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P WAVE DETECTION IN PATHOLOGICAL ECG SIGNALS

DETEKCE P VLNY V PATOLOGICKÝCH SIGNÁLECH EKG

SUMMARY OF DOCTORAL THESIS

TEZE DIZERTAČNÍ PRÁCE

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ABSTRACT

Accurate software for the P wave detection, mainly in long-term monitoring, is an important part of electrocardiogram (ECG) evaluation and subsequent cardiac pathological events detection. The results of P wave detection allow us to obtain more information from the ECG records. According to the correct P wave detection, it is possible to detect and distinguish cardiac pathologies which are nowadays automatically undetectable by commonly used software in medical practice (events e.g. atrioventricular block 1st, 2nd and 3rd degree, WPW syndrome, wandering pacemaker, etc.). This thesis introduces a new method for P wave detection in ECG signals during both physiological and pathological heart function. This novel method is based on a phasor transform, innovative rules, and identification of possible pathologies that improve P wave detection. An equally important part of the work is the creation of two publicly available databases of physiological and pathological ECG records with annotated P waves. The dissertation is divided into theoretical analysis and a set of publications representing the contribution of the author in the area of P wave detection.

KEYWORDS

electrocardiogram, ECG analysis, QRS complex detection, P wave detection, phasor transform, pathological ECG signals, atrial fibrillation, ventricular premature contraction, ECG database, P wave annotations

ABSTRAKT

Důležitou součástí hodnocení elektrokardiogramu (EKG) a následné detekce srdečních patologií, zejména v dlouhodobém monitorování, je detekce vln P. Výsledky detekce vln P umožňují získat ze záznamu EKG více informací o srdeční činnosti. Podle správně detekovaných pozic vln P je možné detekovat a odlišit patologie, které současné programy používané v medicínské praxi identifikovat neumožňují (např. atrioventrikulární blok 1., 2. a 3. stupně, cestující pacemaker, Wolffův-Parkinsonův-Whiteův syndrom). Tato dizertační práce představuje novou metodu detekce vln P v záznamech EKG během fyziologické a zejména patologické srdeční činnosti. Metoda je založena na fázorové transformaci, inovativních pravidlech detekce a identifikaci možných patologií zpřesňující detekci vln P. Dalším důležitým výsledkem práce je vytvoření dvou veřejně dostupných databází záznamů EKG s obsahem patologií a anotovanými vlnami P. Dizertační práce je rozdělena na teoretickou část a soubor publikací představující příspěvek autora v oblasti detekce vlny P.

KLÍČOVÁ SLOVA

elektrokardiogram, analýza EKG, detekce komplexu QRS, detekce vlny P, fázorová transformace, patologické signály EKG, fibrilace síní, komorová extrasystola, databáze EKG, anotace vln P

BIBLIOGRAPHIC CITATION

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DECLARATION

I declare that I have written the doctoral thesis titled “Detection of P wave in ECG signals with pathology” independently, under the guidance of the supervisor, and using the technical literature and other sources quoted within the thesis and detailed in the list of literature in the final section.

As the author of the thesis, I furthermore declare that, as regards the creation of the work, I have not infringed any copyright. In particular, I confirm that I have not violated anyone’s personal and/or ownership rights and I am fully aware of the consequences of breaking Regulation § 11 of the Copyright Act No. 121/2000 Coll., as amended, and intellectual property rights or changes in related Acts (the Intellectual Property Act), as amended, inclusive of possible consequences resulting from the provisions of the Criminal Act No. 40/2009 Coll., Section 2, Head VI, Part 4.

Brno, 16 July 2022 .....

Ing. Lucie Šaclová

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My gratitude belongs also to my family, especially my mother, grandparents, and my husband, for their encouragement and support throughout my studies.

At this point, I would like to mention that I got married during my doctoral studies. Some articles are therefore published under my maiden name – Lucie Maršánová.

Brno, 16 July 2022 .....

Ing. Lucie Šaclová

TABLE OF CONTENTS

1. INTRODUCTION

Cardiovascular diseases are currently one of the most common causes of death worldwide [1]. Electrocardiography is still the most commonly used method for the examination of the heart's function, due to its simplicity, non-invasive character, and the cost of the procedure [2]. An electrocardiogram (ECG) is a curve that reflects the electrical activity of the heart and provides information about heart function. The ECG describes two main heart activities: atrial activity (represented by P wave) and ventricular activity (represented by QRS complex and T wave) [3]. Automatic detection of the QRS complexes, P waves, and T waves, represents one of the most important steps during the evaluation of ECG and subsequently to diagnose the occurrence of pathology [4].

