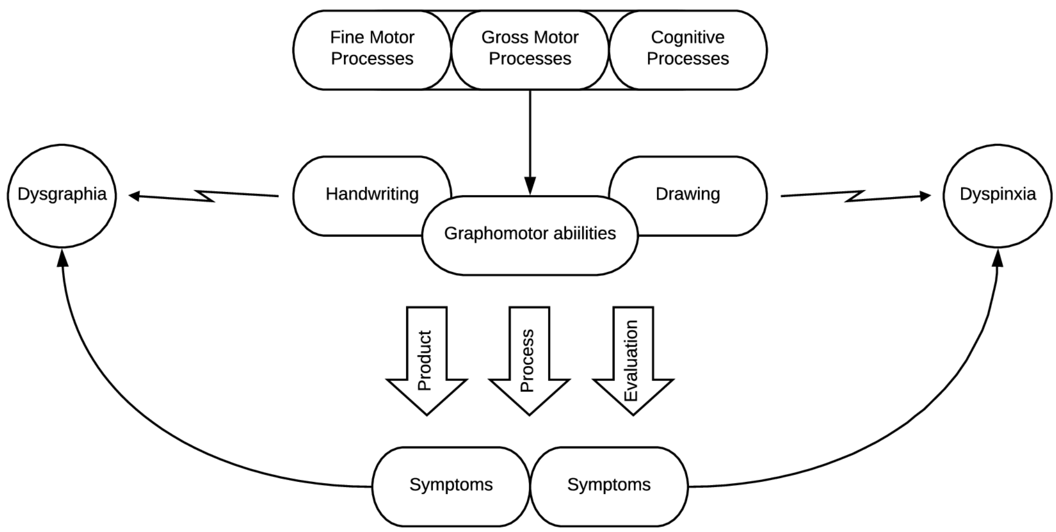


Fig. 1.1: The graphomotor abilities – processes, evaluation, and diagnosis.

This section represents a summary of the theory and possible innovation in the diagnosis of DD in the area of CZR [1].

[1]For this reason the disease names in Figure 1.1 differ from the abroad scientific literature: Artistic Expression Disorder is called Dyspinxia and similary SLD is called Dysgraphia (see Section 1.1.2).

Handwriting and drawing are parts of the graphomotor abilities (GA). The interconnected and underlying processes of GA are fine motor (FMP), gross motor (GMP) and cognitive processes (CP). The focus of this thesis is more on GA, which represents a set of psychomotoric activities that are executed during the graphical expression (writing, drawing, dictation, copying etc.). GA are the prerequisites for the adoption of the elementary school skills, and particularly for writing.

GMP represents overall activities, such as walking, running, jumping, balance, coordination, dancing, etc. GMP issues can possibly negatively influence FMP. The preschoolers have their joints gradually released with the development of GMP [14]. This enables further development of FMP.

To the domain of FMP belongs all activities, which are performed by the small–scale muscle groups, such as movement of hands, GA, mimicry, visual motorics, mouth, feeds etc. [70].

The final domain is CP, which incorporates symbolic and abstract thinking, attention, ideas, concepts, syntactical construction, spelling and also verbal lexicon, working memory, episodic memory, procedural memory etc. [10, 58, 111, 164, 168, 171].

Disruption of processes involved in handwriting is called DD as well as disruption of processes involved in drawing is called Dyspinxia. To this day the DD assessment is executed manually by the OT (abroad) or by the teams of PS and SE (in the Czech Republic).

The measurement of GA proceeds on three levels: product, process and evaluation (scoring). For the assessment of the product there exist global and analytic scales (see Section 1.1.4). For the evaluation there exist questionnaires, such as HPSQ–C/HPSQ. Quantified measurements of the online handwriting signals (process) are called features, which alone or in groups can represent different symptoms of DD (see Section 2.2). The outcome of the computational analysis of GA can be a part of the diagnosis of DD and bring significant improvements, such as lowering costs, higher objectivity, higher accuracy and efficient remediation.

1.1.6 Limitations of current approaches to the diagnosis of DD and motivation to introduce a new solution

At present, occupational therapists examine DD based on the following criteria [48]: legibility and speed of writing, performance time, quality of letter formation, alignment, number of errors, spacing and sizing of letters, etc. Although the clinical assessment of DD provides valuable information about handwriting, it is still limited to a visual inspection of the written product, which does not provide complete information about the process itself. Besides, such assessment is also dependent on the examiner's experience, level of expertise, physical and emotional state, etc. These factors result in an inter-rater variability and less objectivity of the examination [128]. The major drawbacks of current diagnosis of DD [140] are listed in the next paragraphs.

Evaluator

In the evaluation process of the children's handwriting an educational therapist is marginally involved. The reliability of the therapist's judgment is influenced by several factors: current level of experience in the field, physical state of the sight, clarity of precise instructions to the children, etc. For this reason, the final decision of the therapist is more or less subjective. To ensure the objectivity of the assessment, more evaluators should be involved in the procedure, but it is not a cost–effective solution.

Grading

There is a still ongoing discussion regarding measurements of readability (height, width, slant, spacing, degree of line straightness, shape, merit of writing [125]). Also in the matter of criteria such as legibility the evaluation is executed differently: BHK scale is using only binary classification, but HPSCQ–C uses 5-point Likert scale, etc.

Assignment

Examiners can choose various handwriting tasks with different level of complexity and rationale behind them. It is a known fact, that the type of assignment affects the performance outcome [178].

Instructions

The final handwriting performance is also affected by the precise instructions given by the evaluator to the child. Instructions of such kind as: "write as you usually do" or "try to write as you are used to, when you try to write well", could lead to significantly different handwriting performances. So, it is up to the evaluator's integrity, to hold to the same sentences. Also, it is up to the children's previous experience, how it will carry out the instructions.

Writing environment

In some cases children are writing on lined paper, in other on unlined one. Also they can use an inking pen as well as a pencil. As common sense dictates, these various combinations create different environments, where handwriting performance can be also very different.

Writing style

Individuals have different writing styles. They can slightly change during the day or even during the same written passage. Developmental scales need to be sensitive enough to not falsely evaluate children handwriting as problematic. Children with handwriting difficulties may express behavior such as stress, fatigue, or tendency to take breaks during handwriting. These factors need to be also properly observed and quantified.

System of scoring

The whole process and administration of handwriting evaluation should be less time-consuming. Now educational therapists make all processes subjectively and independently on any scales. Due to this fact, the evaluation is still costly, time–consuming, less efficient and child could be misjudged.

Measurements

Time is most commonly measured physical variable in the commonly used handwriting evaluation tools. The normal handwriting without any difficulties is performed in an adequate amount of time and is legible at the same time. Other measurements are performed by the evaluator, who assess attributes of handwriting (number of letters per minute, overall time etc.). This subjective approach lacks accuracy and is unable to measure the time–dependencies of particular strokes of handwriting.

1.2 Online handwriting

The online handwriting (OH) represents a transformation of a regular handwriting process into quantified signals. This transformation is accomplished by the electronic equipment called digitizer/tablet and stylus. The digitizer contains a surface area, on which the handwriting is executed, and the stylus that substitutes a classical writing pen. Moreover, the electronic stylus has an inking tip, which offers almost the same feedback to the writer as a regular pen. This hardware is able to assess several physical variables and convert them into the signals with the sampling frequency around 133 Hz. The digitizers were primarily made for artists, but the several vendors offer open–source libraries for their products, which enable to program unique interfaces specifically designed for the research [108].

During writing an A4 paper is laid down and fixed on the surface of the digitizer. Extracted signals are the following: position of the pen on the digitizer surface ($x-$axis/$y-$axis of on–surface position), position of the pen in air above the digitizer surface as well ($x-$axis/$y-$axis of in–air position), azimuth and tilt of the pen (see Figure 1.2), binary signal denoting on–surface/in–air trajectory (maximal distance between pen and the digitizer surface is 1.5 cm) and pressure of the pen tip on the surface of the digitizer. Since each sample of the trajectory is marked with a time stamp, the sum of signals is called online handwriting.

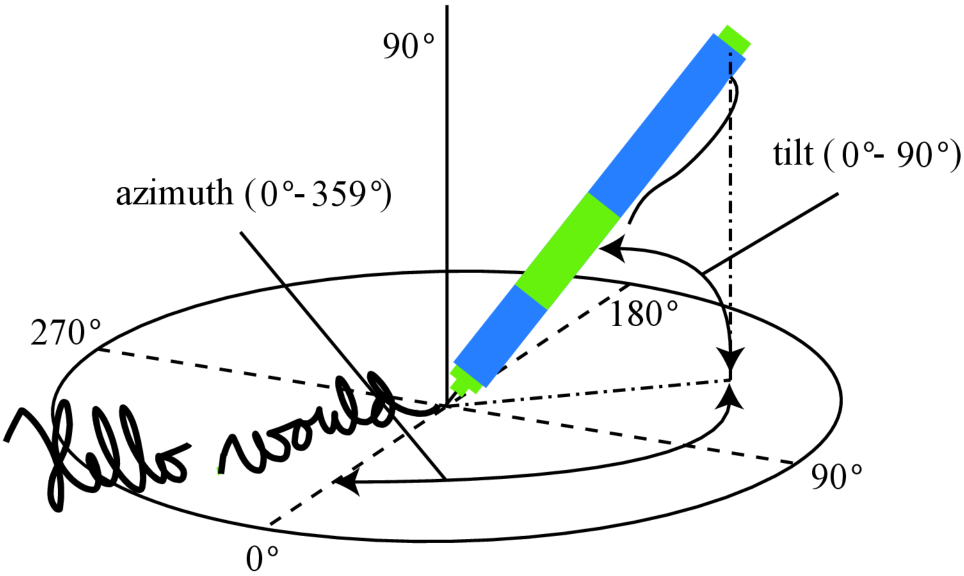


Fig. 1.2: The online handwriting signals assessed by the digitiser: $x-$axis/$y-$axis position, azimuth and tilt.

The quantification of the handwriting process into OH signals enables objective analysis of the process and partially of the product (see Section 1.1.3) of handwriting. The raw, unprocessed signals of OH can have some minor informative value, but advanced mathematical modelling of these signals to create specific features is needed. The derived features describe temporal, spatial, kinematic and more sophisticated characteristics of handwriting (see Section 1.3). These features are analysed either at the exploratory level to determine the strength of relationships to various validation criteria (see Section 1.1.4) or at a more advanced level involving machine learning (ML) algorithms. The ML techniques are able to train models of symptoms on the basis of these features and subsequently, differentiate between typically developed handwriting and handwriting affected by graphomotor difficulties (GD). Moreover, ML models can bring a broader perspective into the identification of GD, because they are trained across the cases of the whole dataset.

Since DD cannot be diagnosed from handwriting alone, the ML models cannot fully substitute PS and SE. Nevertheless, PS and SE need an objective diagnostic tool, which will be able to measure GD which will help with further diagnostic process of preschoolers, children attending the 1 st and 2 nd class or with DD diagnosis in children attending 3 rd and 4 th grade.

For this purpose, the graphomotor difficulties rating scale (GDRS) was proposed which can bring an objective measurement of GD difficulties. To this day there do not exist any objective criteria, how to measure GD in the Czech Republic or in any other country. The design of the proposed GDRS consists of:

- Identification of GD symptoms in the handwriting from PS and SE (see Chapter 2).
- Mathematical modeling of features (see Chapters 2 and 4).
- Development of the objective scale, which can incorporate all the GD symptoms (see Chapter 3).

1.3 State of the art

The advance of technology enables the use of digitisers in DD diagnosis, which allows the acquisition of features that describe online handwriting signals. Handwriting features can be classified as temporal (e.g. duration), spatial (e.g. width/height), kinematic (e.g. velocity, acceleration, jerk), dynamic (e.g. pressure, azimuth, altitude). This list of features is not complete, but those mentioned above can be identified as the elementary features. In addition, more advanced and sophisticated features can be derived, e.g. based on Tunable Q–Factor Wavelet Transform (TQWT), fractional–order derivatives (FD), power spectrum, entropy, etc. Each child that is examined performs various handwriting tasks, that can be divided into: graphomotor elements (Archimedean spiral, rainbow, saw), cognitive tasks (complex figures, recall of complex figures from memory) and handwriting (based on dictation or transcription). This list is also not exhaustive, but the goal is to show that for assessing every aspect of handwriting different tasks are needed.

In the following summary the newest studies are presented. They cover the quantitative analysis of developmental handwriting (2016–2020) based on digitisers, and the focus of this review is mainly on the usage of various parametrization techniques, methods used for analysis and the results that were reported. The relevant topics included in this selection are DD, handwriting and graphomotor difficulties. The detailed summary of metadata from mentioned articles is compiled in Table 1.1.

Acquisition of handwriting in children with and without dysgraphia: A computational approach

Gargot et al. (2020)[57] assessed dysgraphia among French–speaking children who were scored with the BHK test. They collected a large dataset of 280 children, that consisted of healthy individuals and individuals with developmental dysgraphia, excluding comorbidities (DCD, ADHD, etc.). Together 12 features (static, kinematic, pressure, and tilt related) were extracted from online handwriting signals. The significant relationship with BHK scores expressed all the extracted features. Nevertheless, dysgraphic children (as diagnosed by a psychomotor therapist) did not differ from children with typical handwriting in the terms of BHK scores or features. The authors were also able to split cases into three clusters using K–means clustering. The groups can be described as the first containing children with mild dysgraphia, the second containing severe dysgraphia with symptoms related to the kinematic and pressure, and last containing children with severe dysgraphia displaying abnormalities in tilt.

Extending the Spectrum of Dysgraphia: A Data Driven Strategy to estimate Handwriting Quality

Asselborn et al. (2020) [7] used the BHK test in this study to evaluate a sample of children's handwriting. With the use of online handwriting features together with PCA (Principal Component Analysis) and Unsupervised learning (K–Means), they were successful in creating a new global score and four specific scores for evaluating the severity of dysgraphia. Nevertheless, the score thresholds were empirically estimated and not based upon analytic approach. The scale is based on kinematic, pressure, tilt and static (i.e. handwriting size, handwriting density, etc.) features.

Fractional Order Derivatives Evaluation in Computerized Assessment of Handwriting Difficulties in School–aged Children

In this study the goal of Mucha et al. (2019) [183] was to investigate the possibilities of using FD in the computerized assessment of HD (alphabet task) in school–aged children. FD based features brought the benefit of more robust quantification of in-air movements as opposed to the conventionally used ones. These movements are likely to include hesitation/s, uncertainty during writing, stiffness of fingers, etc., which can definitely be linked with HD and are imperceptible to an examiner that sees only a plain written product. The FD and conventional sets consisted of kinematic (velocity, acceleration, jerk), temporal (duration), and dynamic (azimuth, altitude) features. The FD feature derived from vertical velocity demonstrated the strongest relationship in the study with HPSQ–C scores ($\rho = -0.34$, $p < 0.05$).

Computerised Assessment of Graphomotor Difficulties in a Cohort of School–aged Children

Mekyska et al. (2019) [98] were trying to explore the impact of specific elementary graphomotor tasks analysis on the accuracy of computerized diagnosis and assessment of GD. A sample of 76 children were enrolled, who attended 1 st up to 4 th class in an elementary school. Authors employed a state–of–the–art machine learning (ML) algorithm called XGBoost [29], which can work well in small datasets and is able to capture non–linear relationships in the data. They identified the combined loops task as the most discriminative on the basis of classification analysis (accuracy (ACC) was equal to 79 %, sensitivity (SEN) was equal to 50 % and specificity (SPE) was equal to 89 %). The validation criteria was the HPSQ–C score in this case. Also, all graphomotor tasks (see Figure 2.1) were included in the differential and regression analysis. The feature set included mainly conventional features, such as spatial (width, height, etc.), temporal, kinematic, dynamic, and others (e.g. number of interruptions). Although the study showed a poor trade–off between sensitivity and specificity in multivariate analysis, this could have been caused by the incorrect classification made by the special educational counselor.

Automated Detection of Children at Risk of Chinese Handwriting Difficulties Using Handwriting Process Information: An Exploratory Study

In this exploratory study, Wu et al. (2019) [177] were developing classification models for handwriting process data to detect Chinese HD in children (300 cases, aged 6–7). They were able to achieve ACC equal to 77 % and SEN equal to 77 % when predicting HD using SVM classifier. The best ML model contained 7 features (dynamic, kinematic, temporal). The assessed task included 49 Chines characters. The HPSQ by teachers was chosen as a validation criteria. This was the first study introducing ML techniques into identification of HD based on the online handwriting in Chinese children.

Analysis of Kinematic Parameters Relationships in Normal and Dysgraphic Children

Authors Morello et al. (2019) [100] were analyzing kinematic and temporal parameters extracted from the handwriting movement of Italian children (68 cases, 2 nd up to 5 th grades of primary school). The children completed a sequence of "lelele", and copied as accurately as possible (A test) and as fast as possible (F test) a sentence containing all letters of Italian alphabet. Clear differences were found between normal and dysgraphic children in the relationship between the duration of stroke and amplitude of stroke features. This mutual relationship was observed in all used tasks.

Effect of Stroke–level Intra–writer Normalization on Computerized Assessment of Developmental Dysgraphia

Authors Zvoncak et al. (2018) [180] were investigating new intra–writer normalization methods (IWN) in the direction of improving computerized DD assessment based on the quantitative analysis of online handwriting. Altogether 97 children were enrolled in this study, who attended 3 rd and 4 th grades of primary school. The handwriting (copy of paragraph) was parametrized using a conventional set of features (spatial, kinematic, temporal) that were consequently normalized by four newly designed IWN. Autors employed regression analysis with an ML algorithm named XGBoost [29]. The analysed validation criteria were the HPSQ–C and HPSQ questionaires. The analysis was performed separately for each IWN technique, and also for each trajectory (altogether 20 scenarios). With the use of stroke level l_2 norm normalization of in–air features they were able to decrease the computerized DD assessment error from 22.6 % to 17.8 %. The best IWN–based ML model contained 4 more features than the conventionally–based ML model (4 features).

Inter–relationships between objective handwriting features and executive control among children with developmental dysgraphia

In this study Rosenblum et al. (2018) [130] were aiming to describe handwriting and executive functions and their inter–relationships among children with DD in comparison to controls (64 cases, aged 10–12 years, native Hebrew speakers and writers). Results indicate that children who were identified by their teachers as having DD based on HPSQ indeed showed significantly inferior writing abilities related to the performance time and global legibility. Also, children with DD had significantly higher BRIEF scores [60] than children with typical development. This indicates a lower executive function control. The only features extracted from handwriting were total time, pressure and mean of the stroke height. The relationships between features and validation criteria were discovered by employing MANOVA.

Improvement of handwriting automaticity among children treated for graphomotor difficulties over a period of six months

Wicki et al. (2018) [173] investigated the development of handwriting automaticity in young Swiss children employing a longitudinal design, including monthly measurements over six months (48 cases, aged 5 to 10 years). The study reveals a poor automaticity of handwriting movements among young children attending psycho–motor therapy, with steady improvement over time. The authors observed a persistent lack of automaticity in some children even after attending graphomotor therapy after several months. The analysed tasks were garlands, arcades, double loops and simple words. The validation criteria included fine motor skills measurements and visual perception tests. The only investigated online handwriting feature was the avarage number of velocity changes while writing (NIV). The employed analysis included Spearman's correlation coefficient and t–tests.

Automated human–level diagnosis of dysgraphia using a consumer tablet

In this study Asselborn et al. (2018) [8] developed a diagnostic methodology for assessing developmental dysgraphia. They extracted 53 handwriting features on the dataset of 298 children from France (attending 1 st up to 5 th grades of primary school), that were all scored by the BHK test. The feature set included kinematic, pressure, static (e.g. space between words, etc.), and tilt related features. The children copied a paragraph of text for 5 minutes. Deploying the Random forest classifier, they were able to achieve 96.6 % sensibility and 99.2 % specificity of the trained model. The median of power spectral of speed frequencies was selected as the most discriminative feature with the importance of 15.71 % in the trained model.

Understanding handwriting difficulties: A comparison of children with and without motor impairment

Prunty et al. (2017) [123] examined handwriting in children with dysgraphia, children with dysgraphia and DCD (Developmental Coordination Disorder), compared to children without handwriting difficulties or any significant movement difficulties (altogether 42 cases, aged 8 to 14 years, enrolled in United Kingdom). They were considering aspects of both the product and process of handwriting and also temporal and kinematic features (execution speed, percentage of pausing). More precisely, the validation criteria assessed legibility, quality of letter formation, number of words per minute, spacing, etc. The writing tasks included alphabet writing and free writing. The results were carried out by employing ANOVA. Despite the extensive range of measures, the authors in this study were unable to clearly distinguish between the dysgraphia and DCD groups. On the other hand, both DCD and dysgraphia groups displayed difficulties across the range of measures in comparison to the typical development controls, including handwriting speed, legibility, and the handwriting process measures.

Identifying Developmental Dysgraphia Characteristics Utilizing Handwriting Classification Methods

In this study, Rosenblum et al. (2017) [133] focused on identifying and characterizing dysgraphia among Hebrew writing children (99 cases, aged 8 to 9 years, 3 rd graders). Their goal was to use mainly language–independent feature extraction methods (i.e. temporal, spatial, dynamic and static features). Nevertheless, some of the proposed features were highly task dependent (e.g. number of loops, negative curvature fraction, etc.). The executed task consisted of a six–word sentence (A), repeating a single letter (B) and lower loops drawing (C). With the use of ML, they were able to train the SVM model with 90 % accuracy to identify HD. Results of correlation analysis showed features related to the total time of writing as the most significant (task A, $r = 0.57$, $p < 0.01$). The children were identified as having HD by the scores on the HPSQ questionnaire.

Identification and Rating of Developmental Dysgraphia by Handwriting Analysis

In this study, Mekyska et al. (2017) [96] were dealing with the automatic rating of DD in children using advanced parametrization techniques and the intrawriter normalization approach. All children (27) were writing in Hebrew language and were aged between 8 and 9 years. The dysgraphic children were identified via HPSQ questionnaire. The executed task included sequential cursive writing of a Hebrew letter (similar to the rainbow task – see Figure 2.1). They were able to introduce 51 new features, such as kinematic (e.g. jerk), temporal (e.g. std of duration of the on–surface/in–air strokes), spatial (e.g. length of in–air trajectory), dynamic (e.g. index of dispersion of pressure) and advanced (e.g. features based on entropy). Authors observed that features based on altitude/tilt/pressure had significant discrimination power. More importantly, the discrimination power of the proposed diagnostic methodology achieved 96 % sensitivity, and specificity (ML model CART (Classification and Regression trees); 7 features). When employing regression analysis with the ML model based on the CART algorithm, the lowest estimation error of HPSQ scores was 10 % (13 features).

Tab. 1.1: The overview of the state of the art literature

Year	Authors	Tasks	Hardware	Features	A	Analysis method	DS	Scales	Age	Grade	CN
2020	Gargot et al. [57]	Copying a text with simple mono-syllabic words and later with more complex words	WI3, WI4	TE, SP, KI	RA	Bootstrap analysis, K-means clustering	280	BHK test	8-10	-	FR
2020	Asselborn et al. [7]	5 sentences from BHK test	iPad with e-pencil	KI, DY, AD	RA	PCA, K-Means	448	BHK test	5-12	-	FR
2019	Mucha et al. [183]	Alphabet	WI Pro L (PTH-80) with WP	KI, AD	DA	Mann-Whitney U test, Spearmann cor. coef.	55	HPSQ-C	8-10	3-4	CZ
2019	Mekyska et al. [98]	Archimedean spiral, upper loops, lower loops, sawtooth, rainbow, combined loops combination	WI Pro L (PTH-80) with WP	TE, SP, KI, DY	DA, RA	Mann-Whitney U test, Spearmann corr. coef., MM (SFFS with XG-Boost)	76	HPSQ-C, special educational consellor diagnosis	8-11	3-4	CZ
2019	WU et al. [177]	Copying of 49 chinese characters	W DTZ-1200W	TE, SP, KI, DY	DA	MU (CART, SVM, ANN, NB, KNN) together with MM (SFFS)	300	HPSQ	-	-	CH
2018	Zvončák et al. [180]	Copying of paragraph	WI Pro L (PTH-80) with WP	TE, SP, KI	RA	MU (XGboost) together with MM(SFFS)	97	HPSQ, HPQS-C	9-10	3-4	CZ
2018	Rosenblum et al. [130]	Copying of paragraph	WI2 with WP GP-110	TE, SP, DY	DA	Mann-Whitney U test, Anova, Manova, Spearman and Pearson corr. coef., three stepwise multiple RA	64	HPSQ, HHE, BRIEF	10-12	-	IS
2018	Wicki et al. [173]	Garlands, arcades, double loops, word “ein” (three times each)	WI4 (PTK-640) with WP	KI	LA	Correlational analysis, Linear mixed-effects models, t-test	48	MABC-2, DTVP-2	-	0-2	SW
2018	Asselborn et al. [8]	Copying of paragraph	WI3, WI4	SP, KI, DY	DA	MU (RF), correlation analysis	298	BHK	-	1-5	FR
2018	Morello et al. [100]	Series of three cursive test (“lelele”, copy of paragraph as fast as possible and than as acurate as possible)	WI2	TE, KI	DA	T-test, Slope and intercept values of linear regression analysis	68	Standard evaluation protocols (unknown)	-	2-5	IT
2017	Prunty et al. [123]	Alphabet writing, free writing	WI4 with WP	TE, KI	DA	Anova, Ancova, Mann-Whitney U test	42	MABC-2, BPVS-2, BAS-II, teachers identification, DASH, HLS	8-14	-	EN
2016	Rosenblum et al. [133]	Copy of five-word sentences, two alphabet letters	WI2 with WP	TE, SP, DY	DA	MU (SVM, 10-fold cross validation), Pearson corr. coef.	99	HPSQ	-	-	IS
2017	Mekyska et al. [96]	Sequence of seven letters	WI2 with WP	KI, DY, AD	DA	Correlation analysis, Mann-Whitney U test, MU (LDA, RF, CART) together with MM (SFFS)	54	HPSQ	8-9	3	IS

WIx – Wacom Intuos and type; WP – Wacom Inking Pen; TE – Temporal features; SP – Spatial features; KI – Kinematic features; DY – Dynamic features; AD – Advanced features; A – Analysis type; RA – Regression analysis; DA – Differential analysis; LA – Longitudinal analysis; PCA – Principal component analysis; MM – Machine learning - Multivariate analysis; MU – Machine learning–Univariate analysis; SFFS – Sequential forward feature selection ; CART – Classification and regression tree; SVM – Support vector machine; ANN – Artificial neural network; NB – Naive Bayes; RF – Random forest; LDA – Linear discriminant analysis; DS – Database size; BHK – Brave handwriting kinder; HPSQ – Handwriting proficiency screening questionnaire; HPSQ–C – Handwriting proficiency screening questionnaire for children; HHE – Hebrew handwriting evaluation; BRIEF – Behavior rating inventory of executive function; MABC–2 – Movement assessment battery for children - 2 nd edition; DTVP–2 – Developmental test of visual perception - 2 nd edition; BAS–II – British ability scales - 2 nd edition; DASH – Detailed assessment of speed of handwriting; HLS – Handwriting legibility scale; VMI – Visuomotor integration test; CN – Country; FR – France; CZ – Czech Republic; CH – China; IS – Israel; SW – Switzerland; IT – Italy; EN – England;

2 Symptoms of GD and their quantification

As previously stated, there is a great need for precise and objective measurement methods, which would bring clarity, modernization, lowered the cost, and support the current diagnosis of DD. The online handwriting analysis provides an ideal instrument, that should be utilized and taken advantage of. The previous section provided a review of the current state of the art in the diagnosis of HD and GD based upon online handwriting analysis. The majority of newly designed features are either based upon the mentioned research or were specifically tuned for the purpose of this work. The comprehensive list of features in this chapter presents a robust mathematical model, which is utilized to assess complex symptoms of GD (see Figure 1.1). Moreover, the symptoms were identified by psychologists (PS) and special educationalists (SE). To prepare an environment where the symptoms of GD can be manifested, an extensive handwriting protocol was designed in cooperation with PS and SE.

This chapter presents altogether 76 newly designed features to assess 8 symptoms of the handwriting product and 16 symptoms of the handwriting process. The new GD assessment protocol consists of 36 different tasks which is the most detailed protocol in the field. This new approach of quantification of GD, where the combination of identified symptoms, specific handwriting/graphomotor tasks, and advanced signal processing techniques are applied, represents one of the main outcomes of this thesis.

The description of the designed protocol can be seen in Section 2.1. The next Section 2.2 provides details of the outlined quantitative methods assessing identified symptoms of GD.

2.1 The new protocol

As already mentioned in Section 1, the GA represents a coordination of complex psychomotor activities, that are in action during graphical performance, such as: handwriting, drawing, copying, painting, drafting, etc. The GA level is gradually increasing with the periodic use, but the speed of its development is individual. Nevertheless, children of the same age have their GA development usually at the same level [170].

The level of GA is used as the marker of school readiness for the preschoolers. At this age the ability to draw specific graphomotor elements, or ability to draw in general, is often observed. The level of GA can also inform about the level of the fine motor movement, visuomotorics or visio–spatial ability of the child. [15].

The important aspect of GA is also the visual feedback, which controls the spacing and orientation of the handwritten product on the page and also monitors its adequate shape. This visual feedback is a key activity in the process of copying or imitating of graphomotor elements and in a painting process as well [93].

The first graders (around the age of 6–7) should be able to draw triangle, rhombus, circle, cross, square [143, 164]. As building blocks of handwriting, several graphomotoric elements can be named: Archimedean spiral, upper loops, lower loop, combined loops, saw and rainbow. The child should be able to draw all these elements when attending the first grade at the elementary school [13].

With the maturing of handwriting other cognitive processes are also connected, such as phonological memory, range of visual attention, visual memory and adequate sequencing of individual handwritten products [93].

Individual tasks were designed with the aim to assess GA among preschoolers and also among children from the 1 st to the 4 rd grade of primary school. Therefore, the actual set of tasks for each grade is different to some extend and reflects the appropriate complexity and difficulty. To this day, such a complex protocol as this one there was not yet published. State of the art scientific literature reports researched tasks, such as writing [7] or graphomotor elements [98]. Next, all tasks of the protocol will be described with the actual template examples.

The whole protocol can be divided into three groups of tasks. The first group involves the 7 basic graphomotor tasks (see Table 2.1). Namely: Archimedean spiral (TSK1), Small Archimedean spiral (TSK2), Upper loops (TSK3), Lower loops (TSK4), Saw (TSK5), Rainbow (TSK6) and Combined loops (TSK7). The tasks were ordered from the simplest to the hardest following the developmental stages of writing. The actual tasks template can be seen in Figure 2.1.

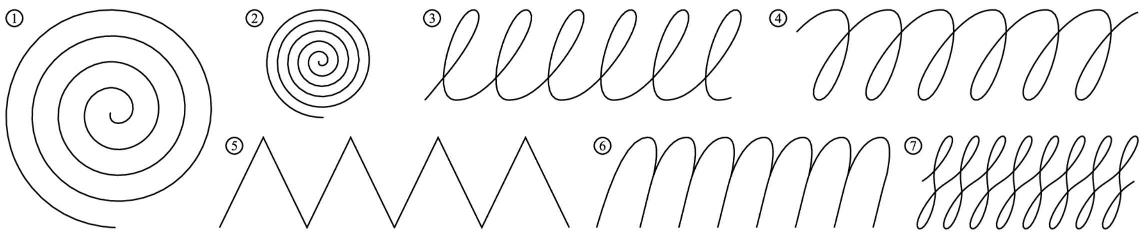


Fig. 2.1: The template for graphomotoric tasks (numbered): Archimedean spiral (1), smaller Archimedean spiral (2), upper loops (3), lower loops (4), saw (5), rainbow (6) and combined loops (7).

The tasks TSK1 and TSK2 are designed in order to compare the handwriting execution of each one of them. The smaller version (TSK2) is harder to perform due to the tighter space between each line, thus requiring a fine–motor movement activation.

Next, the tasks TSK3 and TSK4 should be executed from left to right with a single stroke. For children it is less difficult to perform TSK3, as its execution is involving counterclockwise rotation of the hand. Similarly, the TSK4 is more difficult to execute for children, as it involves clockwise rotation [14].

In order to successfully execute TSK5, the child has to be able to draw a skew line and also, to change the direction of the line. If not, the sharp edges will be rounded due to the inability of the child to properly end the drawing of the line [16].

The TSK6 can be executed by the child, when the tasks TSK3 and TSK4 have been mastered at some level. This task involves the movement, when the child has to end one curve and in the next move follow the already written line to start another curve (so–called “reverse movement”) [21].

Finally, TSK7 represents the combination of TSK3 and TSK4. Its goal is to test the children’s spatial abilities.

The second group of tasks was placed into the protocol with the aim to assess the cognitive processes that engage during handwriting. These tasks can be called Recognition and recall of basic figures (TSK8–TSK17), Advanced recall of basic figures (TSK18–TSK21), Horizontal reflection of basic figures (TSK22–TSK26) and Recognition and recall of complex figures (TSK27, TSK28). The collection of all 27 tasks is described in Table 2.2 and the template examples are illustrated in Figures 2.2 and 2.3.

The steps to complete tasks TSK8–TSK17 are the following: first the child is copying the figure (i.e. TSK8) and then the template and the drawing are covered. The child is then asked to draw the particular task from memory (i.e. TSK9). The rest of the tasks are filled in the same way, but with little differences in the templates. The dots serves as the guides for drawing a line. These tests aim to assess the visuomotor coordination (cooperation of fine motor movement together with visual perception) [90].