The detection of ventricular activity has been studied in many previous works mentioned in [5] with successful results, but the automatic and reliable detection of atrial activity is still an unsolved problem. This applies especially in the case of ECG signals with pathology occurrence. Most of the methods for P wave detection have been evaluated on physiological signals (normal sinus rhythm) and rarely consider the occurrence of pathology e.g. [6], [7], [8], [9]. This can be seen in real medical practice in commonly used software for ECG signal evaluation, which was verified during the author´s seven years-long work in the cardiology clinic Mudr. Petr Bouchal in Brno. The detection of P waves in ECG signals with pathology is the topic of this thesis.

The information about the P wave (shape, position) is important for diagnosing many types of arrhythmias [10]. The information about positions can be used to diagnose atrioventricular blocks of 1st, 2nd, and 3rd degree. It is a key point for the differential diagnosis between tachycardias of supraventricular and ventricular origin, and it can be used for the identification of junctional and ventricular ectopic beat or rhythm, detection of atrial fibrillation, or flutter. If the shape of the P wave is changed – e.g. peaked, notched, inverted, or enlarged, it may indicate pathology, e.g. atrial hypertrophy or enlargement. It may signify retrograde conduction from the AV node to the atria during junctional rhythm or traveling pacemaker [11]. The results of automatic P wave detection allow to gain more information from the ECG record and simplify the daily work of cardiologists.

In medical practice, there is a large number of commercial software solutions used for the automatic analysis of long-term ECG, e.g. [12], [13], [14], [15], [16], [17], [18], [19]. However, none of them can reliably evaluate ECG records without detailed manual revision provided by a trained ECG expert or a cardiologist [4]. This is a very time-consuming procedure. Many errors, which must be corrected during manual revision, are connected with the wrong detection of the P wave during automatic ECG evaluation by software [20], [21]. There exist only a small number of published works, in which P wave detection was tested on signals with pathologies occurrence [22], [23], [24], [25]. However, they do not provide sufficient results. Moreover, they were tested only on a few signals [23], [24], [25] containing just one type of pathology for which the algorithm was designed or they were tested on a small number of pathologies [22].

In addition, none of them was tested on the publicly available dataset. Therefore, it is highly desirable to improve existing methods for P waves detection during pathology and/or to develop new and robust methods which enable more accurate processing and analysis of ECG records.

The main reason why P wave detection is more difficult than detection of other ECG components are their above-mentioned exclusive characteristics: a) P waves have a low voltage resulting in a low signal-to-noise ratio (SNR), which applies especially in long-term monitoring; b) P waves have no exclusive time and frequency characteristics; c) P waves have high interpatient variability; d) in the case of atrioventricular (AV) dissociations, P waves do not respect normal time ordering of an ECG sequence (P wave can be missing, or redundant); e) in the case of tachycardia, P waves can be hidden within T waves; f) in the case of atrial fibrillation or atrial flutter, P waves are missing; g) in the case of ventricular ectopy, P waves are usually not present [2], [10], [20]. All of these facts must be considered when creating a robust algorithm for P waves detection. It means that the reason why the results of P waves detection algorithms in pathological signals are insufficient is the ignorance of the pathophysiology function of the heart and its manifestation in ECG signals. Without a detailed understanding of this topic, it is not possible to design an algorithm able to reliably detect P waves within pathologies.

Another reason why research in this field is not successful is that there is no publicly available database of ECG signals with pathologies and correct P waves annotations. The methods are usually tested only on part of the publicly available QT database [26], [27] and frequently used but not publicly available CSE database [29], [30] both predominantly with physiological records. There are publicly available P waves annotations of MIT-BIH Arrhythmia database [28] from Elgendi et al. [31], automatically annotated part of QT database [26], [27] and Lobachevsky University Electrocardiography Database (LUDB) [32], but these contain many mistakes or incomplete annotations. Therefore, for the research progress is very important to close this gap and create a new database with correctly annotated P waves in ECG signals with pathology. For this purpose, two publicly available databases [33], [34], [35] were created and published on Physionet [26] by us.