The tasks TSK18–TSK21 are more advanced version of previous tasks. Here the child has no dots, that would help with the guiding of the lines and also the template examples represent different sets of angles between lines that are harder to grasp.

The child’s assignment in tasks TSK22–TSK26 is to draw the tasks in mirrored/reversed version around the horizontal line. In this group the guiding dots are also present.

And finally, the TSK27 represents a unique complex figure, that the child has to redraw onto a blank paper. It is inspired by the Rey–Osterreith complex figure [126]. After 3 minutes the child has to draw the figure from memory (TSK28). In the meantime, the child is asked to fill the HPSQ–C questionnaire (which saves the total time of the protocol completion).

The last group of tasks includes writing tasks. Namely: Signature (TSK29),

Tab. 2.1: The graphomotor tasks TSK1–TSK7

TSK	Task	Grade	Description
1	Big Archimedean spiral	0–4	Archimedean spiral (left threads) approximately 15 cm high/wide with 4 loops.
2	Small Archimedean spiral	0–4	Archimedean spiral (left threads) approximately 7.5 cm high/wide with 5 loops.
3	Upper loops	0–4	Six consecutive connected loops approximately 6 cm high and 22 cm wide.
4	Lower loops	0–4	Six consecutive connected loops flipped upside down (approximately 6 cm high and 22 cm wide).
5	Saw	0–4	A saw with 4 teeth approximately 6 cm high and 24 cm wide.
6	Rainbow	0–4	Seven consecutive connected rainbows approximately 6 cm high and 20 cm wide.
7	Combined loops	0–4	Eight combined loops approximately 9 cm high and 24 cm wide.

TSK represents the abbreviation of the task; Task denotes the task name; Grade informs about the usage of the task among grades; Description denotes the physical description of the task.

Copy of a sentence written in cursive letters (TSK30), Copy of a paragraph/sentence written in capital letters (TSK31, TSK33 and TSK35 respectively), and finally Dictation(TSK32, TSK34, TSK36). The description of tasks and their content is shown in Table 2.3.

The signature task (TSK29) is not widely used in the quantitative analysis of children's online handwriting (see Table 1.1). Nevertheless, it is a well–known task used in the recognition of the health condition, such as the presence of Parkinson's disease [161] or in the identity identification [87].

The content of the sentences and paragraphs were designed by the SE specifically for each grade of the primary school and also for preschoolers. Firstly, the child is copying a sentence from a cursive writing template into the cursive writing on the paper (TSK30). In the next step the child is copying block letters into the cursive

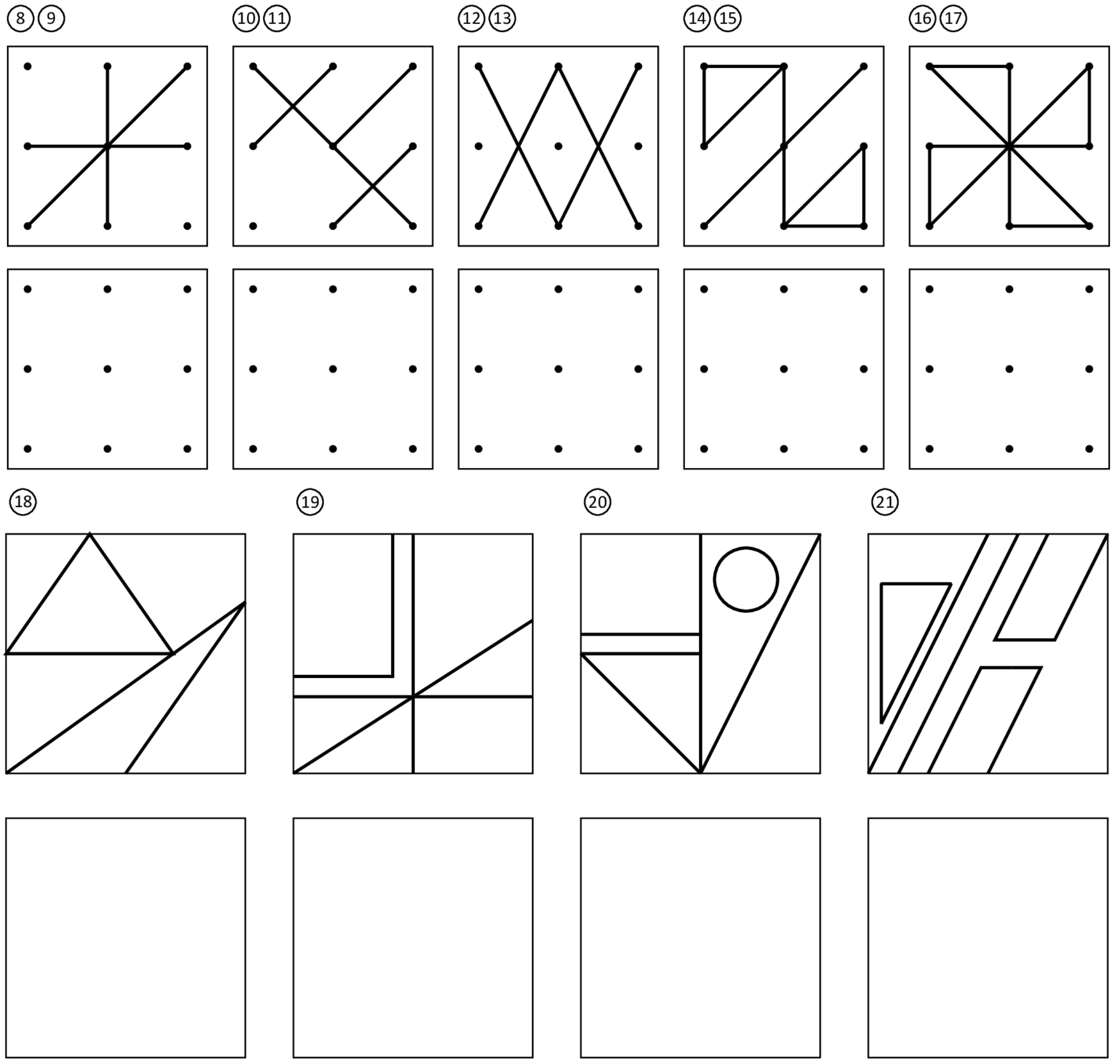


Fig. 2.2: In all the tasks above the child has to copy the figures to the lower boxes. The difference between tasks TSK8 – TSK17 and TSK18 – TSK21 is in the dots, which are helping with the guidance of the line and also in the overall difficulty. Detailed information about numbered tasks can be found in Section 2.1

writing too (TSK31, TSK33, TSK35). The last task of the protocol is a dictation (TSK32, TSK34, TSK36). It has been proved, that the dictation and the copying tasks differ, for the stimulus in dictation is auditory and in the copying task it is visual [119].

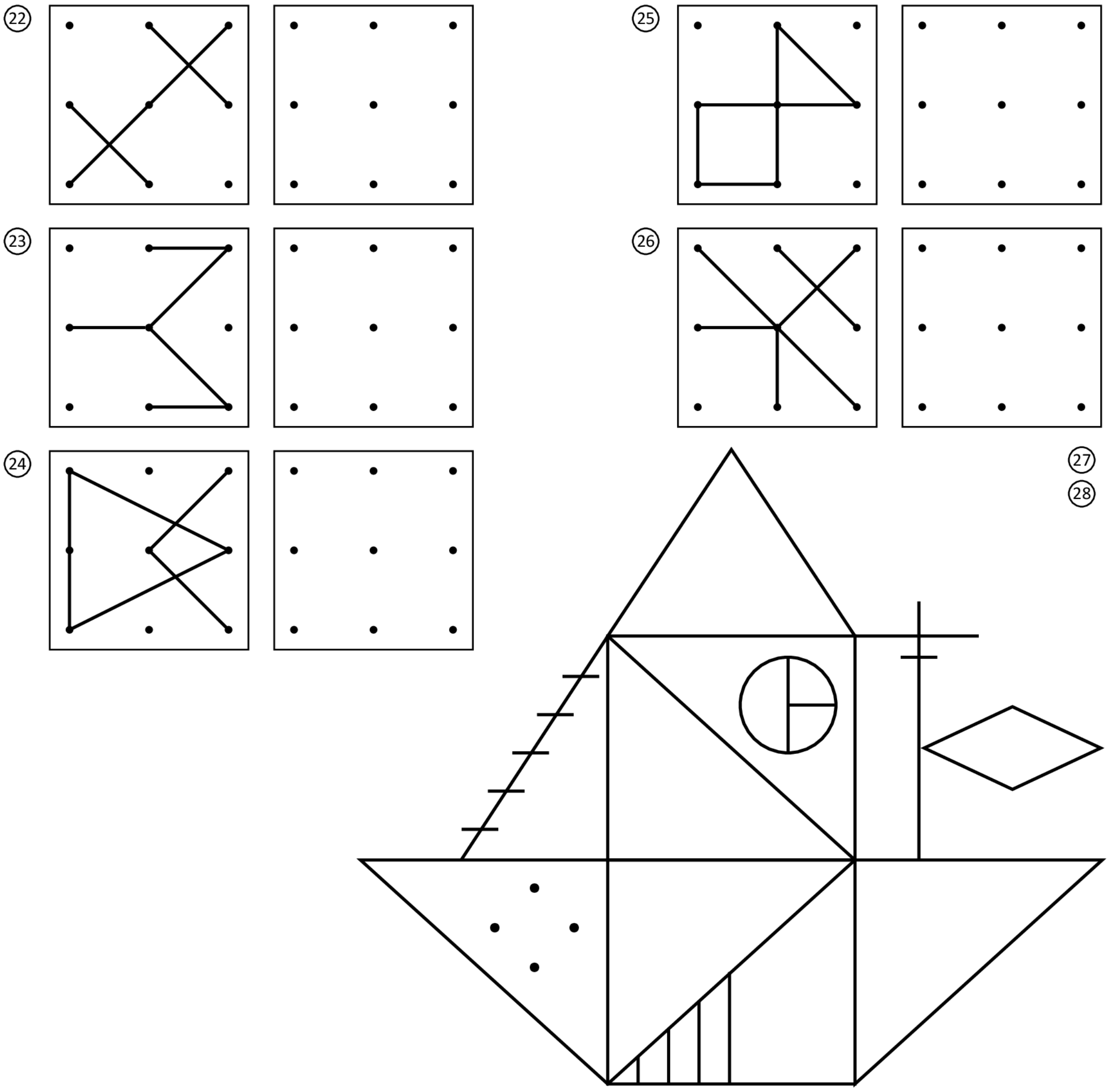


Fig. 2.3: In the tasks TSK22 – TSK26 the child has to mirror/reverse the image around the horizontal axis to the other box. Task TSK27 represents the template of the complex figure, that the child has to copy to the blank paper. After three minutes the child is asked to draw the figure from memory (TSK28). Detailed information about the numbered tasks can be found in Section 2.1

2.2 Quantitative methods and GD symptoms assessment

The following paragraphs summ up the possible symptoms of GD (see Section 1.1.3) that can be assessed by the proposed protocol and consequently by the proper quantitative analysis.

To recapitulate general symptoms that are manifested in children's handwriting

Tab. 2.2: The complex graphomotor tasks TSK8–TSK28

TSK	**Task**	**Grade**	**Description**
8–16[a]	COG of basic figs.	0–4	COG of a basic fig. which is constructed as a connection in a net of 9 points (placed in a 4.5/4.5 cm square).
9–17[b]	CALL of basic figs.	0–4	CALL of a basic fig. (immediately after the COG) which is constructed as a connection in a net of 9 points (placed in a 4.5/4.5 cm square).
18—21	COG of basic figs.	0–4	COG of a basic fig. placed in a 5.5/5.5 cm square.
22—26	Horizontal FLE of basic figs.	2–4	Horizontal FLE of a basic fig. which is constructed as a connection in a net of 9 points (placed in a 4.5/4.5 cm square).
27	COG of a complex fig.	2–4	COG of a complex fig. of a ship (printed on A4 paper).
28	CALL of a complex fig.	2–4	CALL (after 3 minutes) of a complex fig. of a ship.

TSK represents the abbreviation of the task; Task denotes the task name; Grade informs about the usage of the task among grades; Description denotes the physical description of the task; COG denotes recognition; CALL denotes recall; FLE denotes reflection; fig./figs. means figure / figures; [a] means tasks 8, 10, 12, 14, 16; [b] means tasks 9, 11, 13, 15, 17.

suffering from GD, as identified by SE and PS: the line in drawings is often uneven, hesitant and disproportional or consists of interceptions. The GD is also manifested in the higher pressure on the tip of the pen, and also in the variation of the tilt or azimuth angle of the pen. The pressure can be also deficient, which results in thinner lines. The overall handwriting strokes are executed with a wavering flow and the handwritten product contains a higher number of mistakes. The speed of writing is lower in general when maintaining the handwritten form. Moreover, the child has problems with harmonization of processes connected with fine motor movements, which leads to unnecessary movements. Also, the children have problems to incorporate the proper shapes of graphomotor elements or letters [16, 21, 86].

To assess the mentioned symptoms, several quantitative methods there were designed. Before they can be described, there has to be stated information about signal pre–processing. Section 1.1.4 introduced the online handwriting signals (see Figure 1.2). These signals are firstly divided into the on–surface strokes (a section of

Tab. 2.3: The writing tasks TSK29–TSK36

TSK	Task	Grade	Description
29	Signature	1, 3, 4	If a child is not able to sign using CU, she/he tries to perform it with the capital ones.
30	Copy of a sentence written in CU	1	"Zajíc žije v lese." – The child is using CU.
31	Copy of a paragraph written in CP	1	"Hana ráda maluje. Banány vybarví žlutě." – The child is using CU.[2]
32	Dictation	1	"Radek jede na kole. Sestra se jmenuje Katka."[2]
33	Copy of a paragraph written in CP	2	"Brzy bude jaro. Sluníčko již hřeje. Gusta a Hana tancují." – The child is using CU.[2]
34	Dictation	2	"Eva má malého psa. Lenka je na houpačce. Adámek leze do koruny stromu."[2]
35	Copy of a sentence written in CP	3, 4	"Gusta, Lenka, Hana a Stáňa jsou spolužáci. Brzy je čeká vysvědčení. Po prázdninách budou chodit do čtvrté třídy." – The child is using CU.[1.5]
36	Dictation	3, 4	"Zítra přijede strýček David popřát Evičce k svátku. Spolu s ním přijede i bratranec František. Maminka Karolína připravuje pohoštění."[1.5]

TSK represents the abbreviation of the task; Task denotes the task name; Grade informs about the usage of the task among grades; Description denotes the description of the task; CU denotes cursive letters; CP denotes capital letters; All tasks are performed on lined paper: [2] denotes 2 cm between lines, [1.5] denotes 1.5 cm between lines.

uninterrupted on–surface trajectory), in–air strokes (sections of the in–air trajectory between on–surface strokes), or they are analysed as a whole. From these sections or from the whole signals individual features are than further derived.

The naming convention of features is INF:DIR–FN (HL). The INF represents information about the feature: on–surface (ON)/ in–air (AIR) trajectory, tilt (TILT), azimuth (AZIM) or pressure (PRESS). DIR stands for direction in which the movement is analysed, such as: global (G), horizontal (H) or vertical (V). The mark FN represents the actual feature name. And finally HL stands for the statistic, which was used to convert the vector into a scalar value (optional).

Identified symptoms of GD and their quantifying features were further divided into two groups following categorization of developmental handwriting difficulties in [140]:

- Symptoms related to the product of handwriting (see Section 2.2.1).
- Symptoms related to the process of handwriting (see Section 2.2.2).

2.2.1 Symptoms related to the product of handwriting

This category contains the symptoms related to the handwriting product (see Section 1.1.3) itself, such as: spatial properties, smoothness of the written line, number of errors, etc. Altogether 8 symptoms were identified. Each symptom can be manifested in several tasks and it is adequately quantified by various features. The quantifying features are described in detail in the following section.

Dysfluency in line

This symptom was identified in all graphomotor and writing tasks (TSK1–TSK7; TSK29–TSK36). The symptom's manifestation is connected with a leading of the line, which can be disturbed by stuttering, freezing, tremor or by unevenness. Several advanced processing techniques were employed to assess this noise–like behavior of the handwriting signal. Each one of them was computed in horizontal ($x-$axis component) and in vertical ($y-$axis component) movement. As this symptom is influencing mainly the handwritten product, only on–surface strokes were selected. The computation sequence is as follows:

1. Separation to strokes (see beginning of Section 2.2).
2. Selection of on–surface strokes only.
3. Calculation of an advanced processing technique for $x-$axis and $y-$axis components.

Regarding the advanced parameters, the first one is based upon the Lempel–Ziv complexity measuring technique [1] and it is estimating the complexity of the sampled signals (ON: {H,V}–LZC). The second one is utilizing the well–known Shannon entropy, which represents a numerical measure of the randomness of a sampled signal [41] (ON:{H,V}–SHE). The next one is based on the Tunable Q–factor wavelet transform (see Section 4), which is measuring the irregularity and hidden complexity of the sampled signal by a residual of the decomposition (ON: {H,V}–SNRX). The last technique aims to assess the shaky/tremor aspect of the drawn line, by transforming a sample deviation from a global path of a line into a frequency spectrum [9]. In the next step the median of the power spectral density is calculated, where the higher values should indicate less proficient writers. This feature is called Median of power spectrum of tremor frequencies – ON: MPSTF (see Figure 2.4).

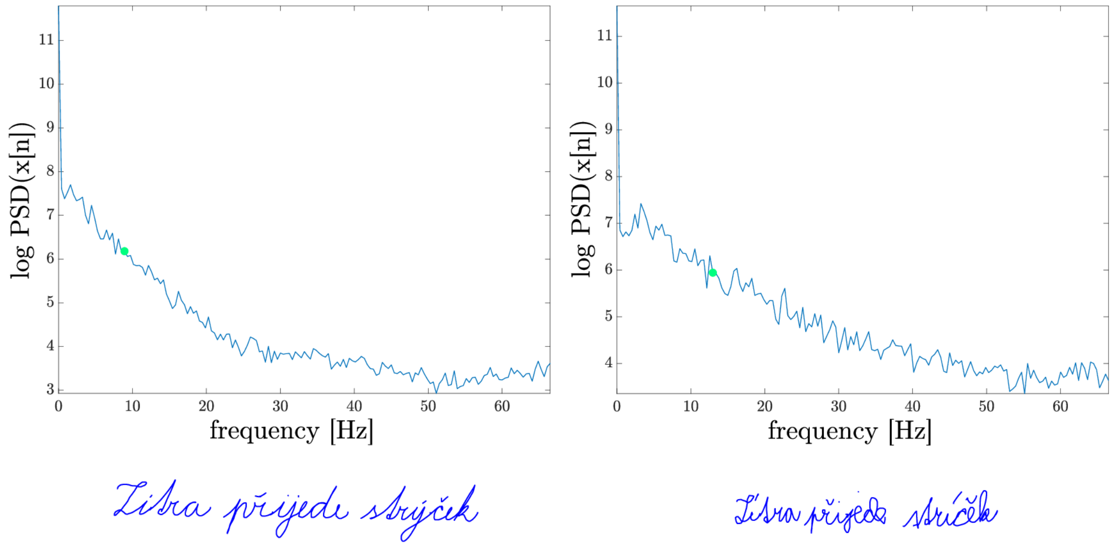


Fig. 2.4: Power spectrum density (PSD; logarithmic scale) of a sample deviation from a global path of the drawn line of the dictation task (TSK36 – text in cursive letters below the graphs represents a portion of the recorded handwriting). The left part represents a data sample from a school girl attending the 4 th grade, without GD (HPSQ–C = 5), right-handed. The green point represents the median frequency of the PSD = 8.9 Hz. The right part's data belong to the girl attending the 4 th grade (different school), right–handed, diagnosed with dysgraphia (HPSQ–C = 18). The shaky movement is manifested in the higher value of ON: MPSTF = 13.0 Hz.

The Archimedean spiral (TSK1, TSK2) is a widely used task in the identification of the severity of the Parkinson's Disease based on the quantitative analysis of online handwriting. Based on the current state of the art literature in the mentioned field [88, 124, 145] several features were employed in order to assess the Archimedean spiral and it's dysfluency in line. Firstly, the $x-$axis and $y-$axis components were transformed from Cartesian coordinates into the polar expression to have a linear relationship $a = \frac{r}{\theta}$, where r denotes the radius [cm] and θ represents the angle [radians]. On the basis of this equation, the feature called First order zero–crossing rate (1stZC) was formed, which measures how frequently this linear transform crosses its own mean (higher number indicates higher irregularity). On the other hand, the next feature called Second–order smoothness (2ndSm) measures how close this linear transform remained to its own mean. Both 1stZC and 2ndSm measures the spiral irregularity. The last feature is called Degree of spiral drawing severity (DoS), which is a 0–4 rating scale based upon the derivative of the First–order smoothness (from which the 2ndSm is derived), 2ndSm and the derivative of 1stZC. This feature measures the overall spiral execution and its irregularity on the scale as: normal – <0,1>, mild – <1,2>, moderate – <2,3> and severely abnormal – <3,4>.

Instability in amplitude of letters

Children with GD can have problems with keeping the same amplitude of particular graphomotor tasks (TSK3–TSK5). With the vertical projection of the task around the $y-$axis, there can be identified local maxima of a periodic character of the $y-$axis component. To assess the differences between each local maximum position in the $y-$axis component, the feature Non-parametric coefficient of variation (i.e. ratio between interquartile range and median) of local maxima in vertical projection – ON: V–LMAX (ncv) was employed. This parameter can describe the degree of variation in the differences between y–positions of the local maxima, where the degree should be higher for children experiencing GD in their handwriting (see Figure 2.5). To assess this symptom in the writing tasks, the feature Non–parametric coefficient of variation of stroke height – ON: SHEIGHT (ncv) was employed. The computation sequence is as follows:

1. Separate handwriting signals into strokes.
2. Select only on–surface strokes.
3. Compute height of each stroke.
4. Calculate ncv of the stroke's height.

Instability in inclination of letters

Healthy children have a more stable and firm position of the hand on the paper during writing, where they tend to fluently transition in both horizontal and vertical direction. On the other hand, children suffering from GD can exert more movement of the hand which is reflected in the change of the azimuth elevation. For this reason, the feature Non–parametric coefficient of variation of azimuth – AZIM (ncv) was extracted from writing tasks, which can assess the degree of variation of the azimuth (see Figure 2.6). Also, similarly to the ON: NCV (see the symptom: Dysfluency in time 2.2.2), the feature Number of changes in azimuth profile – AZIM: NC was extracted. In this case the analysed signal was the azimuth and any velocity wasn't calculated.

Unstable density

As the child is writing, he/she can control the same spaces between letters, words or threads of a spiral. On the other hand, a child suffering from GD is unable to preserve equal spacing and tends to have a higher variability in those distances. For

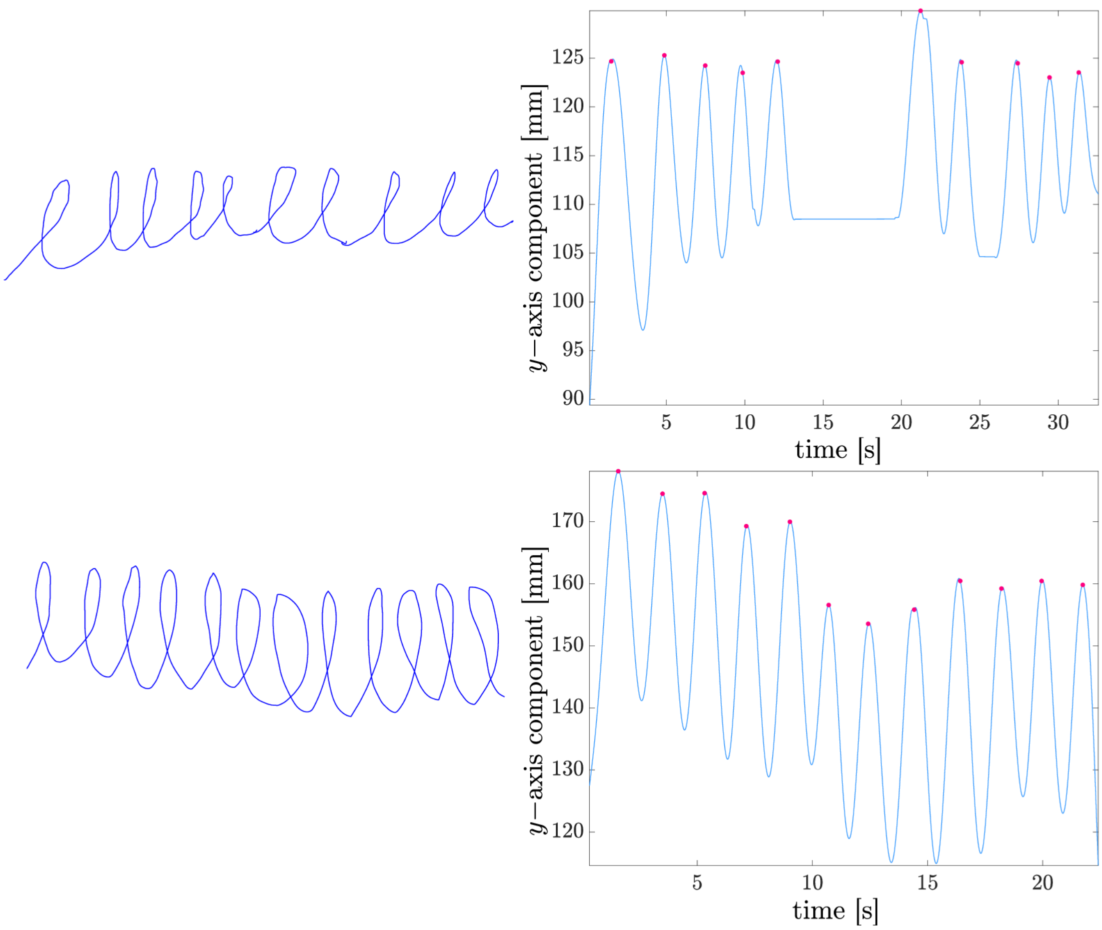


Fig. 2.5: The top row represents the TSK3 record and its adequate y−axis component (vertical projection) which is filtered by Gaussian filter. The red points on the right graph represents the local maxima values. The feature ON: V–LMAX (ncv) calculates their degree of spread, which is in this case 0.01. The upper part data belongs to a school boy attending the 3 th grade with no GD (HPSQ–C = 7), right–handed. The lower part belongs also to a boy attending the 3 th grade (right–handed), but in a different school. He was diagnosed to have a dysgraphia (HPSQ–C = 23). The value of ON: V–LMAX(ncv) is in this case 0.07, which indicates an instability in the amplitude peaks alignment.

this reason a feature from all graphomotor and writing tasks called Density of path – ON: PDEN [7, 9] was extracted. The computing sequence is as follows:

1. Select only on–surface trajectories of x−axis and y−axis components.
2. In the area around the task create a grid of cells with a dimension of 1 mm×1 mm.
3. Detect the number of samples that are present in the area of each cell and save the results into a matrix of the dimension equal to the grid.
4. Select only non–zero cells of the matrix and obtain a vector (V).
5. Calculate the mean of V.

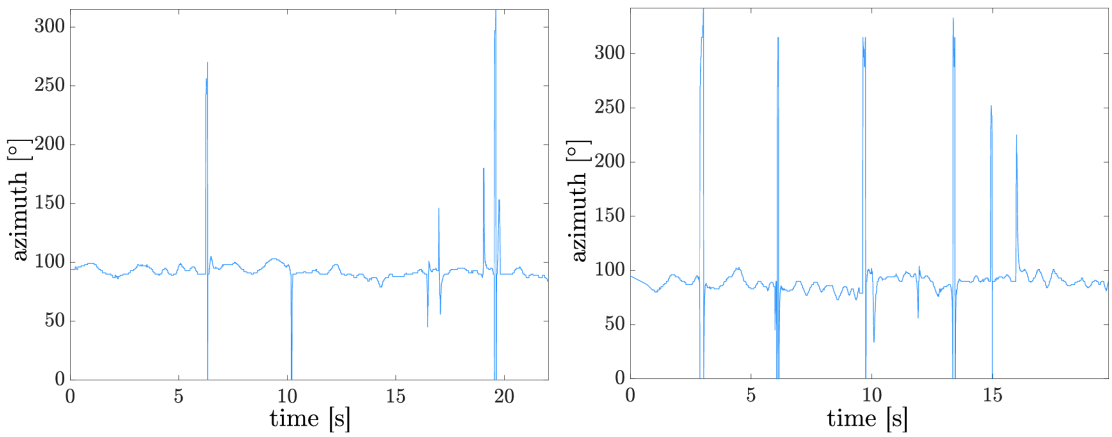


Fig. 2.6: Both graphs depict azimuth signals, which are oscillating around 90°. A digitizer is assessing the pen azimuth in degrees from 0–359 in clockwise direction, where 12 o'clock represents 0°. The peaks are caused by the transition from low to extremly high degree's values (e.g. 0 to 350°). For this reason, the feature AZIM (ncv) was used, which is calculating the degree of spread of the azimuth values, and also its non–parametric version is more resistant to outliers. Both writing recordings belong to school boys attending the 4th grade at the same primary school (both right-handed). The first one had no diagnosed problems with handwriting (left graph, HPSQ–C = 7, AZIM (ncv) = 0.05) and the second one was diagnosed with dysgraphia (right graph, HPSQ–C = 19, AZIM (ncv) = 0.1). The azimuth signals were extracted from the signature task (TSK29, name and surname).

In order to calculate the density of the samples in the created grid, a feature named Density in rectangular area around the handwriting – ON: ADEN was computed. This parameter calculates the average number of samples per grid cell (i.e. it calculates the mean of the matrix in step 3 above).

The variation of density during handwriting can be also observed in upper and lower loops tasks (TSK3, TSK4). The distances between the peaks in the horizontal movement can vary more significantly in children with GD handwriting. The described feature is called Non–parametric coefficient of variation of distance between neighbouring local maxima in vertical projection – ON: V–DLMAX (ncv). The computational sequence is as follows:

1. Select only on–surface signals.
2. Filter the $y-$axis component by a Gaussian filter.
3. Identify local maxima values.
4. Identify x positions of local maxima values.
5. Compute differences between x positions.
6. Calculate ncv of the vector of differences.

To describe the symptom in the area of the Archimedean spiral task (TSK1, TSK2) the feature called Spiral precision index (ON: SPI) implemented according to [26] was employed. This parameter is calculated for each spiral position (x and y) and angle β between the vector originating in the centroid of the spiral and the vector of movement direction. The ON: SPI is calculated as the std of the β values. The next feature used to describe density of the spiral is called Spiral tightness – TGHTNS [88]. It is computed from the polar expression of $x-$axis and $y-$axis components as the number of loops per 1 cm. The last feature is called Variability of spiral width – SWVI [88]. The computational sequence is the following:

1. Convert Cartesian coordinates in to the polar expression.
2. Separate polar data into individual loops (length of 2π radians).
3. Compute the width between each loop (N) for all degrees (matrix 360×N-1).
4. Compute the median of the spaces between loops for all degrees.
5. Calculate ncv from the previous vector.

The mentioned features were calculated (see Table 2.4) for two kids from the Archimedean spiral task (see Figure 2.7).

Tab. 2.4: Features related to the spiral density.

Status	ON: SPI [°]	TGHTNS [loops/cm]	SWVI [–]	Loops [N]
HC	20.27	0.82	0.05	3.7
DD	28.3	0.6	0.4	3.87

Status denotes healthy (HC) or diagnosed children with developmental dysgraphia (DD); features abbreviations: Spiral precision index (ON: SPI), Spiral tightness (TGHTNS), Variability of spiral width (SWVI); N stands for the number of loops.

The quick analysis shows, that even though both children drew almost the same number of loops, the variability of the width of the spiral was higher for the child suffering from GD and she also had a lower ratio of loops per centimeter. The high value of ON: SPI parameter indicates higher variety of movement compared to the healthy girl.