This dissertation is written as a set of commented publications. In Chapter 2, the aims of the thesis are defined. Chapter 3 describes the theoretical background of P waves detection in ECG signals during pathology, the basics of heart physiology and pathology, the current state of research on P waves detection, and existing databases of ECG signals with P wave annotations are listed. Knowledge of this issue is necessary to understand the contribution to P waves detection in presence of pathology made and described in the presented papers. Finally, the important author´s publications with introductory comments are present in Chapter 4.

2. AIMS OF THE DOCTORAL THESIS

The main aim of this thesis is to design a new algorithm for P waves detection in ECG signals able to correctly detect P waves during the pathological function of the heart. Another important aim is to create a new database of ECG signals with annotated P waves.

The specific aims of the thesis are as follows:

1) To understand and describe the manifestation of pathology in ECG in the sense of P waves. To review (to the best of our knowledge) methods used for P waves detection and point out the drawbacks.

   MOTIVATION: Without a detailed understanding of the manifestation of pathology in ECG it is not possible to design an algorithm capable of reliable P wave detection within pathologies.

   SOLUTION: Chapter 3

   CONTRIBUTION: The detailed overview of how a concrete type of pathology manifests in ECG in the sense of P waves and the detailed summary of methods used for P wave detection. It can serve as basic material for future researchers in the area of P wave detection.

2) To design a reliable QRS complex detector in ECG signals.

   MOTIVATION: For reliable detection of P waves, it is necessary to detect QRS complexes at first. If the detection of QRS complexes is not reliable, the subsequent P wave detection will probably fail.

   SOLUTION: Paper 1

   - Maršánová, L. Detection of P, QRS and T Components of ECG Using Phasor Transform. Proceedings of the student conference Blansko 2016;55-58.

   CONTRIBUTION: One of the most reliable QRS complex detectors with a low computational cost.

3) To create a reliable method for the detection of P waves in physiological records.

   MOTIVATION: The successful P waves detector in physiological ECG records is the important starting point for P waves detection in ECG records with pathology.

   SOLUTION: Paper 1

   - Maršánová, L. Detection of P, QRS and T Components of ECG Using Phasor Transform. Proceedings of the student conference Blansko 2016;55-58.

   CONTRIBUTION: One of the most reliable P waves detectors in physiological signals.

4) To design methods for atrial fibrillation and ventricular ectopy detection.

MOTIVATION: The successful detection of the P wave during different types of pathologies is possible only if we consider these pathologies and their specifics. Atrial fibrillation and premature ventricular ectopy are the most common pathologies present in ECG records and affect the P wave detection. Thus, their identification must be solved at first.

SOLUTION: Paper 2, Paper 3, and Paper 4

- Maršánová L, Ronzhina M, Smisek R, Vitek M, Nemcova A, Smital L, et al. ECG features and methods for automatic classification of ventricular premature and ischemic heartbeats: A comprehensive experimental study. Scientific Reports 2017;7.
- Maršánová L, Nemcova A, Smisek R, Goldmann T, Vitek M, Smital L. Automatic Detection of P Wave in ECG During Ventricular Extrasystoles. World Congress On Medical Physics And Biomedical Engineering 2018 2019:381-385.
- Maršánová L, Smital L, Smisek R, Nemcova A, Vitek M. Single-Feature Method for Fast Atrial Fibrillation Detection in ECG Signals. Computing in Cardiology 2020.

CONTRIBUTION: The reliable methods for detection of pathologies (atrial fibrillation and ventricular ectopy) in ECG signal. These methods can be used either during P waves detection or for atrial fibrillation and ventricular ectopy detection on their own.

5) To design a reliable method for P wave detection capable to detect P waves during pathological heart function.

MOTIVATION: None of the commercial software solutions used for automatic analysis of long-term ECG can evaluate records reliably in the sense of P waves without manual revision by a cardiologist. In the ECG research area, there exist only a small number of works, in which P waves detection was tested on signals with pathologies. However, they do not provide sufficient results. Therefore, it is highly desirable to develop new reliable methods for P waves detection which enable more accurate processing and analysis of ECG records.

SOLUTION: Paper 5, Paper 6

- Maršánová L, Nemcova A, Smisek R, Vitek M, Smital L. Advanced P Wave Detection in ECG Signals During Pathology: Evaluation in Different Arrhythmia Contexts. Scientific Reports 2019.
- Šaclová L, Vitek M, Nemcova A, Smisek R, Smital L. Reliable P wave detection in pathological ECG signals. Scientific Reports 2022.

CONTRIBUTION: The novel method for P waves detection in ECG signals with pathology. The method can deal with the detection of P waves during 23 different types of pathology. The method is the most successful of all known algorithms for P waves detection.

6) To create a publicly available database of physiological and pathological ECG records with annotated P waves.

MOTIVATION: There are no publicly available databases with annotated P waves for testing P wave detector accuracy during pathology heart function. Only two databases of physiological signals with annotated P waves are used for P waves detectors evaluation and comparison.

SOLUTION: 2 publicly available dataset, described also in Paper 5 and Paper 6

- Brno University of Technology ECG Signal Database with Annotations of P Wave (BUT PDB) [34]. *Described in: Šaclová L, Vitek M, Nemcova A, Smisek R, Smital L. Reliable P wave detection in pathological ECG signals. Scientific Reports 2022.*
- MIT-BIH Arrhythmia Database P-Wave Annotations [35]. *Described in: Maršánová L, Nemcova A, Smisek R, Vitek M, Smital L Advanced P Wave Detection in Ecg Signals During Pathology: Evaluation in Different Arrhythmia Contexts. Scientific Reports 2019;9.*

CONTRIBUTION: Two new publicly available databases of physiological and pathological ECG records with annotated P waves. The databases are created for the development, evaluation, and objective comparison of P wave detection algorithms.

3. STATE OF THE ART

In this chapter, the theoretical background necessary to understand the problem of P waves detection in ECG during pathology (Aim 1).

There are described P wave characteristics present in ECG during physiological conditions, what P wave reflects, and changes manifested in ECG during pathologies in the sense of P wave. This information is necessary for the proper design of an automatic algorithm for P wave detection. Next are listed the databases which are commonly used for P wave detection algorithms testing. Then, the methods for automatic P wave detection in physiological and pathological conditions are described. Finally, the methods for ventricular premature beats and atrial fibrillation detection are listed. The P wave detection algorithm created during this work uses the identification of these pathologies for the establishment of a method for P wave finding.

3.1. P WAVE

The P wave is the first component of a normal ECG waveform. The whole heart cycle consists of the P wave; Q, R, and S waves, which are together called the QRS complex and T wave. The p wave represents atrial depolarization - conduction of an electrical impulse from the sinoatrial (SA) node through the atria to the atrioventricular AV node. The QRS complex represents ventricular depolarization and T wave ventricular repolarization. [36]

Electrical impulses are generated in the SA node in the right atria by spontaneous electrical depolarization of pacemaker cells. Thanks to the electrical impulses, the heart can perform a mechanical contraction. The electrical impulse arises in such a way that the resting membrane potential in cells of the SA node decreases spontaneously due to the flow of Na+ and Ca++ ions across the plasma membrane with a frequency determined by the autonomic nervous system (sympathetic and parasympathetic). When the threshold for complete depolarization is reached, an action voltage is generated. Impulses from the SA node travel through the Bachmann bundle to the left atrium and through the anterior, middle, and posterior internodal tracts to the AV node. AV node is located in the inferior right atrium and it is the only place in the atrial septum which is not electrically isolated. The important function of the AV node is to delay the propagation of the electrical impulse by 0.04 sec, because of the necessary pause between the contraction of the atria and ventricles. Then, the electrical impulse spreads through the ventricular area of the conductive tissue called His bundle, which is divided in the area of the interventricular septum into the right (right bundle branch - RBB) and the left (left bundle branch - LBB) Tawar arm. Finally, the electrical impulse runs through the Purkinje fibers, which conduct impulses rapidly through the muscle to assist in its depolarization and contraction. above-describedibed physiological propagation of the electrical impulse through the heart produces a physiological sinus rhythm (SR). The changes in the conduction pathway or heart muscle can cause arrhythmias, which will be described in later chapters. [3], [37]

3.1.1. P WAVE PHYSIOLOGICAL CHARACTERISTICS

In physiological/normal ECG signals, the P wave precedes the QRS complex and has an amplitude from 2 to 3 mm (mV). Its duration is from 0.06 to 0.12 sec, morphology is usually rounded and upright and deflection depends on the lead. The first third of the P wave duration corresponds to the right atrial activation, the final third corresponds to the left atrial activation and the middle is a combination of these two. The normal heartbeat is shown in Figure 1. [3]