The last parameter, that can be extracted from specific graphomotor tasks (TSK1 – TSK4, TSK7) and from written tasks is named Number of on–surface intra–stroke intersections (ON: NIAI). First, this feature separates the task into strokes. Then, in each stroke it simply finds those spots where lines are crossing each other and calculates the occurrences. For example, children experiencing GD can make a mistake in the spiral task and upper loops together on some places. On the other hand, healthy children will perform these tasks without any interceptions. In the written tasks it is convenient to divide ON: NIAI by the duration of the task to ob-

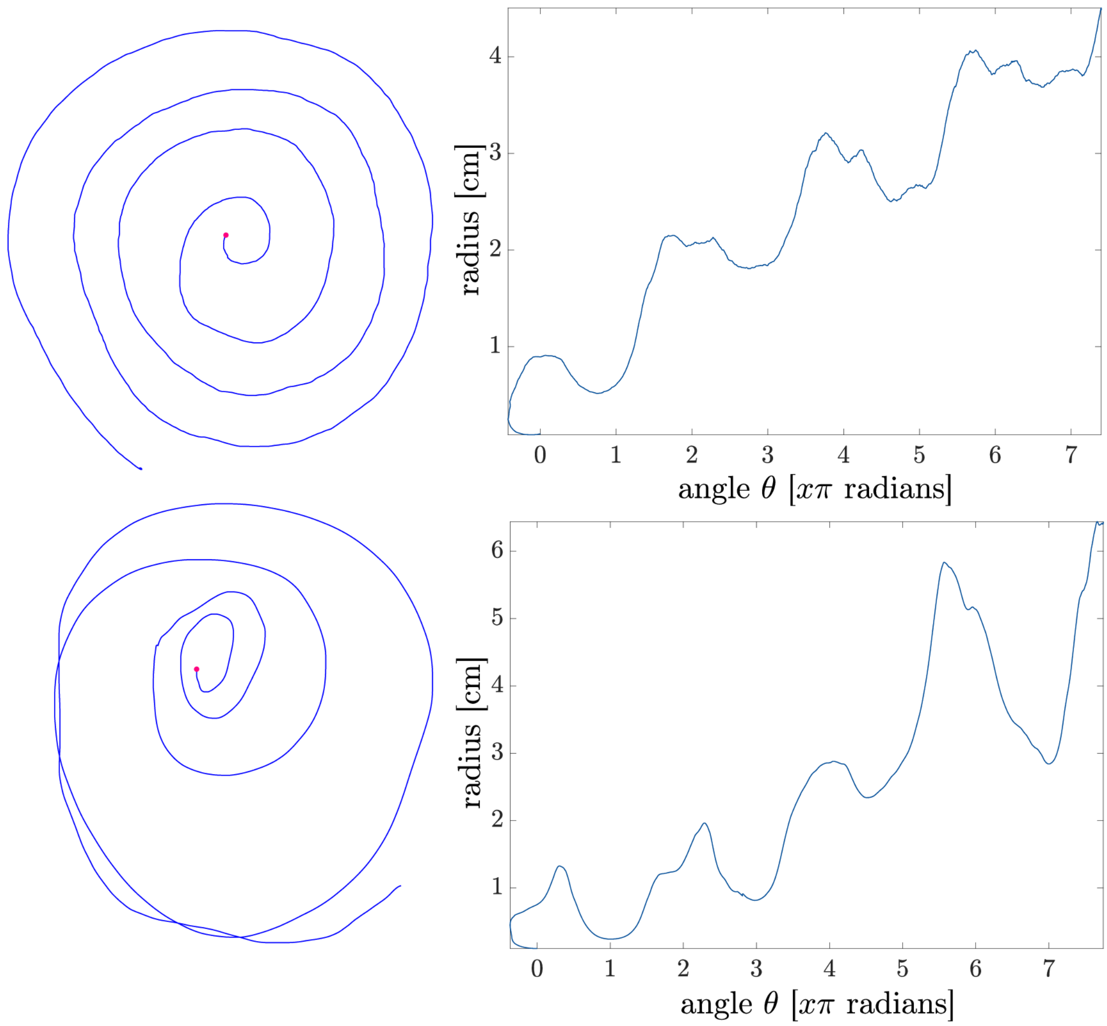


Fig. 2.7: On this figure is bigger version of the Archimedean spiral (TSK1, left part) is drawn together whit its transformation into the polar expression (right part). The red dot in the middle of the spiral marks the starting point of drawing. The top line data were derived from a school girl attending 2 nd grade with no GD (HPSQ–C $= 9$, right–handed). The bottom line also belongs to a school girl attending the 2 nd grade at primary school. But she experiences GD in her handwriting (HPSQ–C $= 23$, right–handed). The $x-$axis of the polar expression is in π radians, meaning that at $x = 6$ 3 loops were already drawn ($6\pi/2\pi$).

tain the number of intersections per second. This feature is called Relative number of on–surface intra–stroke intersections – ON:RNIAI.

Inability to maintain handwriting on a line

Children suffering from GD are often unable to maintain an imaginary horizontal line, on which the task should be performed. The tasks that are hard for children with GD to perform this way are upper loops, saw and rainbow (TSK3, TSK5, TSK6). In order to assess this symptom, the feature named Non–parametric coefficient of variation of local minima in vertical projection – ON: V–LMIN (ncv) was extracted. Again, this parameter is utilising the vertical projection of the task ($y-$axis component). After the identification of the local minima in this periodic signal, the vector of $y-$axis position values is acquired. Consequently, the ncv statistic is calculated with the aim to estimate the degree of the variation of this vector.

Inability to return back in line

This symptom is specific for the rainbow task (TSK6). This task is characterized by the so–called "reverse movement", which is occurring when the child ends one curve of the rainbow and starts to draw another one. For some distance she/he has to follow the line of the previous curve and then finish the new one. Also, the child is instructed to perform the whole task in one stroke, which is difficult for children with severe GD. To assess these interruptions the feature Number of interruptions – NINT was used. It simply calculates the number of transitions between on–surface and in–air trajectories, and vice versa. The next computed feature is called Median distance between the forward and backward lines (on a line going through the middle of the task) – ON: DFB (median). The computation sequence is as follows:

1. Select only on–surface trajectory.
2. Identify peaks (P) and valleys (V).
3. From P and V compute height of each curve (forward + backward movement).
4. Calculate threshold as 50 % of mean heights of all curves.
5. Compute width of each curve between points, that are intersected by the threshold line.
6. Calculate median value of curve's widths.

Children who are suffering from GD are unable to stick the curves of the TSK6 together and thus when the rainbow is intersected in the middle with a line, the corresponding widths of the curves will be a little bit narrower than the curves drawn by healthy children. The example of this feature is provided in Figure 2.8 where the actual widths of the curves, from which the median value is calculated are illustrated. The feature ON: DFB (median) is highly dependent on the child's style of writing, meaning that as the child is advancing in years, she/he can draw the task smaller. For this reason, a normalised version of ON: DFB (median), which is dividing the widths of the curves in the middle by the widths of the curves at the bottom (distance between local minima) was also calculated . From the figures and normalised values of ON: DFB (median) it can be derived (see Table 2.5), that the child experiencing GD is unable to correctly perform TSK6, where the width of the curve should be of constant value from the middle to the bottom.

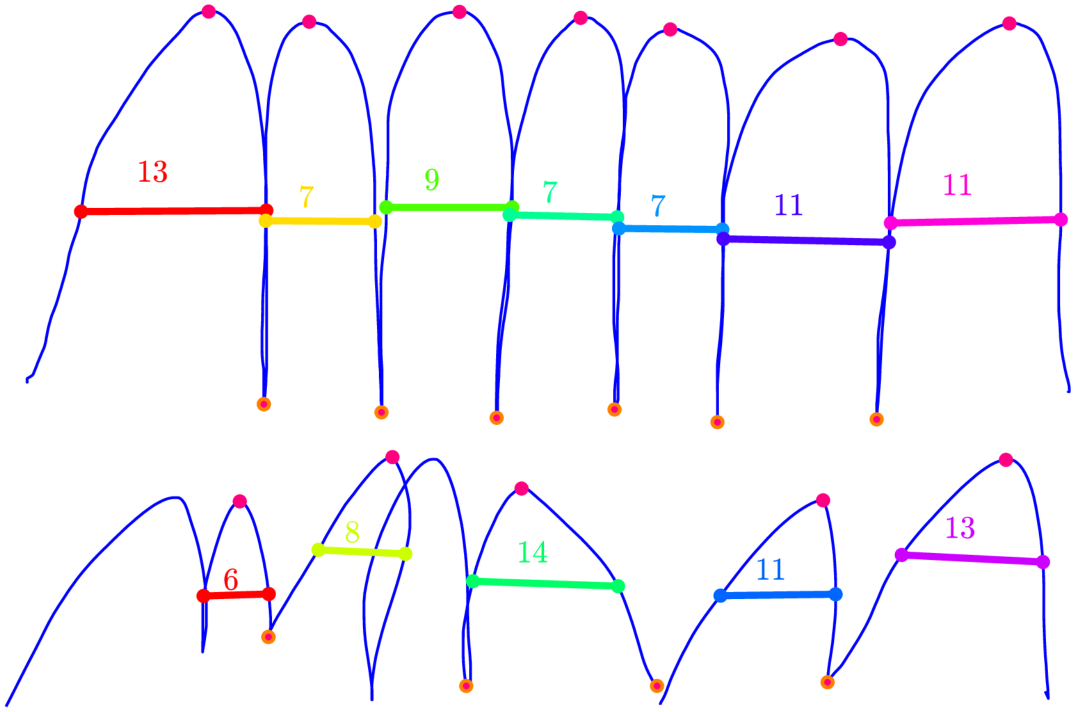


Fig. 2.8: The upper part of the picture is drawn by a healthy schoolboy (HPSQ–C = 12, right-handed) without any GD and attending 4 th grade of primary school. The lower part of the picture is also performed by a 4 th grader schoolboy, but from a different school. He was diagnosed to have DD (but the HPSQ–C = 13 is not indicating that) and he was right–handed. The drawn task is rainbow (blue curves). The red and orange dots are denoting detected local maxima and minima. The horizontal lines are symbolizing width of the specific curve at the mean height of all the curves. The numbers represents the actual calculated width in millimeters. Both pictures are drawn in a different ratio, thus the width lengths do not match. Also, the widths values are rounded.

Uncertainty in leading a line in space

The graphomotor tasks are effective particularly in assessing temporal and fine–motor movement aspects of the writing. Regarding the loop–related tasks (TSK3, TSK4, TSK7), the performance of a healthy child is marked by precise, unwavering, and continuous movement. On the other hand, children suffering from GD can often make mistakes of additional "loops". To calculate all the changes in the horizontal and vertical projection, the feature Number of changes in horizontal/vertical projection (ON: {H,V}–NC) was employed. It computes all extreme values in $x-$axis

Tab. 2.5: Median distance between forward/backward lines in TSK6.

Status	ON: DFB (median)[mm]	ON: NDFB (median)[–]
HC	8.52	1.03
DD	10.81	0.62

Status denotes healthy (HC) or diagnosed children with developmental dysgraphia (DD); features abbreviations: Median distance between the forward and backward lines (on a line going through the middle of the task) – ON: DFB (median), Normalised version stands for ON: DFB which is normalised by the width of each curve.

and $y-$axis components (firstly filtered by a Gaussian filter). The handwriting performance of children experiencing GD is often accompanied by inability to perform sudden changes of direction in the saw task (TSK5), which results in blunt tips of the saw. For this reason, the feature Median velocity at local maxima in vertical projection – ON: V–VLMAX (median) was extracted. The computational sequence is as follows:

1. Select on–surface trajectory of the task.
2. Filter the $y-$axis component (Y) by Gaussian filter.
3. Identify local maxima of Y.
4. Compute velocity vector for the whole task.
5. Identify velocity values at the Y peaks.
6. Calculate median of the peak's velocity vector.

Actual differences in the values of ON: V–VLMAX (median) for healthy and children suffering from GD can be seen in Figure 2.9. The child who has no problems with the execution of the saw task can start and stop drawing to make sharp edges which results in almost zero velocity at the local maxima samples of the $y-$axis component. On the other hand, the child that is experiencing GD is unable to make immediate changes in direction of the line, so it executes the peaks without stopping. This leads to the high velocity values at the local maxima points.

To describe the spatial properties of the saw's tips, the feature Median of width of teeth (on a line going through 95 % of particular tooth height) – ON: DFB (median) was employed. This feature was already used in the symptom Inability to return back in line for the TSK6. The difference is in the threshold value. As the children with GD tend to draw blunt teeth of the saw, the width of the tooth at the 95 % height of the particular tooth should be wider than the sharp tooth's width drawn by healthy children. Also, this feature was normalised by the mean width of all teeth in the saw. This version is called Median of normalised width of teeth (on a line going through 95 % of particular tooth height) – ON: NDFB (median).

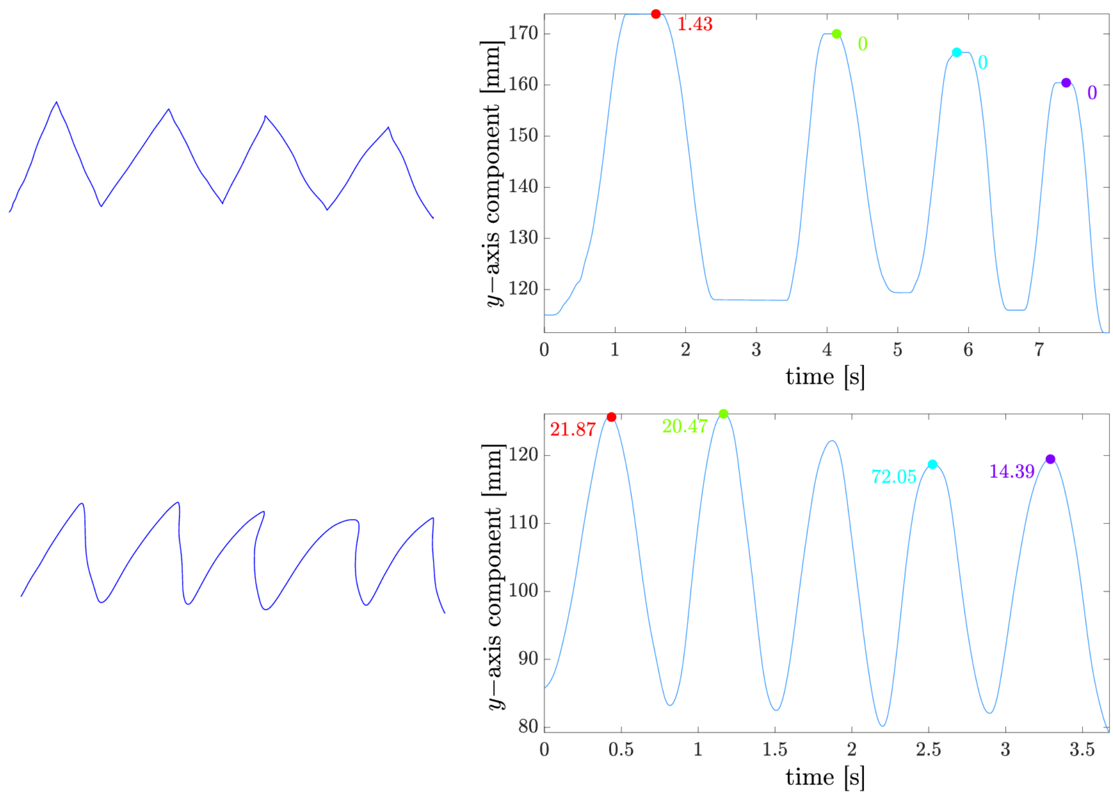


Fig. 2.9: Figure of records of saw tasks (TSK5) from two school boys attending 3 rd grade at different primary schools (both right–handed). The left part of the picture are the actual handwriting records and the right part represents the relationships of a raw $y-$axis components (vertical projection) on time. The circle points represent the velocity at given samples in millimeters per second. The position of the sample was identified as a local maximum value of the $y-$axis component. The upper line belongs to a boy who has no problems with handwriting (HPSQ–C = 5; ON: V–VLMAX (median) = 0mm/s). The lower part is extracted from recordings of a boy, who was identified as having DD (HPSQ–C = 24; ON: V–VLMAX (median) = 21.17mm/s).

Frequent overwriting

It is a common symptom among children experiencing GD in their handwriting (TSK29–TSK36), as they make more mistakes and are trying to correct them. To quantify this symptom, the feature called Number of on–surface inter–stroke intersections – ON: NIEI was extracted. The computation sequence is as follows:

1. Select only on–surface strokes.
2. Compute positions (S) of intersections (line crossings) within each stroke.
3. Compute positions (W) of intersections within the whole task.
4. Discard those positions, that are present both in S and W. Select positions

that are left – unique occurrences (U).
5. Count the number of Us.

The Czech cursive writing is organized in such a way, that generally there is almost no need to make intersections between different strokes (even when writing hooks and commas above characters, there is no intersection between them). So when an intersection between strokes occurs, it is a sign of overwriting, which can be assessed by the mentioned parameter (see Figure 2.10). Also a relative version of this feature called Relative number of on–surface inter–stroke intersections – ON: RNIEI was computed. It simply calculates the number of inter–stroke intersections per second.

Fig. 2.10: This figure shows recordings of the dictation task (TSK34) for 2 nd graders. Each stroke is visualized with a different color, which should help with optical separation. If any distinctive strokes are intersected, these spots are circled around by a black marker. The upper part belongs to a schoolboy who has no problems with handwriting (HPSQ–C = 5, ON: NIEI = 2, right-handed). The lower part belongs to a boy who was diagnosed with DD (HPSQ–C =18; ON: NIEI = 21, left–handed). They both are attending the same primary school. The duration of the upper recording lasted 128.5 seconds and the lower lasted around 112 seconds.

2.2.2 Symptoms related to the process of handwriting

These symptoms are related to the process of handwriting (see Section 1.1.3) and can negatively affect performance time, speed of writing, fine-motor tremor, pressure and handwriting fluency (hesitation). 16 symptoms were identified in this category.

Higher duration of writing

This symptom can be manifested in all graphomotor tasks and also in all written tasks. The first extracted feature is called Overall duration (DUR) and it is computed as the difference between values of the last and the first time stamp. The second one is called Duration of on–surface movement (ON: DUR). The computation sequence is as follows:

1. Separation to strokes.
2. Selection of on–surface strokes only.
3. Computation of the duration of each individual stroke (difference between the last and the first time stamp).
4. Sum of all on–surface strokes durations.

The last feature is named Median duration of on–surface strokes – ON: SDUR (median). The sequence of computation is the same as for the ON: DUR. In the 3 rd step a duration vector of all on–surface strokes is computed. The difference in this last feature is the 4 th step, where the median value of the vector is obtained.

Visuospatial deficits

This symptom's analysis is primarily aimed at assessing the children's hesitation to write a text (TSK29–TSK36), as she/he spends less time writing and more time thinking, contemplating or hesitating. The first feature is called Duration of in–air movement (AIR: DUR) and the computational sequence is the same as for ON: DUR, with the difference in in–air strokes selection in the 2 nd step. In the next step the ratio between ON: DUR and AIR: DUR called Ratio of the on–surface/in–air duration (DURR) was calculated. And finally, the last feature called Median duration of in–air strokes – AIR: SDUR (median) was calculated in the same way as the ON: SDUR (median). The only difference was in the selection of in–air strokes.

The summary of symptoms of higher duration of writing and visuospatial deficits can be seen in Figure 2.11 and Table 2.6. It should be noticed that the two boys are from different primary schools. When comparing feature values extracted from the recordings of a healthy child and a child suffering from GD, major differences can be observed. The child suffering from GD needed almost a minute more to finish the dictation, nevertheless they both spent approximately the same time writing on the surface of the digitizer. But still, the healthy child had a lower duration of the median of the on–surface strokes. When observing the visuospatial deficits, it can be seen, that the child experiencing GD spent at least twice as much time with the pen above the surface of the digitizer. The ratio between on–surface and in–air trajectories durations shows that the child with DD spends almost the same time in both trajectories, but the healthy child doesn't need that much time to spend in–air to finish the task. The median value of in–air stroke duration is also a little bit lower for the healthy child.

Tab. 2.6: Features related to the symptoms: higher duration of writing and visuospatial deficits.

	Higher duration of writing			**Visuospatial deficits**		
Status	DUR	ON: DUR	ON: SDUR$^{\mathrm{m}}$	AIR: DUR	DURR	AIR: SDUR$^{\mathrm{m}}$
HC	136.44	93.51	0.29	38.26	2.45	0.42
DD	195.67	98.71	0.43	91.79	1.08	0.64

Feature abbreviations: DUR [s] – duration, where s stands for seconds; ON: DUR [s] – on–surface movement duration; ON: SDUR$^{\mathrm{m}}$ [s] – on–surface stroke duration, where m denotes median; AIR: DUR [s] – duration of in–air trajectory; DURR [–] – ratio between ON: DUR / AIR: DUR; AIR: SDUR$^{\mathrm{m}}$ [s] – stroke duration of in–air trajectories.

Dysfluency in time

The characteristics of this symptom was identified as the abnormal variation in the velocity profile values. As analysed tasks for this symptom all graphomotor tasks and all written tasks were selected. The first parameter to measure this symptom is called Number of changes in velocity profile (ON: NCV). The computational sequence is as follows:

1. Filtering $x-$axis and $y-$axis components with a low-pass filter [148].
2. Separating signals into strokes and selection only on–surface trajectories.
3. Filtering each stroke with a Gaussian filter.
4. Computing velocity vector.
5. Calculating local maxima/minima of velocity in each stroke.

Also, the Relative number of changes in velocity profile (ON: RNVC) was calculated as the ratio between ON: NCV and the duration of the selected task. The next feature is called Median of power spectrum of speed frequencies (ON: MPSSF) [7], which is assessing the rapid changes in the velocity profile. The computation sequence is the following:

1. Segmentation of $x-$axis, $y-$axis components and the time stamp.

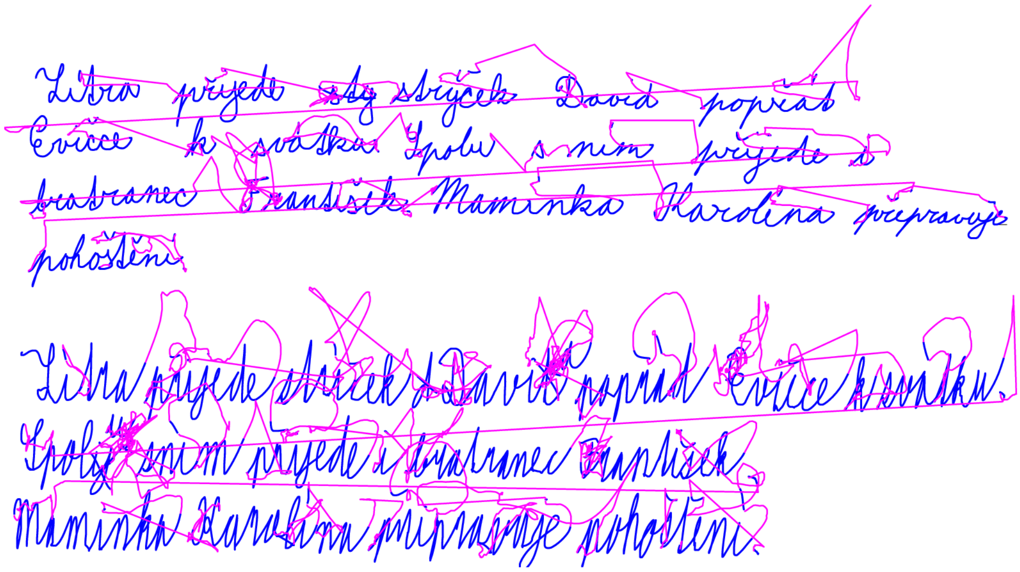


Fig. 2.11: In this figure records of dictation task (TSK36) from two schoolboys attending 4 th grade are presented. The upper part was written by the healthy boy (HPSQ–C = 17; right–handed). The lower part was performed by the boy diagnosed with DD (HPSQ–C = 19; left–handed). The blue color of characters represents on–surface movement and the magenta color denotes in–air trajectories.

2. Computing velocity vector and its Fourier transform for each segment.
3. Calculating averaged spectrum and selecting the median frequency.

These fast changes in velocity (jerks) are manifesting itself in the higher frequencies of the Power spectrum, which results in the shift of the median frequency of the power spectrum. The next feature aims to calculate the actual duration of pen stops during handwriting [120] – Number of pen stops (ON: NPS). The task is analysed as follows:

1. Calculate velocity profile.
2. Identify samples that are of zero speed or lower than 1 mm/s.
3. Pauses has to be at least 15 ms.
4. Time between the two stops cannot be shorter than 30 ms.
5. The smallest stroke duration is 100 ms [68, 168].
6. Count identified pauses.

An example of pen stops as defined in the previous paragraph is shown in Figure 2.12. The figure shows a part of the TSK35, where both healthy and child with GD are copying a sentence written in capital letters. They both had written the same amount of text, but the healthy child was able to perform it more quickly and with fewer pen stops.

Due to the periodic nature of the graphomotor tasks TSK3–TSK7, we can obtain

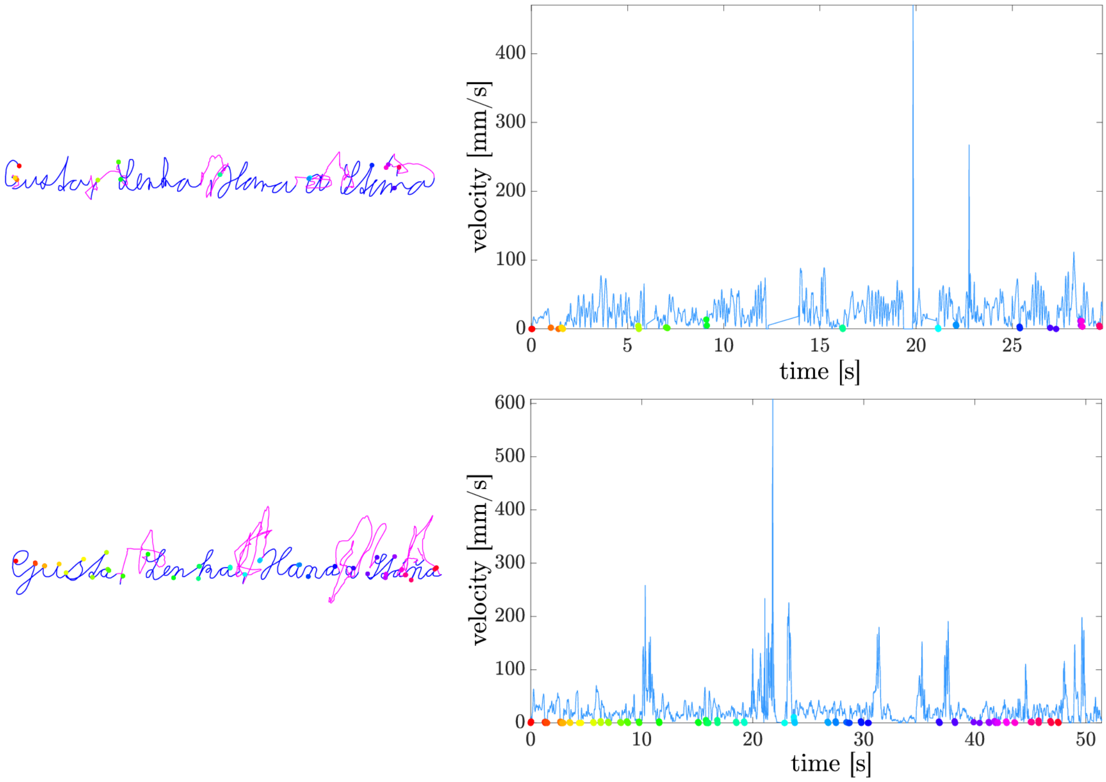


Fig. 2.12: This figure shows a part of the TSK35 (a copy of a sentence written in capital letters) executed by two schoolboys attending different primary schools at 4 th grade. The upper part belongs to the healthy boy, who has no problems with handwriting (HPSQ–C = 11; right–handed). The lower part is a record of handwriting performed by a boy who was diagnosed with DD (HPSQC–C = 22; right–handed). On the right part of the figure are graphs describing the velocity of writing in time in both trajectories (on–surface/in–air). The peaks in the velocity graphs are caused by the transitions between on–surface/in–air trajectories (sometimes the pen is lifted so high, that it can't be detected anymore – the maximum is around 1.5 cm above the surface of the digitizer). The points are denoting actual pen stops. The healthy child produced 14 and the child with GD 43 pen stops. The blue colored lines on the left represent the on–surface movement and the in–air movement is drawn by a line in magenta color.

a periodic function similar to a harmonic function when observing the task in the vertical projection ($y-$axis component). If we identify local maxima, we can calculate the duration between each one of them. This vector of intervals between neighbours (vin) can be described by the scalar value, such as a non–parametric version of the coefficient of variation, which is calculated as: iqr(vin)/median(vin), where iqr denotes the interquartile range. This coefficient is able to determine the degree at which the data varies and this particular version should be more resistant to outliers.

The name of the new feature is Non–parametric coefficient of variation of duration between neighbour local maxima in vertical projection – ON: V–DURLMAX (ncv).

Progressing fatigue

As the children suffering from GD experience higher cognitive demand and their handwriting is not fully automated, their ability to maintain stable performance is decreasing with time. This symptom was assessed in the writing tasks TSK29–TSK36. All features were describing mainly the temporal domain of this symptom. The first feature is named Slope of duration of strokes on–surface – ON: SDUR (slope). The computational sequence is as follows:

1. Separate writing into strokes.
2. Select on–surface strokes.
3. Compute duration of each stroke.
4. Compute the slope of the regression line that fits the vector durations.

The next feature is called Slope of duration of strokes in–air (AIR: SDUR (slope)) and it is computed in the same way as ON: SDUR (slope) with the change of the analysed trajectory. The last feature expresses the ratio between ON: SDUR (slope) and AIR: SDUR (slope) and it is called Slope of ratio of the on–surface/in–air stroke duration – SDURR (slope).

Low tempo

The progressing fatigue is also accompanied by low tempo of handwriting when maintaining the legibility or neatness. The low tempo can be observed also in written tasks TSK29–TSK36. The first feature assessing this symptom is called Number of on–surface strokes normalised by on–surface duration (ON: TEMPO), which can be divided into following steps:

1. Separate writing into strokes.
2. Select only on–surface trajectories.
3. Compute the number of on–surface strokes.
4. Compute the duration of all on–surface strokes.
5. Calculate the fraction of the number of strokes and the duration.

The next feature called Number of in–air strokes normalised by in–air duration (AIR: TEMPO) is almost the same. As can be seen from the name, the difference is in the analysis of in–air trajectories.

Manifestation of both mentioned symptoms can be seen in Figure 2.13 and correspondingly in Figure 2.14. On the first figure recordings of TSK35, seperated into in–air and on–surface trajectories with adequate colors are drawn. The colors were chosen with the aim to get a grasp of individual stroke durations and also of their alternation as well. The coloring was transformed into the graphs, where these stroke durations are plotted against their rank within the movement trajectory. Also, to show the possible fatiqge during this particular task, a line was drawn to fit the trend of the particular movement. Negative slopes for the boy suffering from DD (see Table 2.7) can be seen, indicating that the task execution is for him more challenging than for the healthy boy. Also, the healthy child had a little bit higher tempo when writing on–surface, or when hovering with the pen above the surface of the digitizer.

Tab. 2.7: Features related to the symptoms progressing fatigue and low tempo.

Status	ON: SDUR^{s} [–]	AIR: SDUR^{s} [–]	ON: TEMPO [–]	AIR: TEMPO [–]
DD	$-5 \cdot 10^{-3}$	$-6 \cdot 10^{-3}$	1	1
HC	$4 \cdot 10^{-4}$	$6 \cdot 10^{-4}$	1.2	1.3

Feature abbreviations: ON: SDUR^{s} – Duration of strokes on–surface, where s denotes its slope; AIR: SDUR^{s} – Slope of duration of strokes in–air; ON: TEMPO – Number of on–surface strokes normalised by on–surface duration; AIR: TEMPO – Number of in–air strokes normalised by in–air duration. HC indicates the healthy child and DD describes the child diagnosed with developmental dysgraphia.

Low velocity

The low velocity symptom can be assessed in all graphomotor tasks (TSK1–TSK7) and also in all written tasks (TSK29–TSK36). The velocity can be measured in several directions and for this reason the feature Median velocity is computed in all projections (horizontal, vertical, and global) – ON: {G,H,V}–VEL(median). The sequence of computing is as follows:

1. Separate handwriting signal into strokes.
2. Select only on–surface strokes.
3. Compute velocity in all projections and for all strokes.
4. For each projection vector of velocity compute its median.

The next feature is similar to the previous one. The difference is in the final transformation from vector into scalar values, where the 95 th percentile was used in order to identify the velocity threshold, below which 95 % of values may be found. The feature name is 95 th percentile of velocity – ON: G,H,V–VEL(95p). In the next step the Archimedean spiral (TSK1, TSK2) was also analysed in order to assess its Mean drawing speed (MDS) [88]. Again, the computation sequence is as follows:

1. Convert $x-$axis and $y-$axis components into cm units.
2. Calculate precise duration of each segment in absolute values.

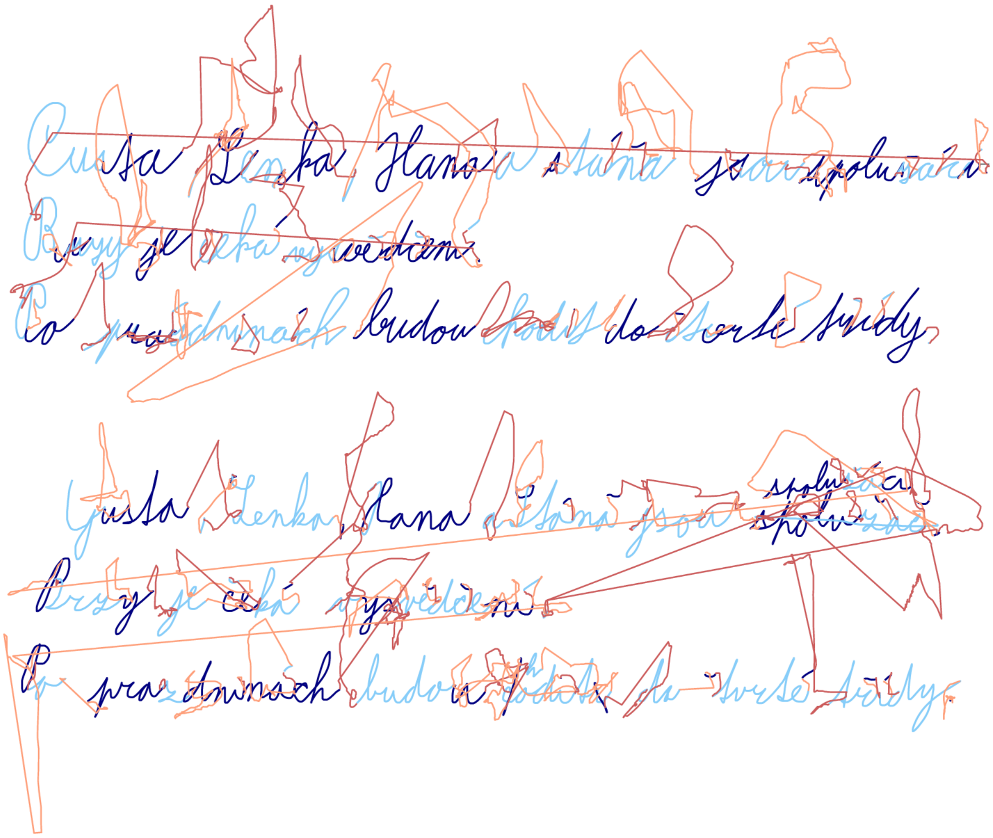


Fig. 2.13: This picture shows the recording of a copying of paragraph (TSK35), where children had to transcribe a capital text to a cursive one. Both children are 4 th graders from the same primary school. The first one (upper part) is a boy, that has no problems with writing (HPSQ–C = 11; right–handed). The second one is also a boy, but he was diagnosed to have dysgraphia (HPSQ–C = 17; right–handed). Each trajectory is drawn in two colors, that are rotating in each stroke. The on–surface trajectory is represented by blue shades and the in–air trajectory is represented by red shades.