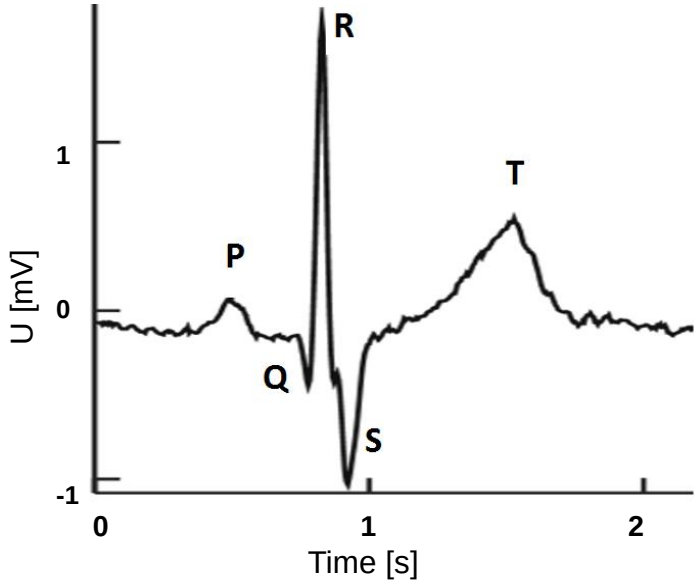

Figure 1 Physiological heartbeat – P wave, QRS complex, and T wave

3.1.2. CHANGES IN ECG DURING PATHOLOGIES IN THE SENSE OF P WAVE

Changes in the conduction pathway or heart muscle can lead to pathology. Some of them are manifested by a change in the shape or position of the P waves. According to the P waves analysis, we can identify the pathology from the ECG signal.

Changes of in P wave positions can indicate pathology e.g.: missing P waves can indicate conduction of electrical impulse created in another place than in SA node during junctional or ventricular ectopic beat or rhythm; P wave is missing also during atrial fibrillation or flutter; separate P wave not followed by QRS complex indicates AV block 2nd degree or 3rd degree. The position of the P wave affects the PR interval which tracks the spread of the electrical impulse from the atria through the AV node. Changes in PR interval duration (normal is from 120 msec to 200 msec) indicate pathology. A short PR interval indicates that the impulse originates somewhere else than the SA node or Wolff-Parkinson-White (WPW) syndrome. Prolonged PR interval shows a delay of impulse conduction through the atria or AV junction – AV block 1st degree. [10], [36], [37], [38]

If the shape of the P wave is changed – e.g. peaked, notched, or enlarged, it may indicate pathology, e.g. atrial hypertrophy or enlargement associated with chronic obstructive pulmonary disease, pulmonary emboli, valvular disease, or heart failure. If the deflection of the P wave is inverted, it may indicate retrograde conduction from the AV node to the atria (impulse originates in the AV node), e.g. in the case of junctional rhythm. Varying shapes of P waves in

one lead indicate that the impulse may be coming from different starting points in atria, which can indicate e.g. traveling pacemaker, or sick sinus syndrome. [3]