3. For each duration segment calculate adequate traveled distance of a line.
4. From both vectors calculate their means.
5. Calculate fraction of mean length and mean duration.

Low acceleration

As mentioned already in several previous symptoms, children with GD are generally slower during writing/drawing. This can be exhibited also in lower acceleration of hand movements. Similarly to the previous symptom, even in this one graphomotor and drawing tasks (TSK1–TSK7; TSK29–TSK36) were selected as assessing tasks. Even the extracted features were the same, the only difference

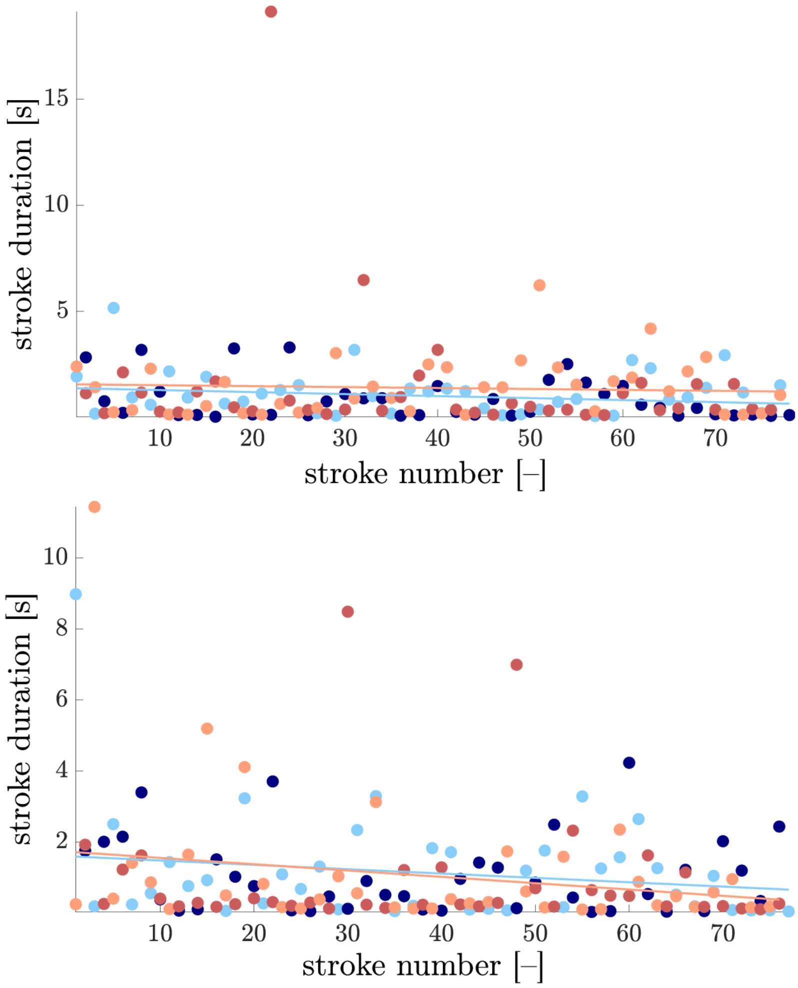


Fig. 2.14: These figures represent the relationship between the individual stroke duration and its rank in time. The blue shaded points represents durations of individual on–surface strokes with alternating color. Also, the in–air strokes have an alternating color, which has the red shade. The stroke number corresponds to the rank within each stroke's trajectory. The stroke duration trend for both trajectories is estimated by the regression line with adequate color. The upper part represents healthy writing and the lower part is a writing affected by GD. The lower graph shows, that not even is the writing performed by strokes with overall lower duration, but also, the trend indicates that the stroke span is slowing down with time.

being the analysed signal (point 4 in previous computation sequence for the parameter ON: {G,H,V}–VEL(median)), which was acceleration. The new features were called Median acceleration – ON: {G,H,V}–ACC(median) and 95th percentile of acceleration – ON: {G,H,V}–ACC(95p).

Low variability of velocity

Children with GD can write slowly, but also their writing tends to be less dynamic and monotonous and of lower variability in velocity. To assess this symptom which effects writing (TSK29–TSK36), the very same feature as ON: {G,H,V}–VEL(median) was extracted only with a difference in the descriptive time series statistic. In this case, the chosen iqr statistic was chosen, which should estimate the range of velocity excluding some outliers/extreme values – ON: {G,H,V}–VEL(iqr).

Low variability of acceleration

As it was with the lower variability of velocity, so it is with the acceleration. The less dynamic/monotonous movement can be also of low variability in acceleration. So the extracted feature is the same as ON: {G,H,V}–VEL(iqr), but the change is in the analysed signal, which is acceleration – ON: {G,H,V}–ACC(iqr).

These four mentioned symptoms are displayed in Figure 2.15, where for each symptom one feature in three different movements (vertical, horizontal, global) was selected. The analysed task was copying of a paragraph written in capital letters into cursive letters (TSK35) – an example of recordings can be seen in Figure 2.13. The source data for the radar plots [101] are put forward in Table 2.8. It can be seen that the boy suffering from DD had lower values in maximal velocity and acceleration in all directions. Also, he was not able to execute his writing in such a variability of speed and acceleration as the healthy boy (also in all directions). This overall reduced quickness of movements can be observed on the mentioned radar graphs, where the lower values of features for the boy with DD are covering a smaller area than the features for the healthy boy.

Gradually decreasing velocity

As handwriting of children suffering from GD is more cognitively and physically demanding, also a gradual decrease in velocity in time can be observed. To asses this symptom in writing (TSK29–TSK36), similarly to the ON: {G,H,V}–VEL(median), a velocity profile for all strokes in all directions was calculated. To describe the gradual decrease of velocity, the slope of the regression line was selected. Thus the new feature was named as Slope of velocity profile – ON: {G,H,V}–VEL(slope).

Gradually decreasing acceleration

As can be expected, a gradual decrease of acceleration of handwriting affected by GD can be also observed. Similarly to the previous symptom, even in this one

Tab. 2.8: Symptoms related to the velocity profile and corresponding feature values – TSK35.

Vertical trajectory				
Status	ON: V–VEL(95p)	ON: V–ACC(95p)	ON: V–VEL(iqr)	ON: V–ACC(iqr)
HC	64.29	1696.43	31.88	1049.11
DD	33.76	803.58	17.51	452.81
Horizontal trajectory				
Status	ON: H–VEL(95p)	ON: H–ACC(95p)	ON: H–VEL(iqr)	ON: H-ACC(iqr)
HC	43.76	1071.43	20.72	535.72
DD	32.86	714.29	15.01	369.9
Global trajectory				
Status	ON: G–VEL(95p)	ON: G–ACC(95p)	ON: G–VEL(iqr)	ON: G–ACC(iqr)
HC	74.61	1746.68	31.94	1072.51
DD	44.21	948.78	18.16	616.84

Abbreviations: V, H, G – vertical, horizontal and global movement; VEL – velocity; ACC – acceleration; ON – on–surface trajectory; 95p – 95th percentile; iqr – inter–quartile range; all parameters are in units of millimeters per second; HC indicates healthy child and DD describes a child diagnosed with developmental dysgraphia.

the writings (TSK29–TSK36) were selected as analysed tasks. The describing parameter is the same as ON: {G,H,V}–VEL(slope), but the only difference is in the analysed signal. The resulted name of the feature is Slope of acceleration profile – ON: {G,H,V}–ACC(slope).

Too high/low pressure on pen tip

Some children who are suffering from GD are putting too high or too low pressure on the pen during handwriting. This can be assessed in the graphomotor tasks (TSK1–TSK7) and in the writing (TSK29–TSK36) as well. The computation is fairly straightforward, where from the pressure signal of the tasks its median value is computed. The new feature is then called Median pressure – PRESS (median).

An unstable pressure on pen tip

As children suffering from GD are hesitating when writing, they can also vary in the exert of pressure on the pen tip more often, where the healthy children express a more stable pressure. To assess this symptom, all graphomotor tasks (TSK1–TSK7) and all writing tasks (TSK29–TSK36) were used. The first employed feature is called Slope of pressure profile – PRESS (slope). It is calculated as the slope of the

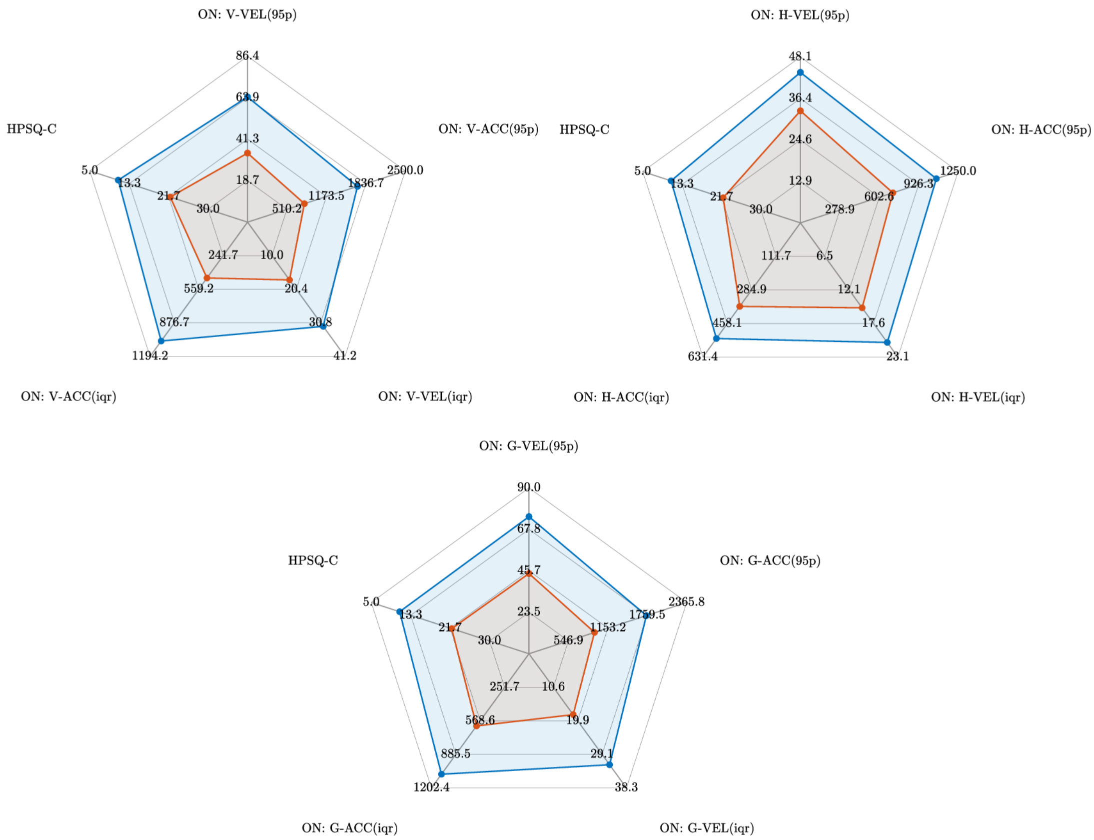


Fig. 2.15: These radar charts are describing handwriting movements from three different angles: vertical, horizontal and global (V, H, G). From each movement velocity (VEL) and acceleration (ACC) are extracted as well as adequate statistics: 95th percentile (95p) and inter–quertile range (iqr). These features were acquired from two schoolboys, who were performing TSK35 (copying paragraph written in capital letters into cursive writing). They both attended at the time the 4 th grade at different primary schools (both right–handed). The healthy boy (represented by blue color) had no problems with handwriting (HPSQ–C = 11). The other boy was diagnosed with DD (HPSQ–C = 22; red color). All axes values of features (and also of the HPSQ–C scale – which are in reversed order) were obtained from the minimal and maximum values of the analysed dataset. As these symptoms of low acceleration/velocity and their low variability are manifested in lower values of the stated parameters (but in higher values of HPSQ–C), the boy experiencing DD covers a smaller area of the radar graphs in comparison with the healthy boy.

linear regression of the pressure signal. To calculate the degree of variation of the pressure, the feature Non–parametric coefficient of variation of pressure was deployed – PRESS(ncv). Also, to count the biggest changes in the values of pressure, the Number of changes in pressure profile was calculated – PRESS: NC. The computing sequence was the same as in the feature ON: NCV, where the only differences were: 1) analysing the pressure signal; 2)the velocity was not computed.

Disability to perform longer strokes

One of the most common symptoms of GD in children's handwriting are frequent interruptions of the fluent on–surface movement and also frequent pen elevations. It can be observed in all graphomotor tasks and also in the writing tasks. The describing feature is called Number of interruptions (NINT) and it can be easily implemented as the number of transitions between 1/0 values in the on–surface/in–air state signal.

The example of symptoms related to the pressure and long strokes can be seen in Figure 2.16. In the mentioned example there is a recording of a boy with DD, who is not able to execute a combined loop (TSK7) in one stroke (NINT > 0). Also, another recording in the figure shows, that the healthy boy was able to finish loops without moving the pen in the air. Even though both boys took the same amount of time to complete the tasks, the boy with DD had twice as much changes in the pressure profile than the healthy boy (see Table 2.9). Also, his writing was executed with a smaller overall pressure – PRESS (median).

Tab. 2.9: Features related to the symptoms: An unstable pressure on pen tip and Disability to perform longer strokes.

Status	PRESS (median) [–]	PRESS: NC [–]	NINT [–]
HC	0.44	25	0
DD	0.24	56	2

Feature abbreviation: PRESS – pressure profile; NC – number of changes; NINT – number of interruptions; HC indicates healthy child and DD describes a child diagnosed with developmental dysgraphia.

Unstable tilt of pen

Children who are experiencing GD in their handwriting tend to change the elevation of the pen more often than the healthy children. This symptom can be observed in all graphomotor tasks as well as in all written tasks. To assess the degree of variation of the elevation in the tilt signal, a Non–parametric coefficient of variation of tilt – TILT (ncv) was calculated. Also, to count the number of biggest changes in the tilt elevation, the feature Number of changes in tilt profile (TILT: NC) was extracted. The computing sequence was the same as in PRESS: NC with the only difference in the analysed signal.

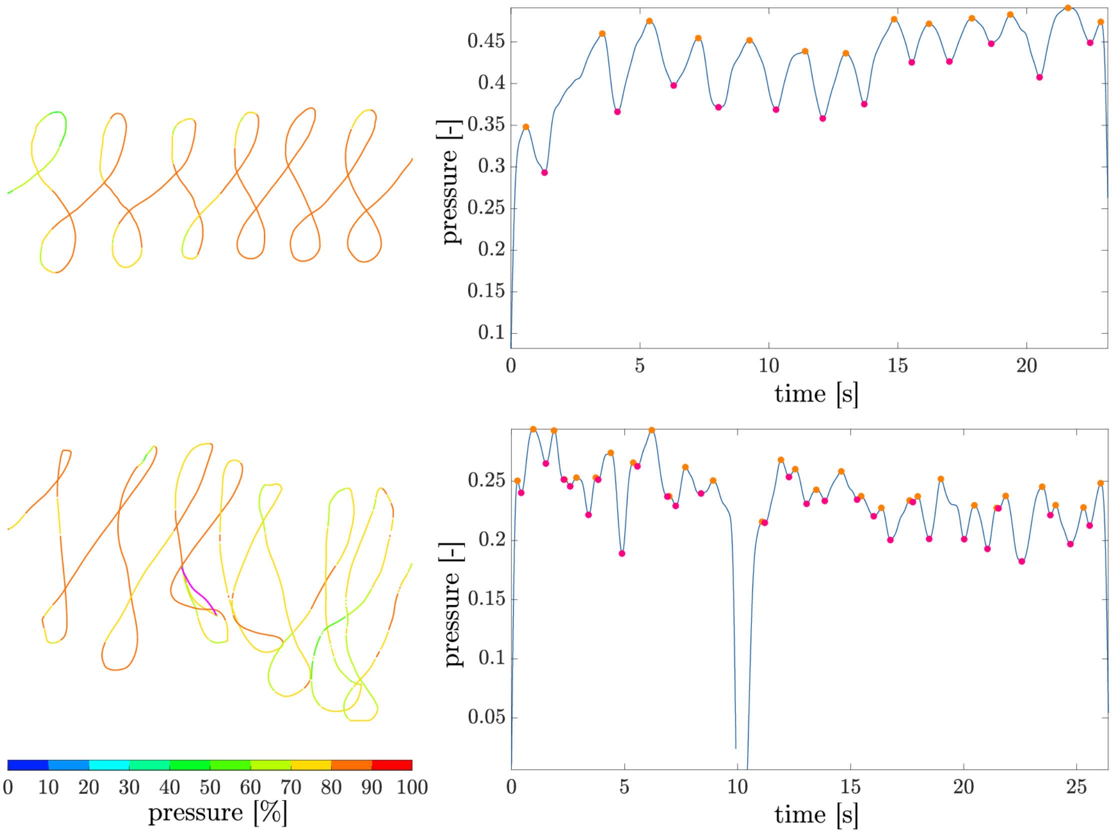


Fig. 2.16: This figure shows recordings of the task combined loops (TSK7). The upper part belongs to a healthy boy (HPSQ–C = 13; right–handed) with no handwriting difficulties. The lower part is acquired from a boy, who was diagnosed to have DD (HPSQ–C = 23; right–handed). Both boys attended the 3 rd grade at the same primary school. On the left side of the picture there are recordings of the task, where the different pressure levels are marked with a different color: from blue as the lowest to the red one as the highest. The pressure level range was derived from a pressure profile of each kid. On the right side there is plotted the pressure signal level plotted over time. The orange and the red points represent local maxima and minima of the pressure signal. On the handwriting record from the boy with DD a short in–air trajectory, which is drawn with magenta color can be seen. The pen–lift can be also seen in the pressure profile at the time around 10 seconds.

Writing under hand

Some children, who are experiencing GD have the habit of staying with the hand on one spot during handwriting. Moreover, they don't move the pen simultaneously with their hand, but instead "slide down" with the pen under their palm. To assess this symptom the feature Non–parametric coefficient of variation of tilt – TILT (ncv) was employed. As the movement of the pen is executed mainly by two fingers, the tilt angle values achieve higher variation. Also, the pressure of a tip of the pen can gradually increase/decrease, which can be assessed by the feature Slope of a pressure profile – PRESS (slope). This parameter selects the pressure signal and fits the pressure curve by line, where the slope estimates the trend in the curve. The next parameter Number of on–surface intra–stroke intersections – ON: NIAI identifies possible intersections within each stroke and counts them. Also, a relative version of this feature called Relative number of on–surface intra–stroke intersections – ON: RNIAI was employed. This features calculates the number of intersections per second. In this case, there can be estimated, that as the writing will be more dense, there will be more intersections per second within strokes. The last parameter is called Slope of stroke width – ON: SHEIGHT (slope). As the children write closer to the hand, their maneuver space is getting smaller and the width of the stroke is also getting shorter. This feature is estimating this trend by a slope of the regression line.

3 The graphomotor difficulties rating scale

In previous chapters the DD symptoms were identified with different quantifying features that can assess them. Following task, described in this chapter, is to design a scale, that can comprise the previous analytical methods and provide a measurement of the current degree of the child's GD severity. As mentioned in the chapter State of the art 1, there are no described approaches in literature, which would explain how to create a scale on the basis of extracted features and corresponding symptoms. The possible designs of graphomotor difficulties rating scale (GDRS) will be described, which have a preliminary character and it is currently the object of ongoing research funded by Czech science foundation (18–16835S: Research of advanced developmental dysgraphia diagnosis and rating methods based on quantitative analysis of online handwriting and drawing).

As previously mentioned, GDRS is mainly in a theoretical stage of the research design, but it is already ahead in several steps and its completion could lead to promising results.

3.1 Symptoms identification

In the first step general symptoms of developmental dysgraphia were identified in cooperation with special educationalists (SE) and psychologists (PS) in the Czech Republic. This different approach benefits from the acquired practical knowledge and experience of the PS and SE, who identified possible GD symptoms. Next, parameters were designed, that can describe individual manifestation of identified symptoms (see Chapter 2). This selection of analysed data enables a clearer interpretability and reduces the complexity of the designed scale.

3.2 Simulations

First, each symptom should be quantified to obtain its severity. It means, the severity could be expressed as a deviation from the normal value of a healthy child (norm). But, as will be seen from the normality tests of the related features, most of them does not have a normal distribution in analysed dataset. Also, it could be expected, that features related to the a praticular symptom can be highly cross–correlated and that the individual features will be dependent on the children's grade and sex.

To illustrate the non–normality of almost all designed features a preliminary analysis was employed on tasks TSK3, TSK4 and TSK35, TSK36. The chosen tasks serve as an examples of graphomotor and writing tasks. From the dataset of 340 children only those attending 3 rd and 4 th grade of primary school were selected (altogether 120 children). Furthermore, all selected tasks were explored and outliers were excluded from the analysis. The feature extraction included almost all designed features with exception of computation–demanding algorithms (Interceptions, Shannon Entropy, TQWT, Lempel-Ziv complexity etc). The chosen methods to discover normal distribution of features were the following:

- Kolgomorov–Smirnov test (K–S)
- Shapiro–Wilk test (SH)
- Kurtosis (K)
- Skewness (S)

Tests K–S and SH indicate normal distribution of a feature, when their p–value is not significant (p–value > 0.05). As acceptable limits for K and S were chosen ± 2 [63]. The results are shown in the Appendices A.1, A.2, A.3, and A.4. From the tests results can be concluded, that no assessed feature has a normal distribution. As these limits are very strict, the slightly lower thresholds were also considered: K and S thresholds were chosen as ± 3; SH test was omitted. The outcome of the analysis with lower thresholds showed, that only around 30 % of features extracted from writing tasks (TSK35 or TSK36) have a normal distribution. The second analysis didn't produce any improvements for the graphomotor tasks (TSK3, TSK4).

Furthermore, there is an agreement between PS and SE, that children diagnosed with DD manifest variable symptoms. In other words, there is no child with manifesting DD through only one symptom. The GD symptoms have a transient character that will mostly disappear around the 4 th grade (11 years of age). The study showed that only 1 out 10 identified children with GD problems in the 1 st year will have problems in the 4 th grade [43].

At this stage, two approaches are considered. Either manifestations of the symptoms will be examined in the whole dataset of the handwriting records, or individual symptoms will be recorded again, separately. The second approach is considered to be a less time consuming and more suitable to be controlled (i.e. the unsteady line in the loop tasks can be recorded without any other contributing symptoms, such as interruptions, or longer writing time). This step may be changed, if it turns out to be invalid. For the mentioned reasons, individual symptoms have to be simulated. Moreover, features extracted from simulations are named s–features. The simulation process consists in recording of handwriting performance under certain conditions, such as unsteady writing line, higher number of stops, changing of acceleration, higher in–air time (see Section 1.1.3). For comparison, healthy records will be recorded as well. The data will be simulated by several participants. Normal healthy drawings and writings of individual tasks will be performed by the dominant hand. The symptoms will be simulated by the non–dominant hand under specific conditions (i.e. with tremor, longer stops, etc.).

After obtaining simulation records, they will be labeled as "healthy control" or as "records with DD". The newly extracted set of s–features can be further optimized either by a genetic algorithm [46, 153, 155] or by the gradient descent algorithm. Genetic algorithms will be able to find adequate weights of each s–feature within the symptoms to obtain the final number (i.e., 1 for the DD case and 0 for the healthy one). The resulting nonlinear function will predict the value of the symptom on the basis of features (identified to be a part of the symptom) derived from real handwriting records.

The gradient descent algorithm computes the degree to which a certain feature contributes to the identification of the handwriting symptom. It identifies features as more positive or more negative in contributing to the severity of the symptom or to the normality of handwriting. The individual contributions of features can be grouped into subscore values [69].

Newly designed symptoms from simulations can be further adapted to the specific sex and age/class. Validation of the symptoms will be tested on real world data from an already acquired dataset. With enough cases a certain degree of generalization could be achieved, which can be tested on the real world data.

The simulation process ensures setting up of all identified symptoms, which could be missing otherwise, because the number and variety of cases (healthy/DD) in a dataset is limited.

The drawback of this approach is the amount of needed simulation records. Also, not everything can be simulated. Especially the in–air movement can be hardly simulated by healthy adult, even when they are experts in the field. For this reason, the symptoms, that could not be easily simulated, will be extracted from the whole dataset after a close examination of the recordings. Several validation criteria exist, that were already used in the current research and will be applied to identify children, who are considered as dysgraphic (HPSQ–C, special educationalist assessment, etc.).

3.3 Features into symptoms

The next challenge is in combining symptoms in such a way, which can result in the GDRS. As it was described in Chapter 2, the individual symptoms can be manifested by different physical phenomena, which can be quantified by several features. For example, the symptom of low velocity is quantified by the 95 % percentile of velocity (ON: G–VEL (95p)), and by the median of the velocity (ON: G–VEL (median)). A certain combination of these features represents the symptom. Consequently, a scale, created by the number of accumulated symptoms, can describe the extent of dysgraphia. Thus, the final score of the scale will not be represented by only one scalar value, but each symptom will represent a subscore of the GDRS.

The major fact to deal with is, that children (both healthy and with DD) differ significantly in the level of severity of the symptoms, and even in the values of individual features, but at the same time can be identified by the external validation criteria with the same score. For example, children identified to be dysgraphic can exert a high value of pressure on the surface of the tablet, and other dysgraphic children can exert a normal pressure force. But the problem is, that both can be identified with dysgraphia on the same level.

After the completion of the symptoms simulations (which are task–dependent), correlation analysis of the new symptoms with all feature space will be computed to exclude the possibility, that some of the significant correlated features are missing in the set of the newly created symptoms. This approach assumes, that features, which are part of the symptoms will be highly correlated with them. Furthermore, any other highly correlated features can be added to the newly created symptoms after consideration of their benefits.

To discover how the features should be summed into symptoms, measures of cross–correlations should be considered. After applying correlations into sums for each symptom, outcomes will be compared to the validation criteria obtained from evaluation by special educationalists and psychologists. If the validity rates of the new scale will be acceptable, it could be stated, that the scale based on objective measurements of critically selected symptoms of DD represents a new GDS.

3.4 Issues of GDRS designs

There are two problems, that can negatively affect both GDRS designs, which are based or validated on the real data recordings:

1. As the dataset consists of a limited number of cases of healthy and dysgraphic handwritings, the derived clusters and their discriminating ability will be negatively affected.
2. Even when the symptoms are simulated, they may prove invalid, as the recorded dataset may be missing significant cases, which would otherwise support the simulated symptoms.

Moreover, norms for sex and age will not be created because there are not enough cases in the dataset. Nevertheless, the newly created symptoms should have a downgrading trend, as the graphomotor abilities are getting better with age. The goal of this scale is to create indexes, that can identify graphomotor difficulties, not the norms for all grades.

A possible solution is to remove the influence of the sex and grades by employing the linear regression. However, the symptoms can be manifested in a form of a nonlinear relationship across grades, which makes the use of this analysis difficult. Also, for this type of reduction of the contributing variables the size of the dataset is too small.

From the psychological point of view, the simulated symptoms can be endorsed as valid if they have an anticipated progress across grades or sexes. In other words, if the overall duration of writing is getting lower across grades, or the occurrences of symptoms are lower for girls, the newly designed symptoms can be considered as valid. If the mentioned trends can be observed, the designed symptoms can be adapted for further optimization.

4 Design of new online handwriting parameters based on TQWT

Baseline features (velocity, acceleration, pressure, number of interruptions, etc.) provide in some cases, enough information for clinical interpretation of common symptoms of handwriting difficulties. But in other cases, with the use of the same task, the more advanced features can shed light on observed symptoms and bring better accuracy of quantitative analysis.

As mentioned in Section 1.3, there are already a few articles, that provide new methods for the parametrization of developmental handwriting. For example, Thibault Asselborn et al. [9] presented the Median of Power Spectral of Speed Frequencies, which had 15.71 % overall importance in the trained model (96.6 % sensibility and 99.2 % specificity). Jiří Mekyska et al. [96] presented in their study a broad set of advanced features, where for example the Teager–Kaiser energy operator [38] derived from pressure had the strongest negative relationship ($r = -0.45$, $p < 0.01$) with the HPSQ total score. And also, Jano Mucha et al. [183] were employing Fractional Order Derivatives together with conventional features in the handwriting difficulties diagnosis, where they discovered benefits of more robust quantification of in–air movements as opposed to the conventionally used ones.

As previous research confirmed, there is a significant profit from the usage of advanced parametrization techniques in quantitative analysis of developmental handwriting. But as can be seen from the current literature (see Table 1.1), the main trend in the research is to use just conventional features. To fill this gap, new advanced parametrization techniques were researched, especially the Tunable Q–factor wavelet transform method. In the next section, a general description of TQWT is presented together with two experiments based on these studies.

4.1 Tunable Q–Factor Wavelet Transform

Usually, the Q–factor of a wavelet transform is chosen according to the oscillatory behavior of the analysed signal. Either it is set to have the high Q–factor for oscillatory signals (e.g. EEG, speech, etc.) or the low Q–factor for non–oscilatory signals (e.g. images). For this purposes, the continuous wavelet transform is suitable, however continuous–time integral transforms are highly overcomplete and not always easily invertible (i.e. having an inverse transform) [33], or they cannot achieve the constant–Q property [83].

The Wavelet Transform with Tunable Q–factor (TQWT) was first published by Ivan W. Selesnick [150]. The TQWT is a modification of the Rational–dilatation wavelet transform (RADWT) [12]. The standard wavelet transform has its Q–factor fixed, and set according to the processed signal behavior [35]. The Q–factor is a measure of the oscillatory behavior of an input signal [159]. When using wavelets for analysis of oscillatory signals the Q–factor is relatively high. When processing signals with little oscillatory behavior the Q–factor is relatively low [150].

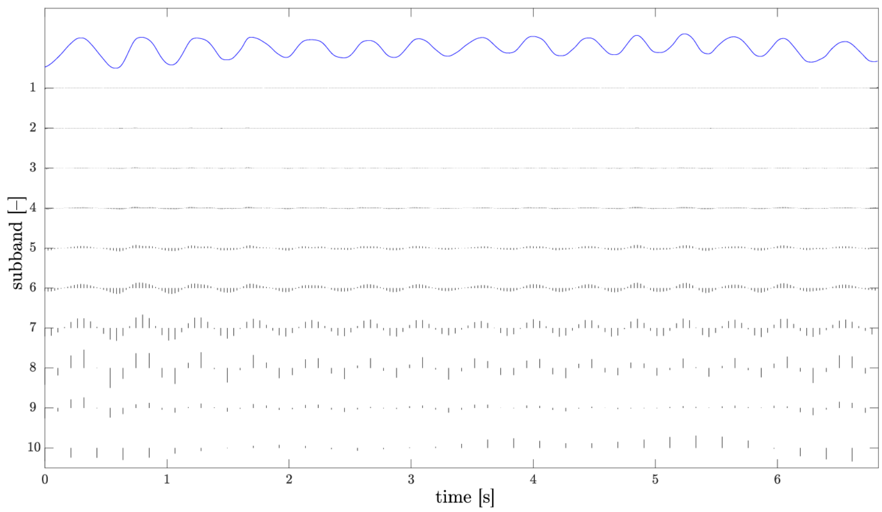
TQWT is based on two–channel filters with low–pass and high–pass stages, that are concatenated on their low–pass output [151]. This multirate filter bank can be described by the following factors:

- f_{s} — Input signal sampling rate.
- N — Length of the input signal.
- J — J-level transform (number of subbands - 1).
- α, β — Scaling factors (filter bank parameters).
- $r = \frac{\beta}{1-\alpha}$ — Redundancy of the wavelet transform (oversampling rate).
- $Q = \frac{2-\beta}{\beta}$ — Q–factor.
- $f_{\mathrm{c}} = \alpha^{j} \frac{2-\beta}{4\alpha} f_{\mathrm{s}}$ — Center frequency f_{c} of the j–th subband.