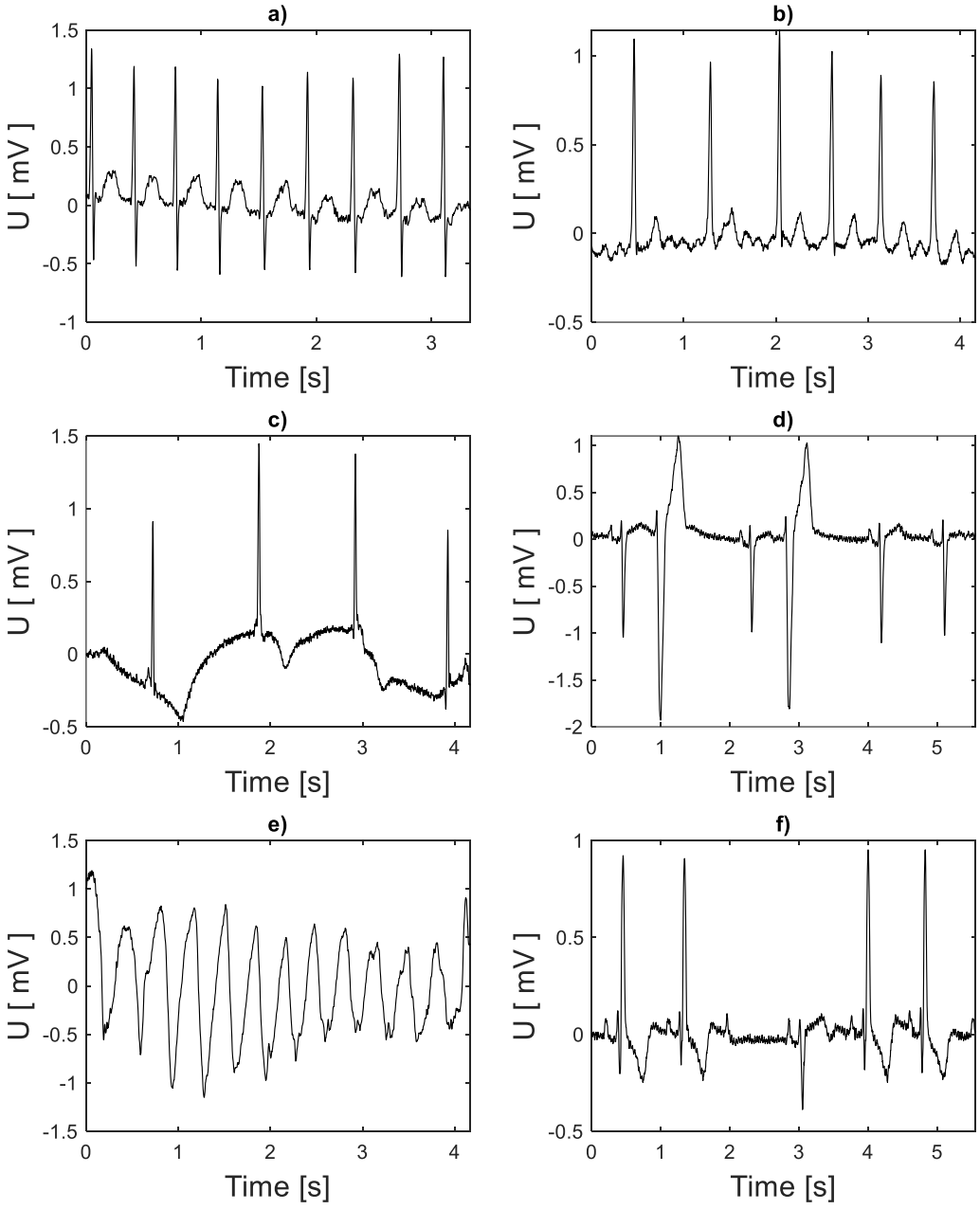

Figure 2 The examples of pathologies in ECG signals: a) atrial tachycardia, b) atrial fibrillation, c) junctional rhythm, d) premature ventricular contraction, e) ventricular fibrillation, f) AV block 2nd degree.

One of the reasons why the results of P waves detection in pathological ECG signals are insufficient is the ignorance of the pathophysiology function of the hearth and its manifestation in ECG signal. Without a detailed understanding of changes in ECG signals caused by various types of pathologies, it is not possible to design an algorithm able to reliably detect P waves

within pathologies. In Table 1, there are described concrete types of pathologies affecting the shape of ECG waveforms, their characteristics, and changes caused by them in ECG signals. The examples of pathologies are shown in Figure 2. [2], [3], [10], [36], [37], [38]

Table 1 Concrete types of pathologies affecting the shape of ECG waveform, their characteristics, and changes caused by them in ECG signal.

Pathology	**Characteristic**	**Changes in ECG signal in the sense of P waves**
Sinus node arrhythmias		
Sinus bradycardia	sinus rate of less than 60 beats/minute	the P wave have a very low amplitude
Sinus tachycardia	sinus rate of more than 100 beats/minute	the P wave may be superimposed on the preceding T wave
Sinus arrest	lack of electrical activity in the atrium, atria are not stimulated by SA node	the entire PQRST complex is missing
Atrial arrhythmias		
Supraventricular ectopic beat (SVE)	impulse originates from atria outside the SA node; may occur in bigeminy, trigeminy, or pair	the P wave is premature, abnormally shaped, and may be lost in the previous T wave, or non-conducted; the QRS complex occurs early
Atrial tachycardia (SVT)	three or more successive ectopic atrial beats at a rate of 150 to 250 beats/minute; 3 types exist: SVT with block, multifocal SVT, and paroxysmal SVT	the P wave is usually upright or lost in the previous T wave
Atrial flutter (AFL)	impulses originate in a single atrial focus, a rate of 200 to 400 times/minute, not all impulses are conducted to the ventricles (usually in conduction ratio 2-4:1)	the P waves blend and saw-toothed appearance F waves arise instead; T waves cannot be distinguished
Atrial fibrillation (AFIB)	in atrial tissue chaotic/asynchronous electrical activity at a rate of 400 to 600 times/minute is present; only	P waves are not present, instead of them are present irregular baseline waves called fibrillatory waves; see Figure 1 b)

	some are conducted to the ventricles; heart rate variability is very high	
Junctional Arrhythmias		
Premature junctional contraction (PJC)	impulse originating in the AV junction acts as a pacemaker and fires either prematurely or out of normal sequence	P wave may fall before, during, or after the QRS complex; usually is inverted
Junctional tachycardia	three or more PJCs occur in a row at a rate of 100 to 200 times/minute	P wave may fall before, during, or after the QRS complex; usually is inverted
Junctional rhythm	three or more PJCs occur in a row at a rate equal or slower than 70 beats/minute	P wave may fall before, during, or after the QRS complex; usually is inverted; see Figure 2 c)
Ventricular arrhythmias		
Premature ventricular contraction (PVC)	originates in the ventricles below the bundle of His; it may occur singly, in clusters of two or more, or bigeminy or trigeminy	the p wave is absent; sometimes retrograde P waves may be present (usually hidden in the QRS complex); the QRS complex occurs early; see Figure 2 d)
Idioventricular rhythm (IVR)	originates in the His-Purkinje system; it can occur as ventricular escape beats, idioventricular rhythm, or accelerated idioventricular rhythm	the p wave is absent; sometimes retrograde P waves may be present (usually hidden in the QRS complex)
Ventricular tachycardia (VTACH)	three or more PVCs occur in a row and the ventricular rate exceeds 100 beats/minute	the p wave is absent; sometimes retrograde P waves may be present (usually hidden in the QRS complex)
Ventricular fibrillation (VFIB)	chaotic electrical activity is present in the ventricles	the P wave is absent; see Figure 1 e)
Atrioventricular heart block		
AV block 1st degree	impulses from the atria are consistently delayed during conduction through the AV node	P waves are of normal shape, but the PR interval is longer than 200 msec

AV block 2nd degree (Mobitz I)	each successive impulse from the SA node is delayed slightly longer than the previous impulse	PR interval gets gradually longer until finally, a P wave is not present before QRS complex
AV block 2nd degree (Mobitz II)	occasional impulses from the SA node fail to conduct to the ventricles	some P waves are not followed by the QRS complex; see Figure 1 f)
AV block 3rd degree	impulses from the atria are completely blocked at the AV node and cannot be conducted to the ventricles	P waves are present independently of QRS complexes

3.2. TESTING DATABASES

One of the reasons why research in the field of P waves detection is not successful is that there is no publicly available database of ECG signals with pathology and correct P wave annotations. The methods are usually tested on a part of the publicly available QT database [26], [27] or the frequently used but not publicly available CSE database [29], [30], both with manually provided P wave annotations. Some authors tested their algorithm on signals selected from other databases (e.g. MIT-BIH Arrhythmia Database [26], [28]) with the annotations of P waves made by the authors themselves. However, the correctness of these annotations cannot be verified. There are publicly available P waves annotations of the MIT-BIH Arrhythmia Database [26], [28] from Elgendi et al. [31], but these contain many mistakes (both in annotations of P waves and other ECG components). There is also an automatically annotated part of the QT database [26], [27], but these annotations contain mistakes. Thus, these annotations cannot be used for testing and comparison of P wave detection algorithms.

It follows, that most of the published methods are tested only on the QT database and CSE database. Although the reported accuracies of existing P and T wave detection algorithms are high, in real practice they are still inefficient. The algorithms need to be tested on long recordings rather than short ECG segments and, of course, on datasets with the presence of a wide variety of cardiac disturbances. Therefore, two new publicly available databases with annotated P waves in ECG signals with pathology [34], [35] was created during doctoral studies. Both databases were published on Physionet [26].