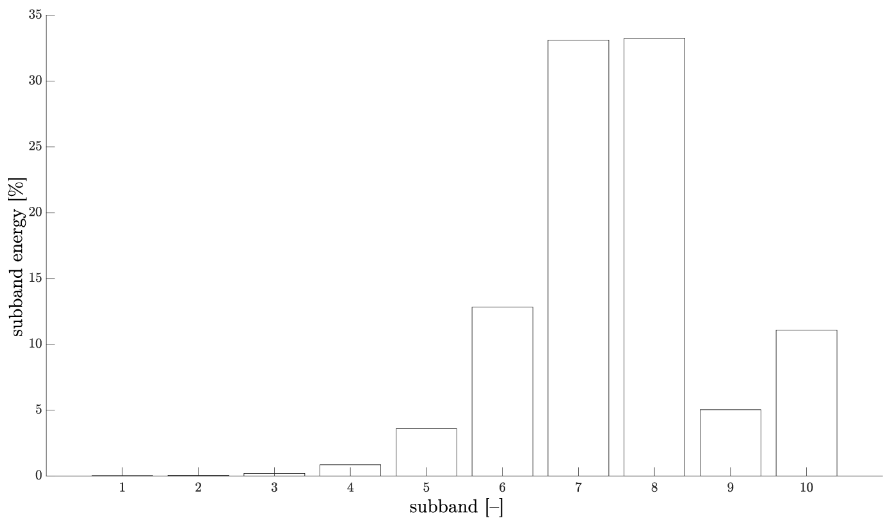
By changing Q, J and r we can make various representations of the input signal in the wavelet domain [159] (TQWT enables easy continuous Q–factor tunning). As can be seen from the definition of Q, the Q–factor is independent of the level j, meaning that the wavelet transform is a constant–Q transform [151]. The TQWT satisfies the Parseval's theorem, which means that the total energy of the wavelet coefficients equals to the energy of the signal [159].

TQWT is conceptually simple, can be efficiently implemented using radix–2 FFTs [150], and its parameters are more clearly related to the Q–factor transform [12, 151]. Moreover, a recent study reported successful utilisation of TQWT for reduction of noise in the multi–talker bubble [159]. The sparsification using an oversampled wavelet transform (TQWT) was successful in minimizing the overlapping between the signal (voice) and noise coefficients. As handwriting also exhibits periodic/oscillating character, a decomposed noise component of a handwriting signal could be linked with an unspecified clumsiness, deficient fine motor skills as well as higher complexity/entropy. This hypothesis is further tested in this thesis.

To illustrate properties of the TQWT transform, an analysis of online handwriting signal in two basic scenarios was performed. The analysis setup for the first scenario was the following: $r = 3$, $J = 9$, $Q = 1$, $f_{\mathrm{s}} = 150\mathrm{Hz}$, $N = 1024$. The original $x-$axis component was extracted from the task called "rainbow". The outcome of the first scenario can be seen in Figure 4.1a, where in the upper part there is the original signal and below are the computed ten components of TQWT, where the first line belongs to the high frequency subband of the wavelet coefficients and the last line represents wavelet coefficients of the last (10 th) low–pass subband. The distribution of the signal through all subbands is drawn in Figure 4.1b, where the indexes of subbands correspond to their f_c in reverse order (i.e. the first has $f_c = \frac{f_s}{2}$). Also, we can see in Figure 4.1b, that the distribution of the signal's energy through subbands is concentrated around the 7 th and 8 th subband.



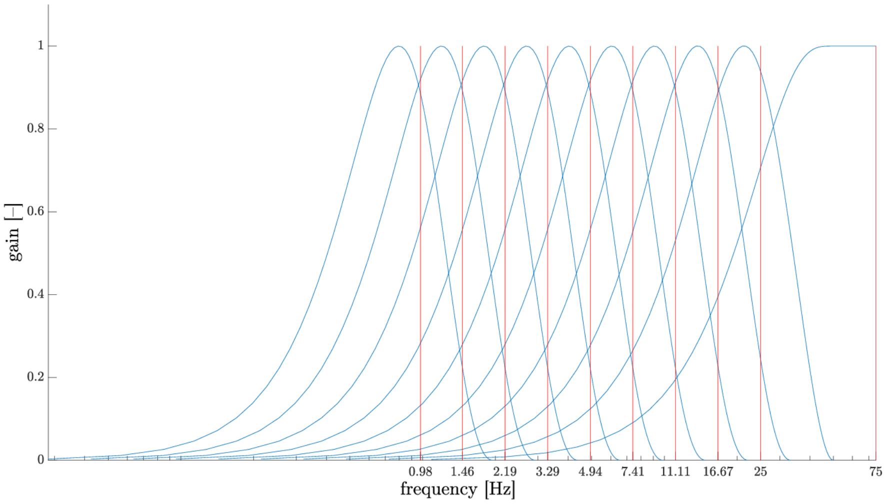
(a) The blue line represents the $x-$axis component from a "rainbow" task. The subbands are ordered from the highest f_c to the lowest. The small vertical lines correspond to the volume of each wavelet coefficient for the j–subband. Settings: $Q = 1,\ J = 9$.



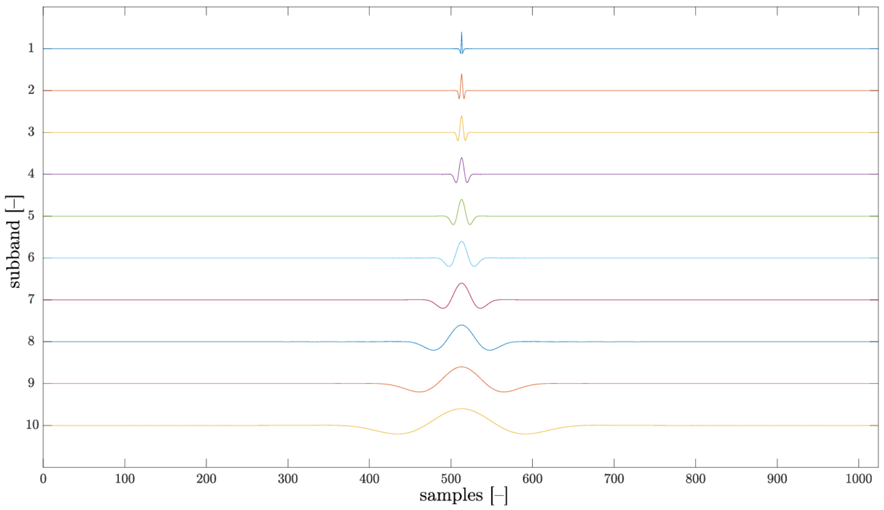
(b) Distribution of the signal energy across the all subbands.

Fig. 4.1: The subbands of the signal and distribution of the signal energy ($Q = 1; J = 9$)

The frequency response of the 10–level wavelet transform can be seen in Figure 4.2a, where central frequencies [1] of each subband are displayed on the logarithmic x−axis and on the y−axis normalized gain. The synthesized j–level wavelets can be seen in Figure 4.2b.



(a) Each red line corresponds to the subband's f_c. The f_c is approximately calculated, and its accuracy is getting worse, when approaching $Q = 1$. The x−axis is in the logarithmic scale. The gain is in normalized values.



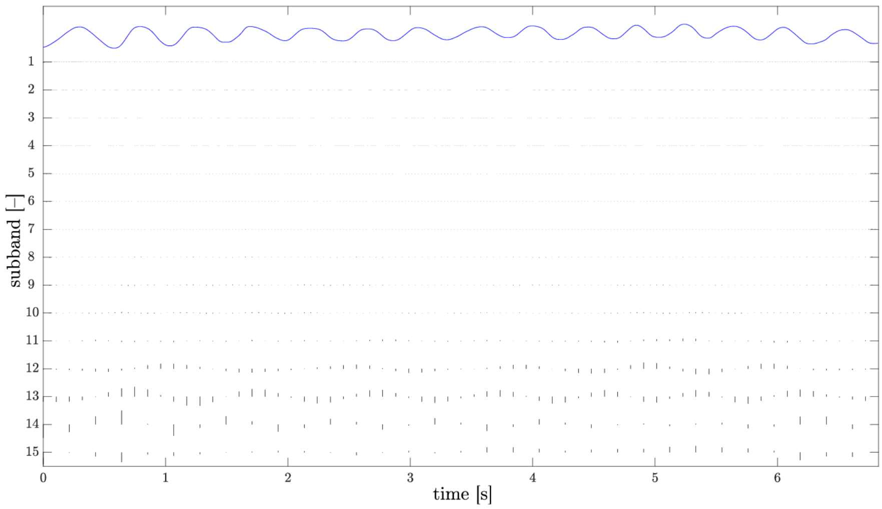
(b) Each line corresponds to only one synthesized wavelet from a j-subband.

Fig. 4.2: The frequency response of the transform and the wavelets ($Q = 1$; $J = 9$)

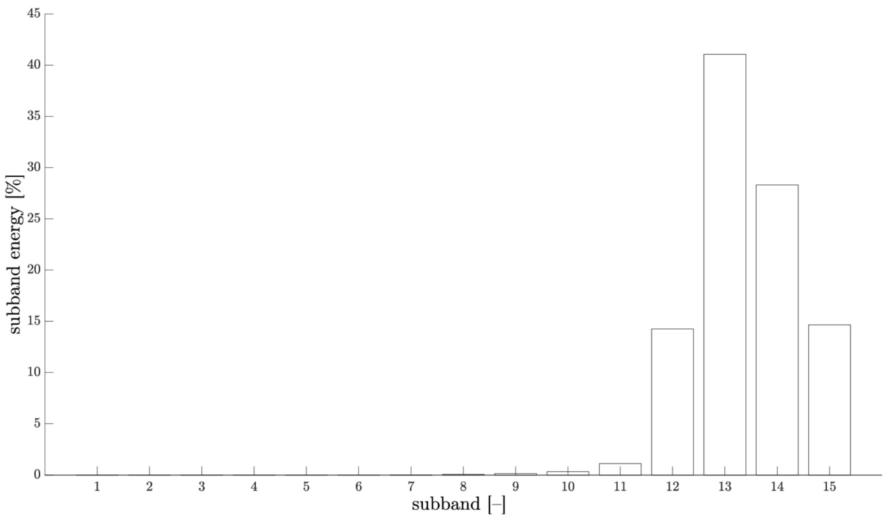
The analysis setup for the second scenario is almost the same, the only difference is in the value of Q and J: $r = 3$, $J = 14$, $Q = 2$, $f_s = 150$Hz, $N = 1024$, the

[1] The approximation equation is $f_c = 0.25\alpha^{j-1}(2 - \beta)$ and its accuracy increases for $Q > 3$.

“rainbow” task. The graphs are similarly organized as in scenario 1. The spread of energy across all the subbands can be seen in Figure 4.3a and in Figure 4.3b. We can conclude that again the mass of energy is concentrated around lower frequencies – more than 50 % of the subband energy is at the central frequencies 1.91 Hz and 2.45 Hz. Frequency response of the wavelet transform is plotted on the Figure 4.4a and finally the characteristic synthesized wavelet for each j-level subband is drawn on the Figure 4.4b.

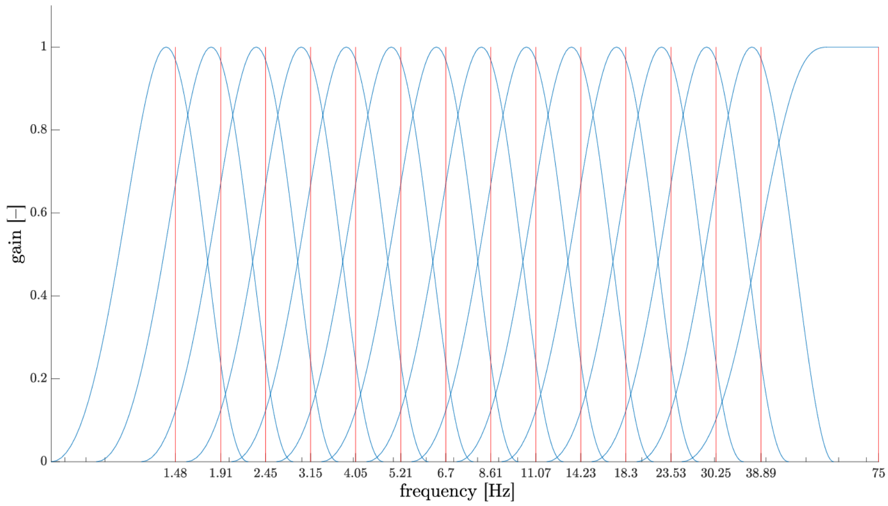


(a) The blue line represents the $x-$axis component from a “rainbow” task. The subbands are ordered from the highest f_c to the lowest one. The small vertical lines correspond to the volume of each wavelet coefficient for the j–subband.

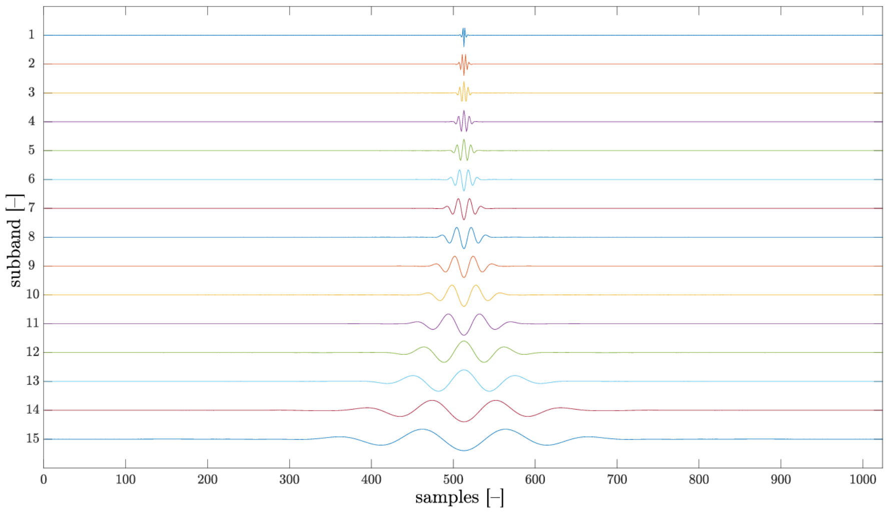


(b) Distribution of the signal energy across all subbands.

Fig. 4.3: The subbands of the signal and distribution of the signal energy ($Q = 2$; $J = 14$).



(a) Each red line corresponds to the subband's f_c. The f_c is approximately calculated, and its accuracy is getting worse, when approaching $Q = 1$. The $x-$axis is in the logarithmic scale. The gain is in normalized values.



(b) Each line corresponds to only one synthesized wavelet from a j-subband.

Fig. 4.4: The frequency response of the transform and the wavelets ($Q = 2$; $J = 14$).

We can see, that with the higher value of Q the synthesized wavelets tend to express a more oscillatory behavior, but on the other hand with $Q = 1$ the wavelets are almost non-oscillatory. This notion together with a sparse set of wavelet coefficients is further expanded. In the following chapters two studies, that are utilizing TQWT transform in the identification of HD based on the quantitative analysis of handwriting are described in detail.

4.2 New Approach of Dysgraphic Handwriting Analysis Based on the Tunable Q–Factor Wavelet Transform

Reference: Zvoncak, V.; Mekyska, J.; Safarova, K.; Smekal, Z.; Brezany, P.: New Approach of Dysgraphic Handwriting Analysis Based on the Tunable Q-Factor Wavelet Transform. In *2019 42nd International Convention on Information and Communication Technology, Electronics and Microelectronics (MIPRO)*, IEEE, 2019, pp. 289–294, doi: 10.23919/MIPRO.2019.8756872.
URL `https://doi.org/10.23919/MIPRO.2019.8756872`

This work [181] proposes a new approach of HD (see Section 1.1.2) assessment utilizing newly designed online handwriting features based on TQWT. This is the first study introducing the TQWT transform in the field of online handwriting analysis. The majority of up–to–date scientific work is based on basic handwriting features, which offer an advantage of a rather easy clinical interpretability. But the DD is associated with higher complexity of handwriting, such as deficient fine motor skills or unspecified motor clumsiness, where conventional features are not sufficient for quantification of these complexities. The tested hypothesis was, that features based on TQWT should better quantify the hidden complexities of handwriting by a residual of the decomposition, where the residual signal should be of a higher energy for the dysgraphic handwriting, as it is more irregular and complex.

This study enrolled altogether 65 Czech pupils attending the 3 rd and 4 th grades of an elementary school. All the children filled the self–scoring questionnaire HPSQ–C (see Section 1.1.4) and performed a copy of a short paragraph (see Figure 4.5), which was selected from a book for the 3 rd grade. As the acquisition tool the Wacom Intous Pro L (PTH–80) (sampling frequency f_s = 133 Hz) with Wacom Inking pen was used. Children were writing on a lined A4 paper, which was laid down and fixed to the digitizer. The electronic inking pen provides a valuable visual/physical feedback which is the same as with an ordinary pen.

The feature extraction was as follows: all raw online handwriting signals (see Figure 1.2) were parametrized in segments according to each stroke and also for the whole paragraph. Then for features represented by a vector the time series statistics (mean, standard deviation, median, relative standard deviation, etc.) [96] were calculated. The subset of baseline features consisted of: kinematic (velocity, acceleration, jerk), temporal (duration), spatial (width, height, length of a stroke) and dynamic (pressure, azimuth, altitude).

As mentioned in the preface to the TQWT (see Section 4.1), the wavelet trans-

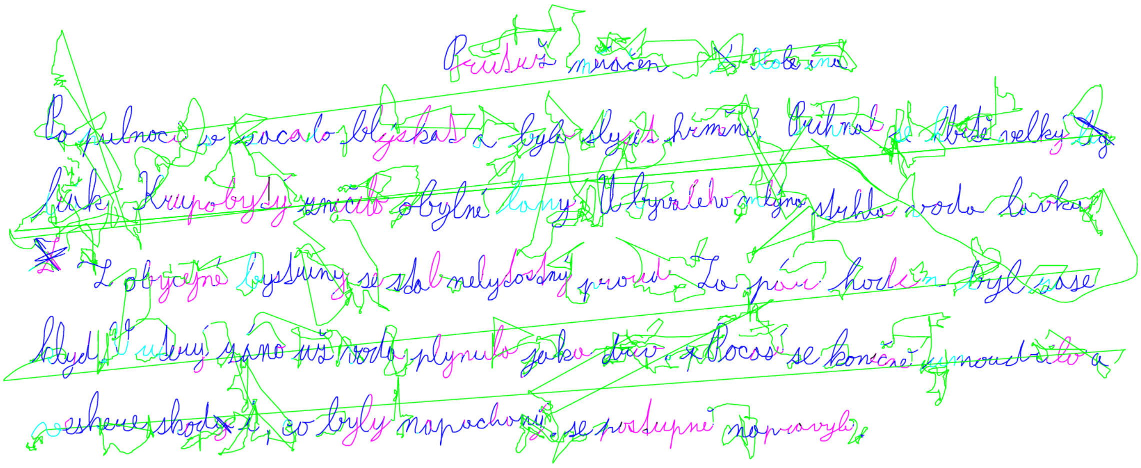


Fig. 4.5: The copy of paragraph written by the children with HD (HPSQ–C = 35). The color of letters represents the tip pressure of the pen (cyan: 0 – 25 %, blue: 25 – 50 %, purple: 50 – 75 %, black: 75 – 100 %). Green strokes around letters represent the in–air trajectories.

form enables us to model an online handwriting signal $x[n]$ into sparse representations, where each representation describes a different oscillatory behavior of $x[n]$. With fine tuning $x[n]$ can be jointly decomposed into the high Q–factor component $x_{\mathrm{HG}}[n]$ and the low Q–factor component $x_{\mathrm{LQ}}[n]$ utilising the Morphological component analysis (MCA) [160]. The TQWT and its decomposition methodology together with Matlab libraries were invented and implemented by Ivan Selesnick [150] and were used in this study. The sparse nature of TQWT (utilising the split augmented Lagrangian shrinkage algorithm–SALSA [4]) together with the joint decomposition into $x_{\mathrm{HG}}[n]$ and $x_{\mathrm{LQ}}[n]$ produce also a third–residual component $x_{\mathrm{RES}}[n]$, which expresses noise–like behavior and is not present in either mentioned components. The $x_{\mathrm{RES}}[n]$ can be calculated as:

$$x_{\mathrm{RES}}[n] = x[n] - x_{\mathrm{HQ}}[n] - x_{\mathrm{LQ}}[n]. \tag{4.1}$$

This residual component may be linked with the poor dexterity, deficient fine motor skills and unspecified motor clumsiness. Therefore a signal–to–noise ratio (SNR) measure based on x_{RES} could hypothetically differentiate between handwriting with and without difficulties. For the purpose of SNR the clean signal x_{CL} (i.e. an online handwriting signal without the effect of possible negative complexities) was calculated as follows:

$$x_{\mathrm{CL}}[n] = x[n] - x_{\mathrm{RES}}[n]. \tag{4.2}$$

In the next step three different approaches of calculating SNR, which are published in [41] were utilized: SNR based on the Teager–Kaiser Energy Operator ($\mathrm{SNR}_{\mathrm{TEO}}$), SNR based on the Squared Energy Operator E ($\mathrm{SNR_{CON}}$), and SNR as the energy ratio of $x_{\mathrm{RES}}[n]$ and $x_{\mathrm{CL}}[n]$, i.e.:

$$\mathrm{SNR_E} = 10 \cdot \log_{10}\left(\frac{E(x_{\mathrm{CL}}[n])}{E(x_{\mathrm{RES}}[n])}\right)[\mathrm{dB}]. \tag{4.3}$$

The TQWT was applied on all raw online handwriting signals and on the temporal features (velocity, acceleration, jerk) as well.

In the following step a thorough statistical analysis, which was divided into three scenarios on the basis of used feature subsets was performed: conventional handwriting features (81 in total) - Baseline; TQWT features only (665 in total) - Scenario 1; combination of conventional and TQWT features (774 in total) - Scenario 2.

In exploratory analysis the Pearsons's and Spearman's correlation between features and HPSQ–C scores was used. To evaluate the discrimination power of each feature, the univariate classification analysis using the Support Vector Machine (SVM, linear kernel) [162] and Random Forest [24] (RF, 40 trees) classifiers was employed. The model training and evaluation were performed using the stratified 10–fold cross–validation with 100 repetitions and with the following metrics: accuracy (ACC), sensitivity (SEN), specificity (SPE), Matthew correlation coefficient (MCC) [89].

In the multivariate analysis the machine learning setup was the same. The final model was trained utilizing the sequence floating forward selection algorithm (SFFS), which is gradually searching for the most discriminant features in the subset. In addition to the last scenario, the feature set was firstly filtered by the minimum Redundancy and Maximum relevance (mRMR) method to lower the dimensionality of the feature space.

The results of the Scenario 1 scenario are shown in Table 4.1, for the Scenario 2 in Table 4.2 and for the baseline scenario in Table 4.3. The best results for each scenario are highlighted in the tables.

Tab. 4.1: Scenario 1

COR / feature name	Spearman's r	Pearson's ρ
SNR_{E} of VNJ	0.36^{**}	0.37^{**}
SNR_{TEO} of RIRP	-0.31^{*}	-0.31^{*}
SNR_{CON} of 95PXP	-0.26^{*}	-0.30^{*}

C	UCA / feature name	ACC [%]	SEN [%]	SPE [%]	MCC [-]
S	SNR_{TEO} of STY	65.3±17.7	71.4±25.7	63.3±28.9	0.3±0.4
S	SNR_{CON} of SEY	65.3±17.9	67.7±28.4	66.2±27.5	0.3±0.4
S	SNR_{E} of HS	65.3±17.6	71.6±26.1	60.4±29.5	0.3±0.4
R	SNR_{CON} of 4MP	68.1±18.1	68.0±27.8	70.6±27.5	0.4±0.4
R	SNR_{E} of 1OEX	67.9±17.5	69.0±27.7	68.6±27.6	0.4±0.4
R	SNR_{E} of IRY	68.3±16.9	66.7±26.9	70.7±27.2	0.4±0.4

	MCA / feature name	ACC [%]	SEN [%]	SPE [%]	MCC [-]
S	SNR_{E} of IRX	69.2±18.0	75.4±25.3	64.2±29.0	0.4±0.4
	SNR_{E} of RIXA	76.9±16.2	81.0±23.6	73.9±26.1	0.5±0.3
	SNR_{E} of 95XO	77.0±16.4	82.0±23.1	74.3±26.1	0.5±0.3
	SNR_{E} of 90XO	78.5±15.7	84.3±22.1	73.4±25.8	0.6±0.3
	SNR_{CON} of RRY	78.6±16.1	85.2±20.8	73.0±26.2	0.6±0.3
	SNR_{CON} of RIRYP	79.2±15.6	86.2±20.2	73.3±26.2	0.6±0.3
R	SNR_{E} of IRXS	66.3±17.8	66.3±28.1	67.3±27.9	0.3±0.4
	SNR_{CON} of 1OEYP	74.0±17.0	73.0±26.7	75.8±26.7	0.5±0.4
	SNR_{CON} of RINTQ	74.8±17.3	76.3±25.9	74.5±26.2	0.5±0.4
	SNR_{E} of 90PXP	75.1±16.8	77.3±25.0	74.0±26.8	0.5±0.4
	SNR_{TEO} of 1OEYP	76.5±16.2	78.5±23.7	76.9±24.8	0.5±0.3

COR – Correlation analysis, C – Classificator, UCA – Univariate Classification Analysis, MCA – Multivariate Classification Analysis, †† – In–air, ‡‡ – On–surface, R – Random Forest Classifier, S – Support Vector Machine, M – Mean, Std – Standart deviation, VNJ – vertical normalized jerk ††, STY – Shannon entropy of TEO of y position ‡‡, RIRP – relative interdecile range of pressure p, 95PXP – 95th percentile of x position ††, SEY – Shannon entropy of y position ‡‡, HS – height of stroke ‡‡, 4MP – 4th moment of pressure p, 1OEX – 1st order entropy of x position ††, IRY – interdecile range of y position ‡‡, IRX – interdecile range of x position ‡‡, RIXA – relative interpercentile range of x position ††, 95XO – 95th percentile of x position ‡‡, 90XO – 90th percentile of x position ‡‡, RRY – relative interdecile range of y position ††, RIRYP – relative interdecile range of y position ‡‡, 1OEYP – 1st order entropy of y position ‡‡ , IRXS – interdecile range of x position ‡‡, RINTQ – relative interquartile range of y position ‡‡, 90PXP – 90th percentile of x position ‡‡, * – $p < 0.05$, ** – $p < 0.01$, *** – $p < 0.001$.

Tab. 4.2: Scenario 2

	MCA / feature name	ACC [%]	SEN [%]	SPE [%]	MCC [-]
S	SNR_{E} of 90XO	69.5±17.8	76.9±25.7	65.5±27.7	0.4±0.4
	M of velocity ††	77.8±15.5	80.6±22.6	76.1±24.9	0.6±0.3
	Std of jerk ‡‡	82.7±15.0	84.7±22.1	82.2±21.8	0.7±0.3
	SNR_{CON} of 90XO	84.6±14.3	87.7±20.5	82.0±22.5	0.7±0.3
	SNR_{CON} of MADX	84.6±14.1	88.5±18.1	82.1±22.7	0.7±0.3
	SNR_{TEO} of FCY	84.6±14.4	89.0±18.5	82.1±21.7	0.7±0.3
	SNR_{TEO} of FCX	84.5±14.4	89.0±18.0	82.0±22.7	0.7±0.3
	SNR_{CON} of FCX	84.2±14.6	88.7±17.9	82.5±22.3	0.7±0.3
	SNR_{CON} of FCY	84.7±14.3	88.7±18.7	82.5±22.4	0.7±0.3
R	SNR_{E} of IRX	66.0±17.1	66.5±27.4	67.5±27.1	0.3±0.4
	MOSW	75.3±16.1	74.0±26.4	77.7±24.7	0.5±0.3
	SNR_{TEO} of PXY	77.3±16.6	74.3±26.5	80.9±23.8	0.5±0.4
	SNR_{E} of 90XO	78.4±15.7	76.9±24.8	81.2±22.8	0.6±0.3
	SHS	79.6±15.7	79.1±23.7	81.0±24.9	0.6±0.3
	SNR_{E} RINTERP	79.7±15.1	79.2±23.6	81.9±23.6	0.6±0.3
	SNR_{E} of 95XO	80.3±15.1	79.4±24.4	81.9±23.5	0.6±0.3

COR – Correlation analysis, C – Classificator, UCA – Univariate Classification Analysis, MCA – Multivariate Classification Analysis, †† – In–air, ‡‡ – On–surface, R – Random Forest Classifier, S – Support Vector Machine, M – Mean, Std – Standart deviation, 90XO – 90th percentile of x position ‡‡, MADX – mean absolute deviation of x position ††, FCY – first correlation coefficient of y position ††, FCX – first correlation coefficient of x position ††, IRX – interdecile range of x position ‡‡, PXY – position of max. of y position ††, RINTERP – relative interpercentile range of y position ††, 95XO – 95th percentile of x position ‡‡, MOSW – Mean of speed of writing ††, SHS – Std of height of stroke ††, * – $p < 0.05$, ** – $p < 0,01$, *** – $p < 0.001$.

Tab. 4.3: Baseline scenario

C	COR / feature name	Spearman's r		Pearson's ρ	
	M of velocity††	-0.36^{**}		-0.38^{**}	
	M of height of stroke‡‡	0.37^{**}		0.34^{**}	
	Duration of writing††	0.31^{*}		0.28^{*}	
C	**UCA / feature name**	**ACC [%]**	**SEN [%]**	**SPE [%]**	**MCC [-]**
S	M of velocity††	64.1±17.4	70.6±25.7	59.3±28.9	0.3±0.4
S	M of height of stroke‡‡	63.5±18.2	65.0±28.1	63.7±28.2	0.3±0.4
S	M of jerk††	61.6±17.2	84.3±20.9	40.7±28.5	0.3±0.4
R	Std of altitude	66.7±17.6	69.6±27.4	65.0±28.1	0.3±0.4
R	Length of writing‡‡	65.2±18.5	59.8±28.5	71.7±27.7	0.3±0.4
R	M of vertical jerk‡‡	63.8±18.0	59.0±28.7	70.5±28.1	0.3±0.4
	MCA / feature name	**ACC [%]**	**SEN [%]**	**SPE [%]**	**MCC [-]**
S	SHOS	66.7±17.4	75.6±26.0	58.1±29.3	0.3±0.4
S	M of velocity††	66.6±18.9	76.1±26.4	59.1±29.8	0.3±.4
S	M of duration of stroke‡‡	73.5±17.1	80.8±23.5	68.8±27.4	0.5±0.3
R	Std of altitude	66.7±17.9	69.1±27.3	65.4±29.0	0.3±0.4
R	SVnJ††	65.6±18.4	69.2±27.7	64.3±29.3	0.3±0.4
R	Std of length of stroke‡‡	69.5±17.7	71.8±27.2	68.3±27.9	0.4±0.4

COR – Correlation analysis, C – Classificator, UCA – Univariate Classification Analysis, MCA – Multivariate Classification Analysis, †† – In-air, ‡‡ – On–surface, R – Random Forest Classifier, S – Support Vector Machine, M – Mean, Std – Standart deviation, SHOS – Std of height of the stroke ‡‡, SVnJ – Std of the vertical normalized jerk, * – $p < 0.05$, ** – $p < 0,01$, *** – $p < 0.001$.

From the correlation analysis, where $\mathrm{SNR_E}$ of the vertical normalized jerk expressed a strong positive relationship with HPSQ–C scores ($\rho = 0.37$, $p = 0.0022$), we can approve the hypothesis, that HD manifests itself even in higher energies of the residual component of TQWT. If we compare the trained models in the baseline and Scenario 1, we can conclude that, for the task (copy of paragraph) the TQWT features performed slightly better than the conventional ones (best model in Scenario 1 had MCC = 0.58 as opposed to the best model in baseline with MCC = 0.49). The trained model with combination of TQWT and conventional features showed the best performance (MCC = 0.7). This confirms the notion, that even simple conventional features perform well in the environment of the writing tasks. And also, that to further improve the classification accuracy, advanced parametrization techniques are needed.

If we perform a comparison of these results with other studies, those presenting performances of SVM classifiers, authors Zhimming et al. [177] were identifying HD in the children's handwriting with slightly worse results of ACC = 75 %. On the other hand, Mekyska et al. [96] were able to achieve ACC = 96.4 %, when identifying DD on the bases of HPSQ scale utilising the RF (this study had the best performance RF–based model with ACC = 80.3 %). But these publications cannot be precisely compared, because each team used a different set of parameters, different tasks, different cohort and language.

If we take a closer look at the most relevant features in the best discriminative models (see Table 4.1 and 4.2), the features related to the azimuth or tilt are missing.

From that we can conclude, that the complexities of handwriting linked with HD are manifested mainly in on–surface/in–air x and y trajectories, pressure and velocity profile features.

The goal of this study was to introduce new TQWT based features in the field of the quantitative analysis of online handwriting. The results confirmed, that the residual component of TQWT contains some information about irregularities associated with the HD. Another finding was, that a model trained with TQWT features–only improves the HD identification accuracy by around 5 % in comparison with the model based only on baseline features. The combination of both subsets performed even better, where the trained model achieved ACC = 84.7 %. The comparison of results with other studies couldn't be done, as no other research was published on this dataset. But the aim of this study was to compare TQWT and baseline features and this was achieved.

The limitations of this article are as follows. The first one is the small number of participants in the dataset, which hinders the possibility of generalization of the results. The second one is related to the TQWT, because further optimisation of the transformation could increase it's capabilities to differentiate HD (in this study just recommended settings were used [150]). And the last limitation was the subjectivity of the trained models, which is caused by the nature of HPSQ–C, where the children are subjectively assessing themselves.

4.3 Advanced Parametrization of Graphomotor Difficulties in School-aged Children

Reference: Galaz, Z.; Mucha, J.; Zvoncak, V.; Mekyska, J.; Smekal, Z.; Safarova, K.; Ondrackova, A.; Urbanek, T.; Havigerova, J. M.; Bednarova, J.; et al.: Advanced Parametrization of Graphomotor Difficulties in School-Aged Children. *IEEE Access*, vol. 8, 2020: pp. 112883–112897, doi: 10.1109/access.2020.3003214.
URL `https://doi.org/10.1109/access.2020.3003214`

Section 1.1.2 briefly introduced the complexity of DD and its various stages/symptoms. The DD can manifest itself in the difficulty of writing of a text (HD), but also in the difficulties of drawing a simple graphomotor element, which represents the basic building blocks of cursive writing (graphomotor difficulties–GD). The therapeutic intervention and timely diagnosis of GD in school–aged children is of great importance. For this reason this study presented a computerized decision support system for the identification and assessment of GD in school-aged children. Currently, in the Czech Republic this kind of objective methodology is still missing.

The improvement of identification of GD in online handwriting was achieved using novel advanced parametrization techniques based on modulation spectra (MS), fractional order derivatives (FD) and TQWT. In this study [54] 53 Czech–speaking children attending 3 rd and 4 th grades were enrolled. They attended several different schools in the Czech Republic. During the acquisition the children were asked to copy altogether 7 elementary graphomotor tasks (TSK). The tasks are numbered from 1 to 7 as follows: Archimedean spiral, smaller Archimedean spiral, upper loops, lower loops, sawtooth, rainbow and a combined loops. The actual tasks from the template, that the children were copying can be seen on in Figure 2.1. The children were drawing on A4 paper, that was laid down and fixed to the Wacom Intous Pro L (PTH–80) digitiser. Similarly to the previous study, even here the Wacom Inking Pen was used.

The participating children filled the ten–item, language independent, screening questionnaire HPSQ–C. The used protocol (TSK with HPSQ–C) was designed in cooperation with psychologists (PS) and special educationalists (SE). For the purpose of this study, the children were divided into two groups: the healthy controls (HC) and the children with graphomotor difficulties (GD). To overcome the possible subjectivity of children's self–assessment (HPSQ–C), the children were divided into these two groups by an expert (remedial teacher), who was examining the handwritten product on the PC after the examination. She/he had no information about the HPSQ–C score, sex or any sociodemographic information about the examined child. The drawing performance in all tasks from randomly selected children from both groups can be seen in Figure 4.6.

Various types of handwriting features that could be separated into the following subsets were extracted: conventional features (CONV), modulation spectra features (MS), fractional order derivative features (FD) and TQWT features. As can be seen from Figures 2.1 and 4.6, all the tasks should be performed in a single stroke. The quantitative analysis showed, that multi–stroke signals occurrence was only marginal. Thus, in the feature extraction procedure in–air trajectories were omitted. All vector–valued features were transformed to scalar values using standard time series statistical methods: mean, coefficient of variation estimates (cv) and other (some TQWT features used additional statistical functions, that will be explained further). Also, all features were named by following convention: TSK INF: DIR-FN (HL), where TSK stands for a specific numbered task, INF specifies on–surface/in–air movement (ON/AIR) or dynamic features (see below), DIR denotes vertical (V) or horizontal (H) projection, FN represents the feature name and HL stands for the statistical function (optional). As all features are related only to the on–surface trajectories, the ON is redundant and thus not mentioned.

The CONV subset can be further categorized into: a) spatial features - width

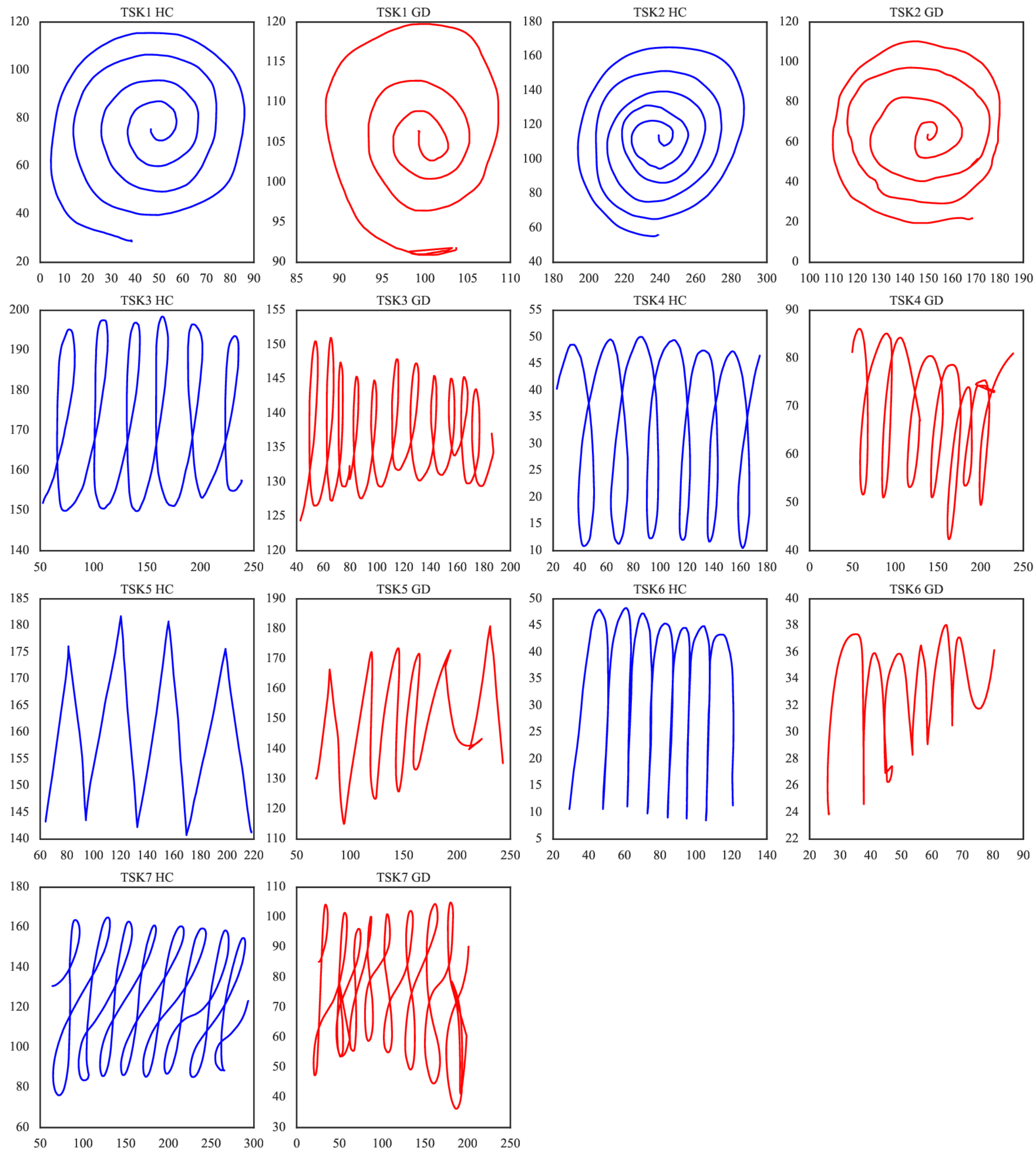


Fig. 4.6: The recordings of drawings of randomly selected children from groups HC (blue lines) and GD (red lines). The units are in millimeters.

(WWIDTH), height (WHEIGHT), length (WLEN), of the whole writing and also of the strokes (i.e. SWIDTH, SHEIGHT and SLEN); b) kinematic features - velocity (VEL), acceleration (ACC), jerk (JERK), in both horizontal and vertical projections; c) dynamic features - pressure (PRESS), azimuth (AZIM) and tilt (TILT). This subset of features was considered as the baseline.

The next two subsets of features, namely FD and MS, are described in detail in [54]. Here the FD and MS features are mentioned only briefly, for they are the main contribution of other authors.

And finally, the last subset of features was based on TQWT. In the previous study it was proved that the HD manifests itself in the higher energies of the residual component of the decomposed signal computed by TQWT. In this study the hypothesis is, that TQWT could also describe limited motor skills, poor dexterity and muscle tone or unspecified motor clumsiness in handwriting of children suffering from GD.

The parameter settings of TQWT was based on recommended settings [150] and on the analysis of graphomotor signals mentioned in the Section 4.1. The equations for computing the clean signal, the residual component and the SNR were the same as in the previous study (see Equations 4.1, 4.2, 4.3). With the aim to quantify and describe the residual component in more detail, additional statistics was provided.

The energy E of the residual component was computed as

$$E(x_{\mathrm{RES}}[n]) = \sum_{n=0}^{N-1} x_{\mathrm{RES}}[n]^2. \tag{4.4}$$

Next, absolute value of the first order derivative of $E(x_{\mathrm{RES}}[n])$ was computed as $E_d(x_{\mathrm{RES}}[n]) = |E'(x_{\mathrm{RES}}[n])|$. To describe the variability of $E_d(x_{\mathrm{RES}}[n])$, the slope of its cumulative sum was computed as

$$E_\Delta = \Delta C(E_d)[n], \tag{4.5}$$

where $C(E_d)[n]$ for $n = 0, 1, \ldots, N-1$ stands for the cumulative sum of the E_d, and Δ refers to the slope of a function. In other words, the E_Δ should express the higher values of residual components with high value variability. And finally, to count significant changes in $E_d(x_{\mathrm{RES}}[n])$, the number of peaks of E_p above the median value is computed.

The naming convention for TQWT–based features is FN and can be described as follows: F stands for the name of the feature, N stands for the specific type of TQWT feature: Signal–to–noise ratio (SNR), RES (csum) for E_Δ, and RES (npeaks) for E_p.

Regarding the statistical analysis, all features with missing values were discarded. The whole feature space was tested for normality using the Shapiro–Wilk test [154]. Consequently, all non–normally distributed features were transformed utilising the Box–Cox method [22]. After the re–inspection of adjusted features, it was decided, that not all features were fully–normalized. For this reason, the whole feature space was considered as non–normally distributed. This notion resulted in the usage of non–parametric statistical methods in the subsequent analysis. After the consultation with psychologists and special educational counsellors, as the possible confounding factors in the analysis the following were selected: age, gender and grade.

The Spearman's correlation applied to the mentioned characteristics together with all features showed that the gender was not a statistically significant covariate. For this reason, only the effect of age and grade was considered. As the number of features in each feature set (i.e. CONV, FD, MS and TQWT feature set) was relatively high and not the same, the pre–selection filter method mRMR was employed. Selecting a relevant subset in each feature set with minimum redundancy and cross–correlation among the features is important especially in the classification analysis, thus ensuring the same starting complexity of feature space for each model.

In the next step the Mann–Whitney U–test with the significance level α of 0.05 was performed to compare the distributions of all features between HC and GD children groups. To discover the strength of the relationship between features and children's group status (HC/GD), the Spearman's correlation coefficient with α of 0.05 was computed. The p–values in both methods were adjusted using the False Discovery Rate (FDR) to control the influence of the multiple comparisons issue.

Next, the binary classification model to identify children with GD utilizing RF classifier was trained. To increase the prediction power of the model [64] and to ensure that the model will be trained using only the information–rich subset of the features, which will reduce the risk of overfitting, the feature selection method SFFS was used. Before the classification, all processed features were standardized to have mean = 0 and standard deviation = 1. The trained models were evaluated employing a stratified 5-fold cross-validation with 20 repetitions. The classification performance was measured using: ACC, SEN, SPE and MCC. MCC was also used during the feature selection to control addition/removal of the features. To evaluate the statistical significance of the prediction performance of the trained models, a non–parametric statistical method called permutation test was conducted. It used the same ML testing settings as in the training phase, and was set to perform 1000 permutations at the significance level of 0.01.

The results of the analysis can be seen in the following paragraphs. After filtering each subset of the feature–type (mRMR), cross–correlation matrices using the Pearson's correlation coefficient were evaluated. As can be seen from Figure 4.7, each matrix has 15 features and some of them are highly correlated between each other. Nevertheless, it was decided, that the feature space complexity will be not reduced any further, so that with the threshold 15 features in each subset, all relevant features can be preserved.

The comparison of results of the correlation analysis (Spearman's correlation coefficient) and Mann–Whitney U–test method can be seen in Table 4.4. The top 5 features were selected from each feature–type subset according to the MCC value (from high cross–correlated pairs only one of them was selected). The significant features (p–value = 0.05) according to the MCC were: a) CONV subset–5/5 prior

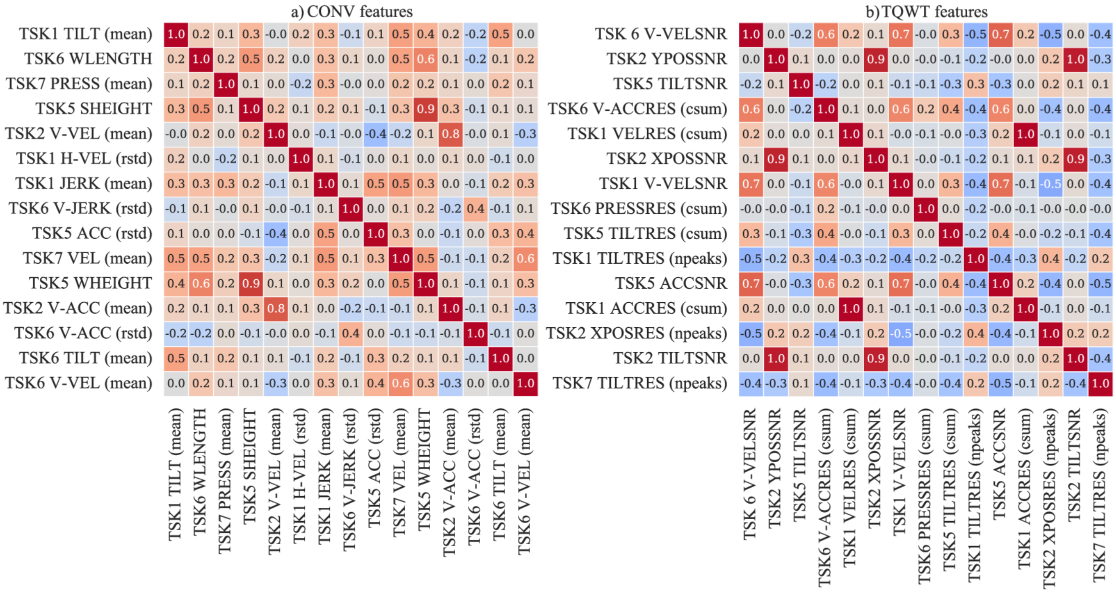


Fig. 4.7: Cross-correlation matrices for feature sets TQWT and CONV (Pearson's correlation coefficient (r), 15 features per feature-type) computed after pre-selection (mRMR). The strength of the relationship is on the linear scale <-1,1> with corresponding colors: blue at minimum and red at maximum. Explenation of abbreviations can be found in Section 4.3.

adjustment, 1/5 after adjustment; b) TQWT subset–3/5 prior adjustment, 1/5 after adjustment. The strongest relationship between a feature and the HC/GD status according to the Spearman's correlation coefficient revealed the following features: a) CONV: TSK1 TILT (mean), $\rho = -0.42$, $p < 0.01$; b) TQWT: TSK6 V–VELSNR, $\rho = -0.39$, $p < 0.01$ (after the adjustment, the TQWT feature was marked as not significant with $p = 0.07$). In Figure 4.8 the most discriminating features for each feature–type can be seen as violin plots.

The achieved results regarding the classification analysis are mentioned in Table 4.5, where for each trained model values of evaluating metrics and their p–values (1000 permutations, $**$ denotes a p–value < 0.01) are specified. To obtain the most significant features across the whole feature–space (i.e. CONV, TQWT, FD, MS), a model on all analysed features (ALL, together 60 features) was trained and tested. The best models were as follows: a) CONV: ACC = 0.74^{**}, 7 features; b) TQWT: ACC = 0.71^{**}, 2 features; C) ALL: ACC = 0.84^{**}, 10 features. The features selected by SFFS for each model are mentioned in Table 4.6.

This study introduced 3 novel types of features to improve quantification and identification of GD, namely features based on modulation spectra, fractional order derivatives and features based on the tunable Q–factor wavelet transform. For the

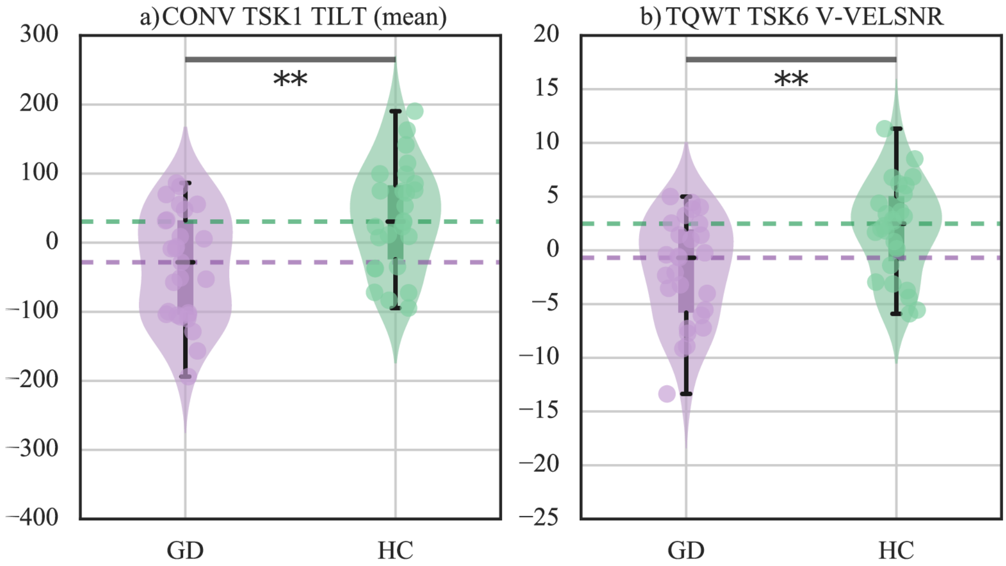


Fig. 4.8: Violin plots of the best discriminating features according to the MCC and Spearman's correlation coefficient selected from subsets CONV and TQWT. The colored background of the boxplots represents horizontally–mirrored kernel density estimations with feature values printed as points. The violin plots are plotted separately for HC and GD groups, where the stars represent a p–value < 0.01 of the Mann–Whitney U–test. The dashed lines represent medians.

Tab. 4.4: Results of the statistical analysis.

feat.	TSK	ρ	p(ρ)	p(ρ)*	p(U)	p(U)*
CONV features						
TILT (mean)	TSK1	-0.42	0.001	0.027	0.001	0.019
TILT (mean)	TSK6	-0.32	0.017	0.129	0.009	0.072
SHEIGHT (mean)	TSK5	-0.31	0.028	0.142	0.015	0.076
WLENGTH	TSK6	-0.25	0.074	0.190	0.038	0.096
WHEIGHT	TSK5	-0.25	0.074	0.190	0.038	0.096
TQWT features						
V-VELSNR	TSK6	-0.39	0.004	0.070	0.003	0.044
V-ACCRES (csum)	TSK6	-0.26	0.061	0.345	0.031	0.177
ACCSNR	TSK5	-0.26	0.069	0.345	0.035	0.177
TILTSNR	TSK2	-0.23	0.110	0.409	0.055	0.206
V-VELSNR	TSK1	-0.21	0.136	0.409	0.068	0.206

[1] feat – feature; TSK – graphomotor task; ρ – Spearman's correlation coefficient; p(ρ) – p–value of ρ; p(ρ)* – adjusted p(ρ); p(U) – p–value of Mann–Whitney U–test; p(U)* – adjusted p(U); for the feature naming convention, see Section 4.3.

purpose of this thesis, only TQWT and CONV features were mentioned. The feature complexity was reduced using filtering methods to the level, where the number of observations was of the same order as the number of features. This approach minimized the effect of the curse of dimensionality and resulted in 15 features for

Tab. 4.5: Results of the classification analysis.

type	MCC	ACC	SEN	SPE	N	p
CONV	0.50 (0.26)	0.74 (0.12)	0.80 (0.19)	0.71 (0.21)	7	**
TQWT	0.42 (0.29)	0.71 (0.14)	0.74 (0.19)	0.68 (0.23)	2	**
ALL	0.65 (0.25)	0.84 (0.13)	0.83 (0.17)	0.81 (0.18)	10	**

[1] the results are shown as mean (standard deviation); type – specific type of graphomotor feature; MCC – Matthew's correlation coefficient; ACC – accuracy; SEN – sensitivity; SPE – specificity; N – Number of selected features; p – p-values computed by the permutation test (1 000 permutations); ALL (combination of all feature-types, i. e. 60 features); for the feature naming convention, see Section 4.3.

Tab. 4.6: Features selected for the trained classification models.

CONV	TQWT	ALL
TS6 V-ACC (cv)	TS2 YPOSSNR	TSK1 H-VEL (cv)
TS1 H-VEL (cv)	TS1 VELRES (csum)	TSK1 TILTVEL0.35 (mean)
TS7 VEL (mean)		TSK2 JERKR5
TS2 V-ACC (mean)		TSK3 JERKR3
TS1 TILT (mean)		TSK2 V-VEL (mean)
TS5 WHEIGHT		TSK6 V-ACC (cv)
TS2 JERK (mean)		TSK1 V-VELSNR
		TSK3 PRESSACC0.1 (cv)
		TSK7 TILTACC0.85 (cv)
		TSK5 TILTRES (csum)

[1] TSK – graphomotor task. For the feature naming convention, see Section 4.3.

each feature–type with minimal cross–correlation. From the pre–selected features it can be seen, that not all graphomotor tasks (TSK1–TSK7) are covered by them (TSK3 and TSK4 are missing) and that the distribution of tasks per feature–type is varying. This supports the notion, that different feature types are potentially more suitable to quantify task-specific demonstrations of GD, which are experienced by school–aged children.

Regarding the statistical analysis and its results in the CONV subsets, the most significant features were basic parameters, namely tilt, stroke height, length and height of writing (drawing). In detail, in the tasks Archimedean spiral and rainbow had the strongest relationship between the mean of the overall tilt and the HC/GD status. This indicates, that in these tasks the children affected by the GD held the pen less steeply than the children from the HC group. Another significant observation can be found when comparing HC/GD groups by length of the line in rainbow tasks and the height of the whole saw task. The difference in the performance underlines the difficulties associated with these tasks. Moreover, the children suffering from GD tend to draw the saw task with a smaller stroke height. If we compare top–ranking features from CONV and TQWT sub–sets, we can see that conventional features were derived mainly from the spatial (height, length) and dynamic (tilt) types. On the other hand, TQWT features consisted mainly kinematic features, such as velocity and acceleration. This fact is in agreement with previous studies [2, 27, 139], which were identifying HD/DD on the basis of quantitative analysis of online handwriting and utilizing kinematic features. From this notion we can conclude, that kinematic features are important in quantifying of drawing as well as handwriting. The importance of kinematic features highlights the advantages of computerized analysis of handwriting, where additional information about the handwritten product/process (which is very unlikely to precisely measure manually) is made available to research and diagnoses.

In the results of statistical analysis done on TQWT sub–sets, as the most significant feature, signal–to–noise ration of vertical velocity of the rainbow task (TSK6) in both methods (Spearman's correlation coefficient and Mann–Whitney U–test) was identified. This observation probably indicates, that children suffering from GD had difficulties with maintaining steady/continuous velocity of strokes in vertical movements of handwriting in this task as opposed to the healthy children, who performed this task without problems. This phenomenon was previously reported in [84], where children with DD experienced problems in vertical movements during handwriting caused by the psychological load and muscular fatigue in the finger system. During handwriting the vertical movement requires a coordinated motion and finer flexions/extensions of more joints and therefore it is more complex than ulnar abductions of the wrist (which plays a key role in the horizontal movement) [40, 168]. In other words, the GD is more manifested in vertical projections of handwriting/drawing. The handwriting of healthy children is more fluent and more automatic and therefore they are able to accelerate/decelerate almost effortlessly. On the other hand, children experiencing GD haven't their handwriting expression fully automated, and therefore have problems to write fluently and in the faster tempo while maintaining legibility. Thus the dexterous handwriting of healthy children can indirectly cause an increase in the noise-level of the residual component of the vertical acceleration (TSK6). Although, the mentioned feature is the second most significant in the TQWT sub–set, it became non–significant after the FDR correction.

Regarding the classification analysis, CONV and TQWT feature subsets achieved similar results (CONV feature–set achieved MCC = 0.5 with 7 features in contrary to the TQWT feature–set, which achieved MCC = 0.42 only with 2 features). This comparison shows, that a single type feature (even when more complex) is not likely to significantly improve the identification of GD that is provided by the conventional features only. However, when all feature types are combined (i.e. CONV, MS, FD, TQWT), the classification performance can be increased by approximately 10 % in terms of accuracy, 3 % in terms of sensitivity and 10 % in terms of specificity, while maintaining almost the same number of features. Recent studies are reporting sensitivity over 90 % [8, 96, 133], which might at first seem be way better, than the results in this study. However, the mentioned studies were identifying HD in children with DD using a complex acquisition protocol comprising writing. The results reported in this study are solely based on the analysis of drawing signals of graphomotor tasks and aim at predicting the presence of GD, which can lead to HD and possibly to DD. The focus on simple graphomotor movements is of a great importance as they represent the building blocks of proficient handwriting, and thus the robust parametrization of GD can be used in the future as an early marker of possible HD/DD in children in pre–school or first–grader age. When training the combining model (ALL), conventional as well as all advanced features were selected. Also, almost all tasks were participating in the combined model (except the lower loops - TSK4). This examination showed, that all features extracted from almost all graphomotor tasks contributed to an improvement in the identification of GD to some extent. Hence, the combination of selected tasks and features advanced the capabilities of ML models to model relationships between the characteristics of online handwriting signals and the presence of GD in school–aged children. It is important to note, that all models were properly tested by a permutation method with the significance level below $\alpha < 0.01$ and thus ensured the statistical significance and validity of ML results.

This study has several limitations. First of all, the size of the dataset is relatively small (53 children), thus the statistical strength of the result's inference is restricted. Also, the analysed cohort is from children attending the 3 rd and 4 th grades of the primary school. To obtain a complex understanding about the relationship between the performance of graphomotor features and children's grade, age, etc., handwriting signals of pre–school children as well as of children attending the 1 st up to the 4 th grade should be analysed. Nevertheless, in the current cohort, children from 3 rd and 4 th grades were observed, where the handwriting should be automatic. At this age, the possibility to identify GD is crucial for the following diagnosis of DD and therapeutic care. Therefore, reported results in this study stand as a baseline for future studies, that should research more information about GD and its longitudinal characteristics. Future studies should also include a diagnosis of enrolled children by several special educational therapists/psychologist to ensure, that the variability in the diagnosis of GD will be addressed. Regarding the ML methodology, various other ML models should be employed and tested in order to obtain general information about the performance of proposed features and to obtain the most robust models for GD identification. Finally, concerning the mentioned limitations, this study should be considered as an exploratory/pilot study, and its results should be confirmed by the following scientific research.

To conclude, in this study three novel feature types were proposed with the goal to provide a complex quantification of GD in school–aged children's handwriting. In each feature type (namely TQWT and CONV) several features that are able to differentiate between healthy children and children suffering from GD were selected. In detail, the significant TQWT features were derived mostly from the velocity profile, which is impossible to grasp by human examiners when simply observing the handwriting process or final handwritten product. Also, the importance of a combination of advanced as well as conventional features over only one feature type was proved, when the performance of the classification model based on all features was significantly improved. In the classification combined model (CONV, MS, FD, CONV) all graphomothor tasks were present (except the lower loop). This confirms the fact, that in order to assess subtle and rather imperceptible manifestations of GD in children's handwriting, various basic graphomotor tasks are needed (which compel coordinated movement of fingers/wrist/elbow/etc. as well as visuospatial cognitive functions). This work was the first one exploring possibilities of TQWT, FD, MS in order to extract advanced graphomotor features with the aim of identification of GD in the handwriting of school–aged children. On the basis of the achieved results, the proposed features are of a great importance in the assessment and identification of GD. Nevertheless, to generalize the obtained results, these findings should be further confirmed by additional scientific research.

5 Discussion and Future directions

This dissertation thesis describes the research of objective diagnostic approach of graphomotor difficulties (GD) on a sample of school–aged children, with the aim to help psychologists and special educationalists in the Czech Republic. The development of the tool is currently focused mainly on identification of GD in children attending 1 st and 2 nd grade of primary school and also as a support of the Development Dysgraphia (DD) diagnosis in children attending 3 th and 4 th grade. The DD is a serious developmental disorder with the prevalence around 3–5 % in the Czech Republic. Moreover, there do not exist any objective diagnostic methods for assessing DD yet and the current diagnosis of GD or DD is based on subjective observation of the handwriting process by an expert evaluator.

The whole chapter is divided into three sections, where the first one (see Section 5.1) aims to compile in detail the whole dissertation thesis and individual aims. Next, Section 5.2 is discussing achieved results of particular aims and provides a broader view of them. Finally, the last Section 5.3 is trying to outline identified limits of this work and potential future topics of research.

5.1 Summary

In the beginning of the first chapter (see Chapter 1), physiological and psychological processes linked to handwriting were described in detail, just as their continuous development from childhood to adulthood. The next part of the chapter was devoted to the etiology of Developmental Dysgraphia (DD) and its description according to two diagnostic manuals (DSM–V, ICD–10). All known symptoms of DD affecting the handwritten product as well as its process were described using with adequate scientific literature. Also, actual methods of diagnosis of DD in the Czech Republic were stated.

Special focus was dedicated to the specification of the most common validation criteria used in diagnosis of DD. To support the understanding of the DD diagnosis, a summary with simplifying graphics was provided. Next, the major limitations of the DD diagnosis were identified: 1) there are no objective methods for DD diagnosis; and therefore, 2) the diagnosis is based on the observation skills of the evaluator. The state–of–the–art of research in the field of DD diagnosis based on online handwriting analysis was reported in detail. Finally, the online handwriting analysis summary was presented.

In the next Chapter 2, symptoms of GD identified by the PS and SE were described. Each symptom had to be discussed with the PS and SE to properly understand its manifestation across the grades of the children. The quantification of these symptoms via parameters is one of the main contributions of the thesis. Several parameters were uniquely designed for this research and have not been published yet. Others are the following state–of–the–art literature in the field of online handwriting analysis.

Moreover, the cooperation with PS and SE included the design of the proper handwriting environment, where the identified symptoms can be manifested. For this purpose, 36 tasks were constructed. Each one aimed to assess a specific characteristics of GD. These tasks were logically grouped into three types:

- Seven graphomotor tasks (GT)
- Twentyone tasks assessing cognitive processes (CT)
- Eight writing tasks (WT)

The GT represent building blocks of cursive letters. Children in the 1st grade should be able to draw them properly and so, abnormalities can be objectively measured. The CT were constructed to test working memory, cognitive load and visual memory. Finally, the WT consist of different types of writing tasks (e.g. dictation, copying sentences etc.), where the fatigue, spacing, alignment and automation can be fully manifested and measured. To this day, a complex protocol assessing GD such is this one has not been published yet.

Every task of the new protocol addresses a specific set of symptoms. For each symptom, several features based on mathematical modeling and advanced signal processing techniques were designed. Each feature/parameter was programmed with the aim to adequately describe a diagnostic trait within the symptom. Following the literature [141], the symptoms were divided into two groups:

- Symptoms of the handwriting product – 8 symptoms; 28 parameters.
- Symptoms of the handwriting process – 16 symptoms; 49 parameters.

Together, twenty–four symptoms of GD were identified and assessed by 77 unique features. For better understanding, each of the quantifying features was defined, properly described and some of them were also illustrated. The complete list of features and symptoms is mentioned in Appendices A.5, A.6, and A.7.

The summarizing list of symptoms with tuned quantifying features represents a new analytical model of GD, which has never been published before. It can significantly contribute to the diagnostic process of GD and also to get a new perspective of understanding the complex symptomatology of DD.

Another benefit of this thesis is outlined in Chapter 3, where a design of the new graphomotor difficulties rating scale (GDRS) is described. This GDRS is a logical outcome of the whole presented work so far. Firstly, a GD protocol with symptoms identified by experts was designed. The next step was to comprise designed features, that quantify the identified symptoms, into GDRS, which can measure the current level of the child's GD.

After checking the dataset content (in which, to some extent, identified dysgraphic children by practicians are lacking), it was decided that there is a real possibility, that not all degrees of GD will be present in the dataset. Thus, it was decided, that individual symptoms will be simulated, to exclude the influence of other symptoms. For presentation of the analysis outcomes, two graphomotor tasks and two writing tasks were selected (see Appendices A.1, A.2, A.3, and A.4). Furthermore, the search for the optimal combination of sets of features that will represent the identified symptom was conveyed to the genetic algorithm and the gradient descent algorithm. Turning now to the values of GDRS, the current progress suggests, that each symptom will represent a sub–score of the scale. This step was supported by the notion, that number of accumulated symptoms will describe the extent of the GD. Finally, the optimization and validation processes were described in detail together with possible issues of the GDRS design.

This newly constructed GDRS scale represents a major benefit to the diagnosis of GD and DD in the matter of modernization, cost-effectiveness, and objectivity. Its utilization can transfer the tacit knowledge from PS and SE and offer it as an analytical tool to other practicians, which can compare their diagnosis to the objective measurements.

The last Chapter 4 is devoted to the integration of the Tunable Q–Factor Wavelet Transform (TQWT) into the online handwriting analysis and its application to GD identification. The TQWT models online handwriting signals $x[n]$ into sparse representations, where each representation describes a different oscillatory behavior of $x[n]$: high Q–factor component $x_{\mathrm{HG}}[n]$ and low Q–factor component $x_{\mathrm{LQ}}[n]$. Another product of the decomposition is the residual component $x_{\mathrm{RES}}[n]$, which express noise–like behavior and it is not present in either $x_{\mathrm{HG}}[n]$ or $x_{\mathrm{LQ}}[n]$. This residual component may be linked with the poor dexterity, inadequate fine motor skills and unspecified motor clumsiness. Therefore, the higher levels of the energy in $x_{\mathrm{RES}}[n]$ can be found in handwriting affected by the GD.

In the next part of the chapter, a detailed summary of two published studies from the author of the thesis were presented. First of them was a conference paper with the title: "New Approach of Dysgraphic Handwriting Analysis Based on the TQWT" [181]. The article reported the use of the TQWT in the analysis of online handwriting, more specifically on writing tasks. Three different approaches to calculate the SNR between the clean signal and the residual component of the TQWT (Teager-–Kaiser Energy Operator, Squared Energy Operator and SNR as the energy ratio) were utilized. The analysed dataset consisted of 65 Czech pupils attending 3 rh and 4 th grades, who were evaluated by the HPSQ–C questionnaire. The extensive exploratory analysis included the correlation analysis, univariate classification analysis (ML) and multivariate classification analysis (ML). For the evaluation of the discrimination power of the features, Support Vector Machine (SVM) and Random forest (RF) algorithms were employed. The results showed, that the TQWT brings some information about the irregularities associated with GD. The model trained with TQWT features improved handwriting difficulties (HD) classification accuracy (ACC) approximately about 5 % in comparison with the model based solely on basic features. Moreover, the combination of both subsets performed even better, where the trained model achieved ACC equal to 84.7 %.

The second study with the title: "Parametrization of Graphomotor Difficulties in School–aged Children", dealt with advanced signal processing techniques analysing online handwriting affected by GD on graphomotor tasks (TSK1–TSK7; see Section 2.1). In this study, the TQWT was a part of the employed advanced techniques, which produced a residual component $x_{\mathrm{RES}}[n]$ measured by SNR. Moreover, two newly designed features were used: slope of the cumulative sum of E_d and number of peaks above the median of E_d, where E_d denotes a derivative of $x_{\mathrm{RES}}[n]$. For the study, 53 Czech pupils attending 3 rd and 4 th grade were enrolled. All of them filled the HPSQ—C questionnaire and also selection into groups by the expert (remedial teacher) was used as the second validation criterion. The extracted features were firstly filtered by a comprehensive methodology involving normality tests, manual inspection, minimum Redundance Maximum Relevance method and Mann–Whitney U–test. In the classification analysis RF algorithm which was evaluated by the Matthew's correlation coefficient (MCC). The model based on the conventional feature set achieved MCC equal to 0.5 with 7 features in contrary to the TQWT feature set, which achieved MCC equal to 0.42 with only 2 features. Moreover, the best trained model showed, that the combination of all advanced features (i.e. TQWT, modulation spectra and fractional derivatives) with the conventional ones can significantly increase the classification performance by approximately 10 % in terms of accuracy, 3 % in terms of sensitivity and 10 % in terms of specificity. The significant TQWT features were derived mostly from the velocity profile, which is impossible to grasp by a human examiner when simply observing the handwriting process or a final handwriting product. In the final classification model all graphomotor tasks (except lower loops) were present. This confirms the fact, that in order to assess subtle and rather imperceptible manifestation of GD in children handwriting, various basic graphomotor tasks are needed, which compel coordinated movement of fingers/wrist/elbow/etc., as well as visuospatial cognitive functions.

5.2 Discussion of the conducted research

The comprehensive introduction into the diagnosis (see Section 1) of DD based on online handwriting analysis was needed to provide a background for the following chapters dealing with computerized analysis of online handwriting and its advancement. It is important to point out, that DD is a relatively neglected science field comparing to the amount of scientific research outcomes published in other fields, such as ADHD, Autism or Parkinson's disease. This could be caused by the subtle nature of handwriting and a relatively short time frame when the DD can be detected and treated. The recent acceleration of research in this field [7, 54, 96, 98, 106, 177, 180, 181, 183] can be attributed to the explosive advancement in IT technologies, which enables new ways of exploration in handwriting research.

The research gap was identified after considering the whole diagnostic process of GD or DD respectively, in the Czech Republic. The design and implementation of each step was realized in cooperation with experts in fields of signal processing, psychology, and special education. The objective tool for measurement of GD severity was missing and its research and proper construction will be beneficial to the children suffering from GD/HD/DD. To this day, several products recording and analysing online handwriting of children exist at a certain level, but none of them provides a robust and comprehensive measurement of the severity of GD, which would be supported by profound scientific research [42, 71, 158].

Graphomotor ability protocol

As stated previously, the proposed GD assessment protocol is the most detailed and complex protocol in the field. It was designed with the aim to assess all possible symptoms of GD (see Section 2.2) and adapted to the state–of–the–art literature. The various writing tasks are the most commonly used in research for the analysis of online handwriting affected by GD or HD [3, 8, 85, 130, 133, 173, 180, 183]. In addition, analysis of the GD in basic graphomotor tasks (GT) is rather scarce [3, 100] and different tasks, namely Archimedean spiral, rainbow, saw and upper loops, were mostly introduced by studies co–authored by the author of this thesis [54, 98]. Very similar to the rainbow task, a task with Hebrew word segment was already introduced in the research of GD [96]. Lastly, the research of tasks assessing cognitive processes (CP) were never published in the field of analysis of online handwriting affected by GD. There is only one related study with the hypothesis, that the handwriting features can express a relationship between scores of Rey–Osterrieth Complex Figure [137]. Moreover, the enrolled subjects were adults. Hence, newly designed tasks assessing CP represent an innovation in the analysis of GD and can bring insights into the mental processes of the analysed children, such as working memory, visual memory, visuomotor coordination and extent of attention.

The design of a GD assessment protocol is undoubtedly a great asset but identifying symptoms with corresponding features fits more to the scope of this work and for this purpose will be discussed more in detail. Some of the proposed features have already been used in previous GD analysis, some have been used with different diseases such as analysis of handwriting affected by Parkinson's disease (PD) or have been newly developed entirely. Because the connection of groups of features with specific names has been uniquely proposed in this work, it is unlikely that the same symptom names or manifestations of the GD category naming convention will be used in other scientific literature. For the purpose of the discussion, all features are divided in three groups. The first group contains features, which have already been tested on the samples with GD. The second one includes features tested on data from different fields (i.e., PD). The newly designed features are described in the third category.

Features tested on GD samples

Appendix A.5 provides a comparison of all 53 features from this category considering relevant scientific research. Each feature is described with reference to published articles, where it was used and with information about statistical significance of used tests. Moreover, an information is given, whether the feature was defined exactly as it is in this thesis or just in a similar way.

As all the studies are varying in the used language, sample size, validation criteria, statistical analysis, tasks, age of people in cohorts, the precise comparison of results is not possible. At least it can be stated, that almost half of all proposed features already achieved significant results in identifying GD or HD in children attending primary schools (1 st–4 th grade). The rest of the features were either outperformed by others used in individual studies or their results (statistical significance, ACC etc.) were not mentioned.

Features tested on different disorders

The table in the Appendix A.6 is constructed akin as the table in the previous category and consists of 7 PD features measuring the Archimedean spiral properties. The difference is that the mentioned features had never been used in GD handwriting analysis before. Nevertheless, they prove to be significant in the cited studies (significant statistical test of 5 features) and they measure physical characteristics of the spiral. Those outcomes can be transferred to the analysis of online handwriting affected by GD. For example, as can be seen in Figure 2.7, children identified with DD were not able to complete the spiral without problems. The feature variability of spiral width (SWVI) successfully showed, that a DD child changed the width of individual loops a lot more than a child from the control group (see Table 2.4).

Hence, the proposed features should be suitable for identification of GD in online handwriting signals derived from spiral task. Their significance will be tested in future analysis.

Newly designed features

In this work, 16 newly designed features are proposed (see Appendix A.7), assessing mainly graphomotor tasks (loops, rainbow, saw). They provide detailed measurements of spatial, temporal, and kinematic properties, which are necessary for describing specific symptoms. Moreover, their complex intersection analysis which can detect crossing of two different strokes was also introduced. Such measurement was not yet introduced into the analysis of GD. It can bring clarity to automatic errors counting, as children with HD tend to have more corrections of mistakes in their handwriting [45]. Finally, a rhythmic structure of children handwriting was already reported [118] explaining, that DD children can have deficits mediated by the rhythm of their handwriting [117]. The newly designed features assessing the tempo of handwriting as the number of strokes per duration in a specific trajectory (on–surface/in–air) can prove to be a legitimate concept.

Selecting only specific features (in contrast to using the full set of features that are available), has the advantage in preventing the curse of dimensionality in later analysis, because the estimated size of the completed dataset will be around 500 observations. Also, the approach of tight cooperation with PS and SE during the feature designing can take advantage of their tacit knowledge and experience [31, 62], which should result in more effectiveness and simplicity of designed features. Moreover, the of the features is beneficial for their interpretation and later usage.

76 proposed features are precisely assessing both, graphomotor elements and handwriting, taking into account temporal (ratio of the on–surface/in–air movement, number of on–surface strokes normalized by on–surface duration etc.), kinematic (median of power spectrum of speed frequencies, median velocity in global/horizontal/vertical movement, etc.), dynamic (number of changes in tilt profile, non–parametric coefficient of variation of azimuth, etc.), spatial properties of handwriting/drawing (spiral precision index, slope of stroke width, etc.) and utilizing advanced features such as measurement of complexity or noise–like behavior (TQWT, Shannon entropy, etc.) of online handwriting signals.

Some features are analysing specific tasks from the general point of view (overall duration, pressure, tilt, azimuth, number of interruptions, number of pen stops, etc.) and others are analysing individual strokes separately (number of in–air strokes per in–air duration, relative number of on–surface intra–stroke intersections, density of path, slope of duration of strokes in–air, etc.).

Due to the unique execution of graphomotor tasks, features specific to the tasks had to be designed. Namely these are spiral specific features (degree of spiral drawing severity, first order zero–crossing rate, etc.), loops specific features (distance between neighbor local maxima in vertical projection, local minima in vertical projection, etc.), saw specific features (median velocity at local maxima in vertical projection, median of normalized width of teeth, etc.) and rainbow specific features (median distance between forward/backward lines, duration between neighbor local maxima in vertical projection, etc.).

This detailed quantification of online handwriting signals derived from the comprehend GA protocol will prepare a solid mathematical model, with which the symptoms will be constructed and the GDRS scale can be built on.

Graphomotor difficulties rating scale

The design of Graphomotor difficulties rating scale (GDRS) was outlined in Chapter 3, with description of individual steps. The proposed design represents a novelty in the field of GD handwriting analysis because an automated analytic scale based on mathematical modelling of the product and the process of online handwriting has never been published before. Moreover, this GDRS will contain approximately 500 individual GA expressions, which will ensure generalization of the outcomes. The implementation of s–features, derived from simulated symptoms, together with a genetic algorithm [46, 153, 155] and the gradient descent algorithm [69], ensures optimal settings of the features for each symptom.

Presently, HD and GD are evaluated subjectively, either on global scales or on analytical scales. The first ones give a general judgment of the written product, but their usage is only minor [140]. They are time–consuming and consequently expensive to complete. The other ones are nowadays dominantly used and developed [45, 47, 140, 142]. They assess several aspects of handwriting, such as legibility, letter size, slant and spacing, line straightness, readability, velocity, etc. These scales are less subjective than global scales, but they are still evaluated manually and therefore expensive and cannot provide a detailed insight into the process and the product of handwriting (i.e., accuracy, separation into strokes, fine motor tremor, kinematic and dynamic measures, etc.) [177]. Countless number of new studies (e.g. [54, 96, 141, 169, 181]) prove immeasurable benefits of online handwriting analysis and the GDRS is the next logical step in the research.

Some attempts to create broad automated analytical scales already exist. The first study described [37] is the automation of the BHK scoring process. This implementation only removes the manual aspect from assessing children handwriting. The final BHK scores must be input manually. Also, the software neither informs about any feature values derived from the product/process of online handwriting, nor delivers any measure of GD or HD based on those features.

The second one [7] involved a clustering analysis using PCA (Principal Component Analysis) and K–Means clustering of various handwriting features with BHK scale as a validation criterion. Children in this study were distributed to 5 groups with different range of DD severity according to final BHK score. Authors conclude that children with the same level of DD severity (final BHK score) manifested different values of the same feature. One of the study limitations was setting thresholds for the scores empirically. More methodological issues concerning the study could be found in [36]. On the other hand, the GDRS scale will offer a more detailed scoring system of each symptom. Also, the score of each symptom will be analytically computed by the gradient descent or a genetic algorithm, which will ensure objectivity of the value.

From the extensive state–of–the–art review (see Section 1) it can be deducted, that GD/HD are now dominantly researched either solely from the signal processing point of view, or from the psychological point of view. However, this topic needs to be researched by a wide range of experts from both fields, who cooperate as it is in the matter of this newly designed GDRS scale.

Tunable Q–Factor Wavelet Transform utilization in GD analysis

In Chapter 4 an advanced signal processing technique of online handwriting based upon Tunable Q–Factor Wavelet Transform (TQWT) was introduced. The features derived from the TQWT were specifically designed for online handwriting analysis. They have been already validated and published as a pilot study in the conference paper [181] and later in the IEEE Access journal [54] by the author of this thesis. The TQWT features showed a significant improvement in the HD identification on a handwriting task (paragraph copying). Employing the SVM classification algorithm, ACC was 79 %, in contrary to ACC equal to 75 % of an ML model trained with the same algorithm on the conventional feature subset (CV) [181]. Moreover, the combination of both subsets increased the classification performance of the ML model to ACC equal to 85 % (9 features).

The benefit of TQWT features to the GD analysis was also tested on several graphomotor tasks (TSK1–TSK7; see Section 2.2). The ML model achieved ACC equal to 71 % (Random Forest classifier), where the significant features were derived from the Archimedean spiral [54]. The combination of all features mentioned in the study (i.e. Fractional derivative–FD, Modulation spectra–MS and CV) achieved ACC equal to 84 % (10 features), where the TQWT features were derived from the Archimedean spiral and saw tasks.

The TQWT decomposes online handwriting signals $x[n]$ into components, from which one is the clean signal $x_{\mathrm{CL}}[n]$ and the other is the residual component $x_{\mathrm{RES}}[n]$. The $x_{\mathrm{RES}}[n]$ can be linked to poor dexterity, deficient fine motor skills or unspecified motor clumsiness. For this reason, several techniques to measure the noise level were in the mentioned studies presented, namely: signal–to–noise ratio (SNR) based upon the Teager–Keiser Operator, Square Energy Operator, an energy ratio of $x_{\mathrm{CL}}[n]$ and $x_{\mathrm{RES}}[n]$ (see Equation 4.3), slope of the cumulative sum of E_d and number of peaks above the median of E_d, where E_d denotes a derivative of $x_{\mathrm{RES}}[n]$ (see Equation 4.5). Following the results, almost all techniques excluding Teager—Keiser operator and Square energy operator, were selected as beneficial.

The analysis of TQWT features indicated, that the performance of classification of GD in children could be increased and it could assess an unspecified motor clumsiness and deficient fine motor skills linked with the DD.

The comparison of results with the state–of–the–art literature regarding GD analysis based on machine learning algorithms showed, that TQWT conducted on graphomotor tasks and on writing tasks was overcome by other advanced signal processing techniques (see Table 5.1). Nevertheless, after considering the nationality of enrolled children, the difference in ACC between ML models based upon MS and TQWT features was only 2 %.

Tab. 5.1: Advanced signal processing techniques in literature

Author	**Feat**	**Algo**	**Results**	**Num**	**Task**	**Subset**	**NA**
Mucha (2020) [106]	FD	XGBoost [28]	ERR = 16 %	16	GT	FD	CZ
Galáž (2020) [54]	MS	RF	ACC = 73 %	8	GT	MS	CZ
Asselborn (2018) [9]	SP	RF	SEN = 97 %, SPE = 92 %	53	WT	ALL	FR
Mekyska (2017) [96]	ZLC	RF	ACC = 79 %	1	GT	ZLC	IS

Feat – feature name, Algo – machine learning algorithm, Num – number of features in the trained model, Tasks – analysed task, where GT denotes graphomotor task and WT denotes writing, FD – fractional derivative, MS – modulation spectra, ZLC – Ziv-Lempel complexity, SP – Power spectral features, ERR – estimation error rate, ACC – classification accuracy, SEN – sensitivity, SPE – specificity, RF – random forest, ALL – feature set containing advanced features and also conventional ones, NA – denotes nationality: Czech (CZ), French (FR) and Israeli (IS).

5.3 Limits and future direction

The problems with the inaccurate definition of DD and description of symptoms, mentioned in previous parts of this thesis (see Sections 1.1.3, and 2), may negatively affect diagnostic professionals, such as psychologists (PS) and special educationalists (SE) and cause inconsistencies and disagreement in the final of a diagnosis. Vague definitions of DD consist only of general statements and the important specification of symptoms on the expert level is missing (see manuals DSM–V [5], ICD–10 [175] and MKN–10 [176], which is a Czech translation of ICD–10).

In addition, the symptomatology of the DD depends onlanguage and nationality. The explanation lays probably in orthographic depth of different languages (i.e. the extent to which one phoneme corresponds to one grapheme and vice versa) [146]. For example, it was reported that English children have a harder time to learn reading compared to Czech children (opaque orthography) [25, 76]. Therefore, it can be assumed, that children in England have more problems with learning to spell. This spelling problem occurs as a symptom of DD in English–speaking countries. On the other hand, in the Czech Republic DD is defined strictly as a motor disruption and the language difficulties are linked to Dysorthography and to Dyslexia. Nevertheless, the topic of the orthographic depth has not been yet examined on handwriting and DD.

Regarding the practise, some manifestations of DD in handwriting are based on direct observation and they are passed on from expert to expert via experienced lore. Most of them correspond with the common symptoms but some of them were proved invalid by scientific research. Good examples are laterality or grip [149], which are partially still maintained in the experts' practice.

Turning now to the online handwriting analysis, there is still need for more accurate and symptom–optimized features. The proposed list is not complete (see Appendices A.5, A.6, and A.7) and presumably will be extended. The mathematical models are able to describe almost all symptoms related to the process of handwriting. On the other hand, the analysis of the product of handwriting has some limitations. Currently, there are missing on–line methods to measure symptoms on the letter level, such as a precise measurement of space between letters/words, determination of quality of letter forms in the handwritten product; or on the next level, such as readability of the text or evaluation of the content.

The tasks assessing cognitive processes (CP) have not been quantified yet. Thanks to their novelty and experimental design (they have never been analysed or used by SE or PS before), it is not clear, how DD manifests itself in these types of tasks. More precisely, which of the symptoms or how the symptoms should be simulated (e.g. how to simulate drawing from memory in a child with DD). For this reason, these tasks were left to the later exploration by using other validation criteria or by the data driven approach.

Regarding the sample size at the time of writing of this thesis, data from children were still being collected. The major drawback is the low number of cases identified as DD by SE. Also, inconsistency in external validation criteria has been found between evaluations made by SE (information about diagnosis) and by children themselves (final scores of HPSQ–C), which are not usually in agreement with each other. In some cases, the child obtains higher scores of HPSQ–C, which indicates HD, but at the same time she/he has not been diagnosed with DD (by SE). On the other hand, in some cases the HPSQ–C final scores were close to each other even if one child was diagnosed with DD and the other was healthy (see Figures 2.8, 2.11, and 2.13). Nevertheless, the selection of children records for feature presentations was based on the feature differences, diagnosis, and if possible, on the most distinctive HPSQ–C scores. Also, it was not possible to assess all aspects of all symptoms, as between PS and SE is not a strong consensus, how exactly are different features manifested (e.g. automation of handwriting). This problem is a clear example, why the objective measurement (GDRS) of HD/GD is needed.

Moving on to the future work, proposed features will be tested, some of them can be added to the symptoms, others can be optimized. For instance, the feature measuring distance between the forward and backward lines of the rainbow (TSK 6; see Figure 2.8) can be optimized as a measure of the "tightness" of forward and backward lines, because children with GD are not able to draw the lines together. Also, other advanced features could be deployed, based upon sigma–lognormal models, which describe the velocity of planar movements as the summation of neuromuscular components that have a weighted and time–shifted lognormal velocity profile [44, 113]. In this way a symptom dysfluency can be measured in time as a Signal–to–noise ratio between the original velocity profile and the one reconstructed by the sigma–lognormal model.

After the simulation of symptoms, the GDRS scale will be tested and optimized on the recorded dataset. The GDRS will be validated by additional external criteria, such as BHK (Hamstra–Bletz test) [65], HLS (Handwriting legibility scale) [11] etc. The major benefit would be in providing a longitudinal study, which would observe children outcomes of GDRS through progressing grades and could bring information about typical and/or abnormal development of handwriting.

Also, to measure readability of the handwriting content, image processing techniques based on neural networks should be tested, as it has been already proved in analysis of Parkinson's drawings (e.g. [99, 121, 163, 172]).

Besides, the GDRS could be tested in remediation process of children with DD during their meetings with specialists. This application could objectively measure the improvement of the child's GA, which could be observed in the changes of different subscale scores.

Finally, implementation of the GDRS into practice as an online supportive analytic tool of GD/HD diagnosis is now in progress in the project founded by the Technology Agency of the Czech Republic (TL03000287: Software for advanced diagnosis of graphomotor abilities). The final product will provide an online objective measurement tool to the SE and PS, via processing actively recorded data of children by the Wacom Cintiq digitizer [59, 91]. The data will be sent to the cloud service in real–time. Moreover, the software will report records of handwriting, analysis of features and symptoms, GDRS subscores, and multimedia visualization of the product and process to the evaluator.

6 Conclusion

In Czech Republic, the prevalence of Developmental dysgraphia (DD) is approximately between 3–5 %. It is manifested by difficulties of graphomotor abilities (GA), such as lower automaticity of handwriting, deficient fine motor skills, hesitation during writing, etc. The possible manifestation of the DD can be identified early during the first and second grades of primary school as graphomotor difficulties (GD) and later during third and fourth grade as difficulties in handwriting (HD). The current diagnosis is carried out by psychologists (PS) and special educationalists (SE), who rely on their level of personal experience (tacit knowledge). Thus, the diagnostic assessment performed by an expert evaluator and the final diagnosis is more or less subjective. The accurate definition of GD, HD and DD on the expert level is missing in manuals DSM–V, ICD 10 and MKN 10 (Czech translation of ICD 10). This produces inconsistencies in diagnoses between practicians. Moreover, the latest scientific insights are not applied into practice (invalid effect of the laterality or the type). Hence, the major limitations of the DD diagnosis were identified as: 1) missing objective methods for DD diagnosis; 2) diagnosis based on observation skills of the evaluator. After the exploration of the mentioned research gap the Graphomotor difficulties rating scale (GDRS), which is built on advanced parametrization techniques of online handwriting signals, was proposed as an objective, modern and cost–effective solution. Moving to the individual aims of this thesis:

- The first aim was *to identify symptoms associated with GD in school–aged children and design new parameters quantifying them*. Firstly, the new assessment protocol was presented. It was uniquely designed in cooperation with PS and SE in order to create tasks, where the symptoms of GD/HD could manifest. The proposed GD assessment protocol is the most detailed and complex protocol in the field and consists of 36 different tasks. Seventy–six different features, which describe spatial, temporal, kinematic, dynamic, and other properties of online handwriting were designed to measure the identified symptoms. Some features were already tested on GD samples or on subjects with different disorders/disabilities by other authors, which was proved by adequate scientific literature. Also, 16 newly designed features were proposed. Some examples: intersection analysis, tempo features, features based on the vertical projection, etc. The robust mathematical modeling of symptoms has laid solid foundations for construction of the GDRS.
- The second aim was *to design a new graphomotor disabilities rating scale based on computerised analysis of handwriting*. The challenge of combining features into symptoms was resolved by the symptom simulations. This approach ensures, that symptoms would be constructed via s–features (features extracted

from simulations), that are not influenced by other co–occurring symptoms. Moreover, in this way, different rates of GD severity can be simulated, which would be not possible with the current dataset, that is lacking DD handwriting records. Next, the search for the optimal combination of sets of features that will represent identified symptoms was delegated to a genetic algorithm and the gradient descent algorithm. The final scale will be represented by a set of subscores produced by the symptoms. This step was supported by a notion, that the number of accumulated symptoms will describe the extent of GD. The GDRS has to be further tested by various external validation criteria. Moreover, the sets of features, that quantify identified symptoms may be slightly changed and some features optimized on the basis of a consequent analysis of the acquired dataset.

- The third aim was *to design new online handwriting parameters based on advanced signal processing techniques*. As shown by previous scientific research in the field, a robust parametrization is needed in order to quantify perspicuous and also subtle/hidden complexities of handwriting. This led to the design of parametrization techniques based on the Tunable Q Factor Wavelet Transform (TQWT). The residual product of TQWT was identified to be associated with poor dexterity, deficient fine motor skills or unspecified motor clumsiness. Several approaches were proposed to measure the noise–level of the residual component. The TQWT features performance was tested when identifying HD in a copying task utilizing machine learning (ML) techniques. The achieved classification accuracy (ACC) was equal to 79.2 % employing the SVM classifier, which was 5 % higher than for trained model based upon conventional features only. The results of another analysis were published in the IEEE Access journal, where TQWT features identified GD in graphomotor tasks employing the Random forest classifier (RF). In this setting TQWT features did not perform too well. The trained model achieved ACC equal to 71 %, which was around 3 % lower than the ACC of a model based on conventional features only. Nevertheless, in both studies TQWT features were beneficial to the most discriminating models and proved its importance in the assessment of GD.

The GDRS represents a novel and modern objective measurement tool, that is not yet available in the Czech Republic or in other countries. Its utilization will help in the modernization of DD diagnosis and in the remediation process. With proper research, it could be adapted into other languages as well. Moreover, the methodology can be used and optimized for other diseases, which affect graphomotor abilities, such as Autism, Attention Deficit Coordination Disorder (ADHD) or Developmental Coordination Disorder (DCD).

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List of symbols, constants and abbreviations

ACC	Accuracy
ADHD	Attention Deficit Hyperactivity Disorder
ANOVA	Univariate analysis of variance
BHK	Concise Evaluation Scale for Children's Handwriting
BRIEF	Behavior Rating Inventory of Executive Function
CART	Classification and Regression Trees
CON	Squared Energy Operator
CONV	Conventional features
CP	Capital letters
CP	Cognitive processes
CT	Cognitive task
CU	Cursive letters
CZR	Czech Republic
DCD	Developmental Coordination Disorder
DD	Developmental Dysgraphia
DPSQ	Drawing Proficiency Screening Questionnaire
DSM–V	The Diagnostic and Statistical Manual of Mental Disorders, 5 th Edition
FD	Fractional–irder derivatives
FDR	False discovery rate
FMP	Fine motor processes
GA	Graphomotor Abilities
GD	Graphomotor Difficulties
GDRS	Graphomotor Difficulties Rating Scale
GMP	Gross motor processes
GT	Graphomotor task
HC	Healthy controls
HD	Handwriting Difficulties
HPSQ	Handwriting Proficiency Screening Questionnaire
HPSQ–C	Handwriting Proficiency Screening Questionnaire for Children
ICD–10	The International Statistical Classification of Diseases and Related Health Problems, 10 th Edition
iqr	nterquartile range
IWN	Intra–writer normalization methods
K	Kurtosis
K–Means	K–means clustering
K–S	Kolgomorov–Smirnov test

MANOVA Multivariate analysis of variance
MCA Morphological component analysis
MCC Matthew correlation coefficient
MKN–10 Mezinárodní klasifikace nemocí, 10. edice
ML Machine learning
mRMR minimum Redundancy and Maximum Revelance
MS Modulation spectra
NIV Number of changes in velocity
OH Online handwriting
OT Occupational therapists
PCA Principal Component Analysis
PD Parkinson's disease
PS Psychologists
Q Q–Factor of TQWT
RADWT Rational–Dilatation Wavelet Transform
RF Random Forests
S Skewness
SALSA Split augmented Lagrangian shrinkage algorithm
SE Special educationalists
SEN Sensitivity
SFFS Sequential floating feature selection
SH Shapiro–Wilk test
SLD Specific Learning Disorder
SNR Signal to noise ration
SPE Specificity
SVM Support Vector Machine
TEO Teager–Kaiser Energy Operator
TMHA The Minnesota Handwriting Assessment
TQWT Tunable Q–Factor Wavelet Transform
TSK1 Archimedean spiral
TSK2 small Archimedean spiral
TSK3 Upper loops
TSK4 Lower loops
TSK5 Saw
TSK6 Rainbow
TSK7 Combined loops
TSK8–TSK28 Complex cognitive tasks
TSK29 Signature
TSK30 Copy of a sentence written in cursive letters

TSK31	Copy of a paragraph written in cursive letters
TSK32	Dictation
TSK33	Copy of a paragraph written in capital letters
TSK34	Dictation
TSK35	Copy of a sentence written in capital letters
TSK36	Dictation
WT	Writing task
XGBoost	eXtreme Gradient Boosting

List of appendices

A Appendix

A.1 Preliminary analysis: TSK3

SY	Abbreviation	Description	K	S	K–S	SH	A	B
1	ON: MPSTF	Median of power spectrum of tremor frequencies	1.8	0.5	7.58×10^{-10}	1.42×10^{-10}	0	0
4	ON: ADEN	Density in rectangular area around the handwriting	10	2.5	3.42×10^{-4}	2.17×10^{-13}	0	0
4	ON: PDEN	Density of path	3.2	1	1.08×10^{-2}	1.32×10^{-7}	0	0
5	DUR	Overall duration	5.5	1.5	5.27×10^{-2}	2.78×10^{-8}	0	0
5	ON: DUR	Duration of on–surface movement	5.8	1.5	5.29×10^{-2}	3.63×10^{-8}	0	0
5	ON: SDUR(median)	Median duration of on-surface's strokes	5.3	1.3	1.55×10^{-1}	4.29×10^{-6}	0	0
7	ON: NCV	Number of changes in velocity profile	8.7	2.1	3.43×10^{-3}	5.56×10^{-11}	0	0
7	ON: RNVC	Relative number of changes in velocity profile	3.2	0.4	6.42×10^{-1}	3.03×10^{-1}	0	0
7	ON: MPSSF	Median of power spectrum of speed frequencies	8.6	1.9	4.12×10^{-5}	7.80×10^{-11}	0	0
10	ON: {G}–VEL(median)	Median global velocity on–surface	3.3	1.1	8.95×10^{-3}	7.18×10^{-8}	0	0
10	ON: {G}–VEL(95p)	A 95th percentile of global velocity on–surface	3.2	0.9	1.59×10^{-1}	2.19×10^{-6}	0	0
10	ON: {V}–VEL(median)	Median of vertical velocity on–surface	3.2	1	5.58×10^{-3}	1.31×10^{-7}	0	0
10	ON: {V}–VEL(95p)	A 95th percentile of vertical velocity on–surface	3.5	1	6.01×10^{-2}	9.38×10^{-7}	0	0
10	ON: {H}–VEL(median)	Median of horizontal velocity on–surface	3.5	1.2	6.72×10^{-3}	1.45×10^{-8}	0	0
10	ON: {H}–VEL(95p)	A 95th percentile of horizontal velocity on–surface	3.4	1	1.33×10^{-1}	1.92×10^{-6}	0	0
11	ON: {G}–ACC(median)	Median global acceleration on–surface	11.6	1.3	6.22×10^{-15}	3.33×10^{-16}	0	0
11	ON: {G}–ACC(95p)	A 95th percentile of global acceleration on–surface	3.8	1.1	7.43×10^{-2}	2.00×10^{-7}	0	0
11	ON: {V}–ACC(95p)	A 95th percentile of vertical acceleration on–surface	5.3	1.4	1.48×10^{-2}	1.87×10^{-8}	0	0
11	ON: {H}–ACC(95p)	A 95th percentile of horizontal acceleration on–surface	4	1.2	6.49×10^{-2}	1.12×10^{-7}	0	0
17	PRESS: NC	Number of changes in pressure profile	11.4	2.5	5.46×10^{-4}	7.09×10^{-12}	0	0
17	PRESS(ncv)	Non-parametric coefficient of variation of pressure	3.9	1	1.25×10^{-1}	3.68×10^{-5}	0	0
18	NINT	Number of interruptions	12.4	2.8	7.55×10^{-15}	1.11×10^{-16}	0	0
19	TILT: NC	Number of changes in tilt profile	5.8	1.6	2.74×10^{-4}	7.68×10^{-9}	0	0
19	TILT (ncv)	Non-parametric coefficient of variation of tilt	9.5	2	7.87×10^{-3}	4.96×10^{-10}	0	0
20	ON: {H}–NC	Number of changes in horizontal projection	4.8	1.5	3.68×10^{-8}	8.69×10^{-11}	0	0
20	ON: {V}–NC	Number of changes in vertical projection	8.9	2.2	8.06×10^{-8}	7.27×10^{-13}	0	0

Symptom numbers (SY): 1 – Dysfluency in line; 4 – Unstable density; 5 – Higher duration of writing; 7 – Dysfluency in time; 10 – Low velocity; 11 – Low acceleration; 17 – An unstable pressure on the pen tip; 18 – Disability to perform longer strokes; 19 – Unstable tilt of the pen; 20 – Uncertainty in leading of the line in space, Kurtosis (K), Skewness (S), Kolmogorov–Smirnov test (K–S) – p–value, Shapiro–Wilk test (SH) – p–value, A – 1 denotes normal distribution of the features and 0 the opposite, B – denotes same as the A, but the threshold of the normality tests were significantly lowered.

A.2 Preliminary analysis: TSK4

SY	Abbreviation	Description	K	S	K–S	SH	A	B
1	ON: MPSTF	Median of power spectrum of tremor frequencies	1.7	-0.1	2.98×10^{-7}	1.59×10^{-9}	0	0
4	ON: ADEN	Density in rectangular area around the handwriting	17.9	3.4	3.52×10^{-5}	2.44×10^{-15}	0	0
4	ON: PDEN	Density of path	7.2	1.7	2.22×10^{-2}	2.46×10^{-9}	0	0
5	DUR	Overall duration	36.7	4.8	4.32×10^{-4}	4.44×10^{-16}	0	0
5	ON: DUR	Duration of on–surface movement	4.5	1.3	3.51×10^{-2}	2.17×10^{-7}	0	0
5	ON: SDUR(median)	Median duration of on-surface's strokes	4	0.9	8.03×10^{-1}	4.41×10^{-4}	0	0
7	ON: NCV	Number of changes in velocity profile	4.5	1.3	1.22×10^{-3}	2.56×10^{-8}	0	0
7	ON: RNVC	Relative number of changes in velocity profile	3.9	-0.2	8.66×10^{-1}	3.37×10^{-1}	0	0
7	ON: MPSSF	Median of power spectrum of speed frequencies	13.2	2.6	3.61×10^{-5}	8.14×10^{-13}	0	0
10	ON: {G}–VEL(median)	Median global velocity on–surface	3.5	1	5.30×10^{-2}	2.32×10^{-6}	0	0
10	ON: {G}–VEL(95p)	A 95th percentile of global velocity on–surface	4.6	1.2	7.11×10^{-2}	4.14×10^{-6}	0	0
10	ON: {V}–VEL(median)	Median of vertical velocity on–surface	4.3	1.3	1.97×10^{-2}	3.17×10^{-7}	0	0
10	ON: {V}–VEL(95p)	A 95th percentile of vertical velocity on–surface	3.5	1	5.23×10^{-2}	1.30×10^{-5}	0	0
10	ON: {H}–VEL(median)	Median of horizontal velocity on–surface	3.4	1	1.09×10^{-1}	2.86×10^{-6}	0	0
10	ON: {H}–VEL(95p)	A 95th percentile of horizontal velocity on–surface	4.8	1.3	8.74×10^{-2}	1.16×10^{-6}	0	0
11	ON: {G}–ACC(95p)	A 95th percentile of global acceleration on–surface	4.5	1.2	1.68×10^{-2}	4.98×10^{-7}	0	0
11	ON: {V}–ACC(95p)	A 95th percentile of vertical acceleration on–surface	4.4	1.2	6.56×10^{-2}	9.25×10^{-7}	0	0
11	ON: {H}–ACC(95p)	A 95th percentile of horizontal acceleration on–surface	4.5	1.3	3.98×10^{-2}	2.12×10^{-7}	0	0
17	PRESS: NC	Number of changes in pressure profile	10.2	2.4	7.60×10^{-4}	6.69×10^{-12}	0	0
17	PRESS(ncv)	Non-parametric coefficient of variation of pressure	6.6	1.8	2.04×10^{-2}	3.71×10^{-10}	0	0
19	TILT: NC	Number of changes in tilt profile	2.9	1	3.36×10^{-3}	1.44×10^{-7}	0	0
19	TILT (ncv)	Non-parametric coefficient of variation of tilt	12	2.6	3.27×10^{-5}	5.98×10^{-13}	0	0
20	ON: {H}–NC	Number of changes in horizontal projection	11	2.6	4.78×10^{-8}	2.34×10^{-14}	0	0
20	ON: {V}–NC	Number of changes in vertical projection	8.8	2.4	1.55×10^{-7}	1.83×10^{-14}	0	0

Symptom numbers (SY): 1 – Dysfluency in line; 4 – Unstable density; 5 – Higher duration of writing; 7 – Dysfluency in time; 10 – Low velocity; 11 – Low acceleration; 17 – An unstable pressure on the pen tip; 19 – Unstable tilt of the pen; 20 – Uncertainty in leading of the line in space, Kurtosis (K), Skewness (S), Kolmogorov–Smirnov test (K–S) – p–value, Shapiro–Wilk test (SH) – p–value, A – 1 denotes normal distribution of the features and 0 the opposite, B – denotes same as the A, but the threshold of the normality tests were significantly lowered.

A.3 Preliminary analysis: TSK35

SY	Abbreviation	Description	K	S	K–S	SH	A	B
2	ON: SHEIGHT (ncv)	Non–parametric coefficient of variation of stroke height	7.6	1.8	1.65×10^{-2}	1.02×10^{-8}	0	0
3	AZIM: NC	Number of changes in azimuth profile	4.6	0.6	8.21×10^{-1}	2.82×10^{-2}	0	0
3	AZIM (ncv)	Non–parametric coefficient of variation of azimuth	14.7	2.9	5.96×10^{-4}	2.73×10^{-13}	0	0
4	ON: ADEN	Density in rectangular area around the handwriting	6.6	1.7	1.51×10^{-2}	9.06×10^{-9}	0	0
4	ON: PDEN	Density of path	3.2	0.9	3.72×10^{-1}	4.43×10^{-5}	0	0
5	DUR	Overall duration	7.2	1.8	3.17×10^{-2}	3.70×10^{-9}	0	0
5	ON: DUR	Duration of on–surface movement	5.8	1.6	9.17×10^{-3}	1.21×10^{-8}	0	0
5	ON: SDUR(median)	Median duration of on-surface's strokes	5.6	1.3	1.76×10^{-1}	2.60×10^{-6}	0	0
6	DURR	Ratio of the on–surface/in–air duration	5.7	1.3	1.11×10^{-1}	1.84×10^{-6}	0	0
6	AIR: DUR	Duration of in–air movement	7.9	1.9	1.64×10^{-2}	1.27×10^{-9}	0	0
6	AIR: SDUR (median)	Median duration of in–air strokes	10.6	2.3	4.00×10^{-3}	3.91×10^{-11}	0	0
7	ON: NCV	Number of changes in velocity profile	3.9	0.8	5.46×10^{-1}	3.88×10^{-3}	0	0
7	ON: RNVC	Relative number of changes in velocity profile	3.2	-0.5	3.98×10^{-1}	1.04×10^{-1}	0	0
7	ON: MPSSF	Median of power spectrum of speed frequencies	12.3	2.6	1.24×10^{-4}	1.94×10^{-12}	0	0
8	SDURR (slope)	Slope of ratio of the on–surface/in–air stroke duration	7.3	1	1.02×10^{-1}	6.38×10^{-7}	0	0
8	ON: SDUR (slope)	Slope of duration of strokes on-surface	3.8	-0.6	1.05×10^{-1}	3.26×10^{-3}	0	0
8	AIR: SDUR (slope)	Slope of duration of strokes in–air	12.1	0.9	5.57×10^{-4}	1.64×10^{-11}	0	0
9	ON: TEMPO	Number of on-surface strokes normalised by on–surface duration	12.8	2.4	1.49×10^{-1}	1.92×10^{-10}	0	0
9	AIR: TEMPO	Number of in-air strokes normalised by in–air duration	4.3	1	3.31×10^{-1}	1.66×10^{-4}	0	0
10	ON: {G}–VEL(median)	Median global velocity on–surface	2.5	0.5	1.55×10^{-1}	3.77×10^{-3}	0	1
10	ON: {G}–VEL(95p)	A 95th percentile of global velocity on–surface	2.4	0.4	1.19×10^{-1}	9.17×10^{-3}	0	1
10	ON: {V}–VEL(median)	Median of vertical velocity on–surface	2.7	0.7	3.93×10^{-2}	5.08×10^{-4}	0	0
10	ON: {V}–VEL(95p)	A 95th percentile of vertical velocity on–surface	2.9	0.5	2.56×10^{-1}	4.50×10^{-3}	0	1
10	ON: {H}–VEL(median)	Median of horizontal velocity on–surface	2.7	0.7	1.03×10^{-1}	4.10×10^{-4}	0	1
10	ON: {H}–VEL(95p)	A 95th percentile of horizontal velocity on–surface	2.7	0.6	1.49×10^{-1}	1.90×10^{-3}	0	1
11	ON: {G}–ACC(95p)	A 95th percentile of global acceleration on–surface	2.6	0.5	1.59×10^{-1}	2.85×10^{-3}	0	1
11	ON: {V}–ACC(95p)	A 95th percentile of vertical acceleration on–surface	3.2	0.7	1.19×10^{-1}	6.88×10^{-4}	0	0
11	ON: {H}–ACC(95p)	A 95th percentile of horizontal acceleration on–surface	2.5	0.6	1.13×10^{-1}	1.24×10^{-3}	0	1
12	ON: {G}–VEL(iqr)	Inter–quartile range global velocity on-surface	2.4	0.5	2.30×10^{-1}	4.76×10^{-3}	0	1
12	ON: {V}–VEL(iqr)	Inter–quartile range vertical velocity on-surface	2.8	0.5	1.40×10^{-1}	8.02×10^{-3}	0	1
12	ON: {H}–VEL(iqr)	Inter–quartile range horizontal velocity on-surface	3.2	0.8	7.87×10^{-2}	7.06×10^{-4}	0	0
13	ON: {G}–ACC(iqr)	Inter–quartile range global acceleration on-surface	2.4	0.5	1.07×10^{-1}	2.77×10^{-3}	0	1
13	ON: {V}–ACC(iqr)	Inter–quartile range vertical acceleration on-surface	3	0.8	1.20×10^{-1}	3.59×10^{-5}	0	1
13	ON: {H}–ACC(iqr)	Inter–quartile range horizontal acceleration on-surface	2.9	0.7	1.50×10^{-1}	2.06×10^{-4}	0	1
14	ON: {G}–VEL(slope)	Slope of global velocity on–surface	12.8	2.4	4.80×10^{-2}	2.31×10^{-10}	0	0
14	ON: {V}–VEL(slope)	Slope of vertical velocity on–surface	15.2	2.6	1.15×10^{-2}	2.66×10^{-11}	0	0
14	ON: {H}–VEL(slope)	Slope of horizontal velocity on–surface	5.7	1.4	1.87×10^{-1}	3.92×10^{-7}	0	0
15	ON: {G}–ACC(slope)	Slope of global acceleration on–surface	11.4	2.3	9.70×10^{-4}	1.25×10^{-12}	0	0
15	ON: {V}–ACC(slope)	Slope of vertical acceleration on–surface	12.5	2.5	1.60×10^{-4}	5.43×10^{-13}	0	0
15	ON: {H}–ACC(slope)	Slope of horizontal acceleration on–surface	10.3	2.5	1.30×10^{-4}	2.24×10^{-13}	0	0
17	PRESS: NC	Number of changes in pressure profile	4	0.7	1.76×10^{-1}	5.29×10^{-3}	0	0
17	PRESS(ncv)	Non-parametric coefficient of variation of pressure	3.9	0.9	4.42×10^{-1}	2.81×10^{-4}	0	0
18	NINT	Number of interruptions	8.8	2.1	1.70×10^{-2}	1.06×10^{-10}	0	0
19	TILT: NC	Number of changes in tilt profile	7.1	1.5	1.55×10^{-1}	5.43×10^{-7}	0	0
19	TILT (ncv)	Non–parametric coefficient of variation of tilt	6.1	1.9	5.95×10^{-4}	7.01×10^{-12}	0	0

Symptom numbers (SY): 2 – Instability in amplitude of letters; 3 – Instability in inclination of letters; 4 – Unstable density; 5 – Higher duration of writing; 6 – Visuospatial deficits; 7 – Dysfluency in time; 8 – Progressing fatigue; 9 – Tempo; 10 – Low velocity; 11 – Low acceleration; 12 – Low variability of velocity; 13 – Low variability of acceleration; 14 – Gradual decrease of velocity; 15 – Gradual decrease of acceleration; 16 – Too high/low pressure on the pen tip; 17 – An unstable pressure on the pen tip; 18 – Disability to perform longer strokes; 19 – Unstable tilt of the pen, Kurtosis (K), Skewness (S), Kolmogorov–Smirnov test (K–S) – p–value, Shapiro–Wilk test (SH) – p–value, A – 1 denotes normal distribution of the features and 0 the opposite, B – denotes same as the A, but the threshold of the normality tests were significantly lowered.

A.4 Preliminary analysis: TSK36

SY	Abbreviation	Description	K	S	K–S	SH	A	B
1	ON: MPSTF	Median of power spectrum of tremor frequencies	1.6	0.6	6.66×10^{-16}	7.44×10^{-14}	0	0
2	ON: SHEIGHT (ncv)	Non–parametric coefficient of variation of stroke height	6.6	1.6	5.20×10^{-2}	1.02×10^{-7}	0	0
3	AZIM: NC	Number of changes in azimuth profile	3.4	0.6	3.44×10^{-1}	9.75×10^{-2}	0	0
3	AZIM (ncv)	Non–parametric coefficient of variation of azimuth	14	2.9	5.00×10^{-3}	1.30×10^{-13}	0	0
4	ON: ADEN	Density in rectangular area around the handwriting	4.5	1.3	1.71×10^{-2}	1.00×10^{-7}	0	0
4	ON: PDEN	Density of path	3.6	1	2.17×10^{-1}	4.59×10^{-6}	0	0
5	DUR	Overall duration	5.3	1.6	1.46×10^{-3}	3.50×10^{-10}	0	0
5	ON: DUR	Duration of on–surface movement	6.2	1.7	7.71×10^{-3}	4.97×10^{-9}	0	0
5	ON: SDUR(median)	Median duration of on-surface's strokes	13.5	2.2	1.48×10^{-1}	2.49×10^{-9}	0	0
6	DURR	Ratio of the on–surface/in–air duration	8.3	1.4	5.35×10^{-1}	3.92×10^{-6}	0	0
6	AIR: DUR	Duration of in–air movement	7.5	2	4.66×10^{-3}	8.93×10^{-11}	0	0
6	AIR: SDUR (median)	Median duration of in–air strokes	11.5	2.5	1.19×10^{-2}	1.03×10^{-11}	0	0
7	ON: NCV	Number of changes in velocity profile	5	1.2	2.23×10^{-1}	2.96×10^{-5}	0	0
7	ON: RNVC	Relative number of changes in velocity profile	3	-0.6	6.68×10^{-1}	7.27×10^{-3}	0	1
7	ON: MPSSF	Median of power spectrum of speed frequencies	16.4	2.8	1.14×10^{-3}	8.52×10^{-12}	0	0
8	SDURR (slope)	Slope of ratio of the on–surface/in–air stroke duration	12.2	2.1	6.77×10^{-3}	1.62×10^{-11}	0	0
8	ON: SDUR (slope)	Slope of duration of strokes on-surface	46.4	5.1	2.20×10^{-4}	2.22×10^{-16}	0	0
8	AIR: SDUR (slope)	Slope of duration of strokes in–air	13.6	2.2	4.51×10^{-3}	1.20×10^{-11}	0	0
9	ON: TEMPO	Number of on-surface strokes normalised by on–surface duration	13.1	2.2	2.19×10^{-1}	2.49×10^{-9}	0	0
9	AIR: TEMPO	Number of in-air strokes normalised by in–air duration	2.7	0.3	5.59×10^{-1}	1.58×10^{-1}	0	1
10	ON: {G}–VEL(median)	Median global velocity on–surface	2.4	0.4	3.96×10^{-1}	2.08×10^{-2}	0	1
10	ON: {G}–VEL(95p)	A 95th percentile of global velocity on–surface	2.3	0.3	4.09×10^{-1}	1.98×10^{-2}	0	1
10	ON: {V}–VEL(median)	Median of vertical velocity on–surface	2.9	0.7	2.87×10^{-1}	2.07×10^{-3}	0	1
10	ON: {V}–VEL(95p)	A 95th percentile of vertical velocity on–surface	2.8	0.5	3.58×10^{-1}	3.17×10^{-2}	0	1
10	ON: {H}–VEL(median)	Median of horizontal velocity on–surface	2.1	0.4	1.55×10^{-1}	7.64×10^{-4}	0	1
10	ON: {H}–VEL(95p)	A 95th percentile of horizontal velocity on–surface	2.4	0.5	4.19×10^{-1}	2.99×10^{-3}	0	1
11	ON: {G}–ACC(95p)	A 95th percentile of global acceleration on–surface	2.5	0.4	3.04×10^{-1}	1.79×10^{-2}	0	1
11	ON: {V}–ACC(95p)	A 95th percentile of vertical acceleration on–surface	3.1	0.6	9.80×10^{-2}	4.74×10^{-3}	0	0
11	ON: {H}–ACC(95p)	A 95th percentile of horizontal acceleration on–surface	2.3	0.4	2.11×10^{-1}	3.94×10^{-3}	0	1
12	ON: {G}–VEL(iqr)	Inter–quartile range global velocity on-surface	2.5	0.5	2.32×10^{-1}	2.17×10^{-2}	0	1
12	ON: {V}–VEL(iqr)	Inter–quartile range vertical velocity on-surface	3	0.6	3.91×10^{-1}	3.18×10^{-2}	0	1
12	ON: {H}–VEL(iqr)	Inter–quartile range horizontal velocity on-surface	2.6	0.5	1.57×10^{-1}	3.74×10^{-3}	0	1
13	ON: {G}–ACC(iqr)	Inter–quartile range global acceleration on-surface	2.3	0.3	5.72×10^{-1}	2.96×10^{-2}	0	1
13	ON: {V}–ACC(iqr)	Inter–quartile range vertical acceleration on-surface	3.1	0.8	1.47×10^{-1}	2.91×10^{-4}	0	0
13	ON: {H}–ACC(iqr)	Inter–quartile range horizontal acceleration on-surface	2	0.4	1.80×10^{-1}	3.30×10^{-4}	0	1
14	ON: {G}–VEL(slope)	Slope of global velocity on–surface	6.6	-0.7	2.15×10^{-2}	2.41×10^{-7}	0	0
14	ON: {V}–VEL(slope)	Slope of vertical velocity on–surface	5.2	-0.3	6.70×10^{-2}	9.54×10^{-5}	0	0
14	ON: {H}–VEL(slope)	Slope of horizontal velocity on–surface	12.8	-1.7	1.93×10^{-2}	2.28×10^{-10}	0	0
15	ON: {G}–ACC(slope)	Slope of global acceleration on–surface	8.2	0.1	3.12×10^{-3}	1.36×10^{-9}	0	0
15	ON: {V}–ACC(slope)	Slope of vertical acceleration on–surface	12.4	1.8	1.44×10^{-3}	5.92×10^{-11}	0	0
15	ON: {H}–ACC(slope)	Slope of horizontal acceleration on–surface	9.5	-1.7	5.03×10^{-4}	5.78×10^{-11}	0	0
17	PRESS: NC	Number of changes in pressure profile	4.1	0.8	3.42×10^{-1}	3.10×10^{-3}	0	0
17	PRESS(ncv)	Non-parametric coefficient of variation of pressure	4.9	1	3.97×10^{-1}	2.43×10^{-4}	0	0
18	NINT	Number of interruptions	7.4	1.7	3.31×10^{-2}	3.22×10^{-8}	0	0
19	TILT: NC	Number of changes in tilt profile	5.7	1.4	9.77×10^{-2}	1.68×10^{-6}	0	0
19	TILT (ncv)	Non–parametric coefficient of variation of tilt	13.8	2.8	7.15×10^{-4}	2.83×10^{-13}	0	0

Symptom numbers (SY): 1 – Dysfluency in line; 2 – Instability in amplitude of letters; 3 – Instability in inclination of letters; 4 – Unstable density; 5 – Higher duration of writing; 6 – Visuospatial deficits; 7 – Dysfluency in time; 8 – Progressing fatigue; 9 – Tempo; 10 – Low velocity; 11 – Low acceleration; 12 – Low variability of velocity; 13 – Low variability of acceleration; 14 – Gradual decrease of velocity; 15 – Gradual decrease of acceleration; 16 – Too high/low pressure on the pen tip; 17 – An unstable pressure on the pen tip; 18 – Disability to perform longer strokes; 19 – Unstable tilt of the pen, Kurtosis (K), Skewness (S), Kolmogorov–Smirnov test (K–S) – p–value, Shapiro–Wilk test (SH) – p–value, A – 1 denotes normal distribution of the features and 0 the opposite, B – denotes same as the A, but the threshold of the normality tests were significantly lowered.

A.5 Features validated on GD handwriting

Study	Abbreviation	Name	Sig	Sym	T	U
Mekyska (2017) [96]	ZLC	Lempel–Ziv complexity measuring technique	*	1	P	1
Mekyska (2017) [96]	SHE	Shannon entropy	\	1	P	1
Zvoncak (2019) [181]	TQWT	Tunable Q–Factor Waveleth Transform	*	1	P	1
Asselborn (2018) [9]	MPSTF	Med of power spectrum of tremor frequencies	*	1	P	1
Rosenblum (2018) [130]	ON: SHEIGHT (ncv)	Ncv of local maxima in vertical projection	*	2	P	0
Mekyska (2017) [96]	AZIM (ncv)	Ncv of azimuth	*	3	P	0
Asselborn (2020) [7]	AZIM: NC	Num of changes in azimuth profile	\	3	P	1
Asselborn (2020) [7]	ON: PDEN	Density of path	\	4	P	0
Asselborn (2020) [7]	ON: ADEN	Density in rectangular area around the handwriting	\	4	P	1
Rosenblum (2017) [133]	ON: NIAI	Num of on–surface intra–stroke intersections	*	4,24	P	0
Mekyska (2017) [96]	NINT	Num of interruptions	\	20,18	P,S	1
Mekyska (2019) [98]	DUR	Overall duration	\	5	S	1
Zvoncak (2018) [180]	ON: DUR	Duration of on-surface movement	\	5	S	1
Morello (2019) [100]	ON: SDUR(med)	Med duration of on-surface's strokes	*	5	S	1
Asselborn (2020) [7]	AIR: DUR	Duration of in-air movement	*	6	S	0
Zvoncak (2018) [180]	AIR: SDUR (med)	Med duration of in-air strokes	*	6	S	0
Chang (2013) [27]	DURR	Ratio of the on-surface/in-air duration	*	6	S	0
Danna (2013) [34]	ON: NCV	Num of changes in velocity profile	*	7	S	1
Danna (2013) [34]	ON: RNVC	Rel num of changes in velocity profile	*	7	S	0
Asselborn (2020) [7]	ON: MPSSF	Med of power spectrum of speed frequencies	*	7	S	0
Paz–Villagrán (2014) [120]	ON: NPS	Num of pen stops	*	7	S	1
Mekyska (2017) [96]	AIR: SDUR (sl)	Sl of duration of strokes in–air	\	8	S	1
Mekyska (2017) [96]	ON: SDUR (sl)	Sl of duration of strokes on-surface	\	8	S	1
Galaz (2020) [54]	ON: {G,H,V}–VEL(med)	Med velocity	*	10	S	0
Asselborn (2020) [7]	ON: {G,H,V}–VEL(95p)	A 95th percentile of velocity	\	10	S	0
Galaz (2020) [54]	ON: {G,H,V}–ACC(med)	Med acceleration	*	11	S	0
Mekyska (2017) [96]	ON: {G,H,V}–ACC(95p)	A 95th percentile of velocity	\	11	S	1
Mekyska (2017) [96]	ON: {G,H,V}–VEL(iqr)	Range of velocity excluding some outliers/extreme values	\	12	S	1
Mekyska (2017) [96]	ON: {G,H,V}–ACC(iqr)	Range of acceleration excluding some outliers/extreme values	\	13	S	1
Asselborn (2020) [7]	ON: {G,H,V}–VEL(sl)	Sl of velocity profile	\	14	S	0
Mekyska (2017) [96]	ON: {G,H,V}–ACC(sl)	Sl of acceleration profile	\	15	S	1
Rosenblum (2017) [133]	PRESS (med)	Med of pressure	\	16	S	1
Asselborn (2020) [7]	PRESS: NC	Num of changes in pressure profile	*	17	S	0
Mekyska (2017) [96]	PRESS (sl)	Sl of pressure profile	\	17,24	S	1
Mekyska (2017) [96]	PRESS(ncv)	Ncv of pressure	\	17	S	0
Mekyska (2017) [96]	TILT (ncv)	Ncv of tilt	*	19,24	S	0
Mekyska (2017) [96]	ON: SHEIGHT (sl)	Sl of stroke width	\	24	S	1

Study – main author; year of publication and citation, Abbreviation – abbreviation of the feature, where {G,H,V} denotes global (G) or horizontal (H) or vertical (V) movement; ON denotes on–surface movement, AIR denotes in–air movement if not specified in the name, Name – name of the feature, Sig – significance, where * or \ informs about significance/non–significance of the feature in the cited study, T – type denotes if the feature was assigned to the product (P) or process (S) of handwriting, U – unique denotes if the designed feature in this thesis is exactly the same (1) or is just similar (0) to the one cited in the study, symptom numbers (Sym): 1 – Dysfluency in line; 2 – Instability in amplitude of letters; 3 – Instability in inclination of letters; 4 – Unstable density; 5 – Higher duration of writing; 6 – Visuospatial deficits; 7 – Dysfluency in time; 8 – Progressing fatigue; 9 – Tempo; 10 – Low velocity; 11 – Low acceleration; 12 – Low variability of velocity; 13 – Low variability of acceleration; 14 – Gradual decrease of velocity; 15 – Gradual decrease of acceleration; 16 – Too high/low pressure on the pen tip; 17 – An unstable pressure on the pen tip; 18 – Disability to perform longer strokes; 19 – Unstable tilt of the pen; 20 – Inability to maintain handwriting on a line; 21 – Inability to return back in line; 22 – Uncertainty in leading a line in space; 23 – Frequent overwriting; 24 – Writing under hand, ncv – non–parametric coefficient of variation, med – median, sl – slope, num – number, rel – relative.

A.6 Features validated on PD handwriting

Study	Abbreviation	Name	Sig	Sym	T	U
Luciano (2016) [88]	1stZC	First order zero–crossing rate	\	1	P	1
Luciano (2016) [88]	2ndSm	Second order smoothness	*	1	P	1
Luciano (2016) [88]	DoS	Degree of spiral drawing severity	*	1	P	1
Cascarano (2019) [26]	ON: SPI	Spiral precision index	\	4	P	1
Luciano (2016) [88]	TGHTNS	Spiral tightness	*	4	P	1
Luciano (2016) [88]	SWVI	Variability of spiral width	*	4	P	1
Luciano (2016) [88]	MDS	Mean drawing speed	*	10	S	1

Study – main author; year of publication and citation, Abbreviation – abbreviation of the feature, Name – name of the feature, Sig – significance, where * or \ informs about significance/non–significance of the feature in the cited study, T – type denotes if the feature was assigned to the product (P) or process (S) of handwriting, U – unique denotes if the designed feature in this thesis is exactly the same (1) or is just similar (0) to the one cited in the study, symptom numbers (Sym): 1 – Dysfluency in line; 4 – Unstable density; 10 – Low velocity, ncv – non–parametric coefficient of variation, med – median, sl – slope, num – number.

A.7 Newly designed GD features

Abbreviation	Name	Sym	Task	T
ON: V–LMAX(ncv)	Ncv of local maxima in vertical projection	2	3–5	P
ON: V–DLMAX(ncv)	Ncv of distance between neighbour local maxima in vertical projection	4	3, 4	P
ON:RNIAI	Rel num of on-surface intra–stroke intersections	4, 24	1–4, 7; 29–36	P
ON: V–LMIN (ncv)	Ncv of local minima in vertical projection	20	3, 5, 6	P
ON: DFB (med)	Med distance between the forward and backward lines	21	6	P
ON: {H,V}–NC	Num of changes in horizontal/vertical projection	22	3, 4, 7	P
ON: V–VLMAX (med)	Med velocity at local maxima in vertical projection	22	5	P
ON: NDFB (med)	Med of normalised width of teeth	22	5	P
ON: NIEI	Num of on-surface inter-stroke intersections	23	29–36	P
ON: RNIEI	Rel num of on-surface inter–stroke intersections	23	29–36	P
ON: V–DURLMAX (ncv)	Ncv of duration between neighbour local maxima in vertical projection	7	3–7	S
SDURR (sl)	Sl of ratio of the on-surface/in-air stroke duration	8	3–7	S
ON: TEMPO	Num of on-surface strokes normalised by on-surface duration	9	3–7	S
AIR: TEMPO	Num of in-air strokes normalised by in-air duration	9	3–7	S
TILT: NC	Num of changes in tilt profile	19	1–7; 29–36	S

Study – main author; year of publication and citation, Abbreviation – abbreviation of the feature, where {H,V} denotes horizontal (H) or vertical (V) movement; ON denotes on–surface movement, AIR denotes in–air movement if not specified in the name, Name – name of the feature, Task – denotes type of the task (see Section 2), T – type denotes if the feature was assigned to the product (P) or process (S) of handwriting, symptom numbers (Sym): 2 – Instability in amplitude of letters; 4 – Unstable density; 6 – Visuospatial deficits; 7 – Dysfluency in time; 8 – Progressing fatigue; 9 – Tempo; 19 – Unstable tilt of the pen; 20 – Inability to maintain handwriting on a line; 21 – Inability to return back in line; 22 – Uncertainty in leading a line in space; 23 – Frequent overwriting; 24 – Writing under hand, ncv – non–parametric coefficient of variation, med – median, sl – slope, num – number.

Author's publications

Publications in journals with impact factor

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1. ([181]) Zvoncak, V.; Mekyska, J.; Safarova, K.; Smekal, Z.; Brezany, P.: New Approach of Dysgraphic Handwriting Analysis Based on the Tunable Q-Factor Wavelet Transform. In *2019 42nd International Convention on Information and Communication Technology, Electronics and Microelectronics (MIPRO)*, IEEE, 2019, pp. 289–294, doi: 10.23919/MIPRO.2019.8756872.
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Software

1. ZVONČÁK, V.; MEKYSKA, J.; GALÁŽ, Z.; MUCHA, J.: Labeling software for online handwriting (2019).
2. ILGNER, P.; ZVONČÁK, V.; MUCHA, J.; MEKYSKA, J.; GALÁŽ, Z.: Synchronized record of EEG signals and online handwriting (2019).
3. ILGNER, P.; ZVONČÁK, V.; MEKYSKA, J.; GALÁŽ, Z.; MUCHA, J.: Software for online handwriting record on digitizers with LCD screen (2019).
4. MUCHA, J.; MEKYSKA, J.; ZVONČÁK, V.; GALÁŽ, Z.; SMÉKAL, Z.: HandAQUS; HandAQUS - Handwriting acquisition software (2018).
5. ZVONČÁK, V.; GALÁŽ, Z.; MEKYSKA, J.; SMÉKAL, Z.: Biomedical data visualization tool (2017).

Curriculum Vitæ

Vojtěch Zvončák

Education

2016–2020	Brno University of Technology, Faculty of Electrical Engineering and Communication, Technická 3058/10, 616 00 Brno, degree: Ph.D. (expected in: 2021).
2013–2016	Brno University of Technology, Faculty of Electrical Engineering and Communication, Technická 3058/10, 616 00 Brno, degree: M.Sc (achieved in: 2016).
2009–2013	Brno University of Technology, Faculty of Electrical Engineering and Communication, Technická 3058/10, 616 00 Brno, degree: B.Sc (achieved in: 2013).
2005–2009	Střední průmyslová škola, Zlín, Czech Republic.

Internships

2019	TecnoCampus Mataró, Pompeu Fabra University, Barcelona, Spain.
2017	TecnoCampus Mataró, Pompeu Fabra University, Barcelona, Spain.

Teaching

2020–2021	Assistant lecturer, Signals and systems analysis.
2017–2019	Assistant lecturer, Digital Signal Processing.
2016–2018	Assistant lecturer, Signals and systems analysis.
2016–2017	Assistant lecturer, Object–oriented programming in Java.
2021	Master thesis advisor: Michal Gavenčiak, Research of the new online handwriting features for identification of graphomotor difficulties in children.
2021	Master thesis advisor: Filip Vrba, Removal of the negative MR noise from speech recordings.

2019	Bachelor thesis advisor: Michal Gavenčiak, Semi–automatic computerized system for the segmentation of online handwriting.
2018	Bachelor thesis advisor: Lukáš Balaževič, Android stock market application.
2017	Bachelor thesis advisor: Josef Doleček, Development of laboratory exercises for subject the Signals and systems analysis.

Employment history

2016–∗	*researcher*: Brain Diseases Analysis Laboratory (BDALab), Department of Telecommunications, Faculty of Electrical Engineering and Communication, Brno University of Technology, Technická 12, 616 00 Brno, Czech Republic.
2015–∗	*researcher*: Signal Processing Laboratory (SPLab), Department of Telecommunications, Faculty of Electrical Engineering and Communication, Brno University of Technology, Technická 12, 616 00 Brno, Czech Republic.

Participation in projects

2020–2023	Technology Agency of the Czech Republic (TL03000287): *Software ofr advanced diagnosis of graphomotor disabilities.*
2020–2022	Brno University of Technology (FEKT–S–20–6291): *Multimodal analysis of audio and image signals using sophisticated signal processing methods and machine learning.*
2017–2021	The Marie Skłodowska–Curie Action (734718 CoBeN): *Novel Network–Based Approaches for Studying Cognitive Dysfunction in Behavioral Neurology.*
2018–2020	The Czech Science Foundation (18–16835S): *Research of advanced developmental dysgraphia diagnosis and rating methods based on quantitative analysis of online handwriting/drawing.*
2017–2019	Brno University of Technology (FEKT–S–17–4476): *Multimodal processing of unstructured data using machine learning and sophisticated methods of signal and image analysis.*
2016–2019	Ministry of Health of Czech Republic (NV16–30805A): *Effects of non–invasive brain stimulation on hypokinetic dysarthria, micrographia, and brain plasticity in patients with Parkinson's disease.*

2017–2018 Brno University of Technology: *SystemPas*

Research activity

- Publications in journals with impact factor: 7
- Publications in journals without impact factor: 5
- Publications in conference proceedings: 13
- Publications indexed by WoS: 17
- Publications indexed by Scopus: 17
- H–index according to WoS: 4
- H–index according to Scopus: 5
- Citation count according to WoS (excluding self–citations): 18
- Citation count according to Scopus (excluding self–citations): 27
- Software/tools: 5