Information about the QT database, CSE database and two databases created by our team - MIT-BIH Arrhythmia Database – P waves annotation (MIT PDB) and Brno University of Technology ECG Signal Database with Annotations of P Wave (BUT PDB) are listed in this chapter.

3.2.1. QT DATABASE

The QT database [26], [27] is the most commonly used database for the evaluation of ECG delineation algorithms. The database includes 105 15-minute two-channel ECG records (many

of them are excerpted from other databases), selected to avoid significant baseline wander or other artifacts. The sampling frequency is 250 Hz.

For all records and beats, the automatically found reference positions of P wave peak, P wave onset, P wave offset, QRS complex onset, and QRS complex offset, as well as the position of T wave peak and T wave offset are available. During our work, it was found that the automatically determined annotations contain mistakes. Due to this fact, this set of annotations cannot be used for high-quality research.

For some beats, the QT database includes manual annotations of P wave peak, P wave onset, P wave offset, QRS complex onset, and QRS complex offset, as well as the position of T wave peak and T wave offset. These annotations are available for at least 30 beats per record in 79 out of the 105 recordings. Only normal beats were annotated. The manually annotated part of the QT database includes 3,622 beats.

The QT database is available via Physionet [27] (research source of complex physiological signals). All data are provided in the WaveForm DataBase (WFDB) format. The ECG signals are stored in files with suffixes: **.dat* and **.hea*, and the manual annotations of the P wave and other ECG components are stored in files with suffixes **.q1c* (second annotator) and **.qt1* (first annotator). The automatically established annotations are stored in files **.pu* (based on both leads), **.pu0* (based on lead 1), and **.pu1* (based on lead 2).

3.2.2. THE COMMON STANDARDS FOR ELECTROCARDIOGRAPHY (CSE) DATABASE

The CSE Database [29], [30] is a collection of approximately 1000 short (12- or 15-lead) ECG recordings. The length of each record is 10 s. The sampling frequency is 500 Hz. The CSE database includes the reference positions of the onsets and offsets of the P wave and the QRS complex and the offset of the T wave. The reference median positions of the ECG significant points were determined by 5 cardiologists and 15 various programs. Cardiologists analyzed only every fifth record and records for which the individual programs provided different results. The reference positions of the ECG significant points are available only for one selected cycle of each record. The database is not freely available.

3.2.3. MIT-BIH ARRHYTHMIA DATABASE – P WAVES ANNOTATION (MIT PDB)

The MIT-BIH Arrhythmia Database [26], [28] is the most commonly used database for the evaluation of QRS detectors and it is the most cited database overall [39]. The MIT-BIH Arrhythmia Database includes reference positions for QRS complexes and annotation of QRS complexes types. The database consists of 48 half-hour two-channel ECG records. The sampling frequency is 360 Hz.

From this database, 12 physiological and pathological signals were selected by our ECG experts. Specifically, signals no. 106, 119, 207, 214, 222, 223, and 231 include a large number of different pathologies, no. 100, 101, 103, 117, and 122 do not include pathologies (or only a small number). Our ECG experts have many years of clinical practice and already published annotations of CSE database pathologies [40]. They performed the annotations of selected MIT-

BIH Arrhythmia Database signals: the first expert provided manual annotations, and the second checked them. Unclear parts of the records were discussed by both experts and a consensus was reached. Everything was conducted manually without the use of automated software. To facilitate the work of ECG experts, the free software tool, SignalPlant [41], was used for the manual marking of P waves.

The database was published on Physionet. All data are provided in the WFDB format. The ECG signals and annotations of QRS complexes are available on the website of the MIT-BIH Arrhythmia database [26], [28] in files with suffix **.dat* and **.hea*. The annotations of P waves are stored in files with the suffix **.pwave*.

3.2.4 BRNO UNIVERSITY OF TECHNOLOGY ECG SIGNAL DATABASE WITH ANNOTATIONS OF P WAVE (BUT PDB)

The BUT PDB [33],[34] consists of 50 2-minute 2-lead ECG records with various types of pathologies. The ECGs were selected from 3 existing databases of ECG signals - MIT-BIH Arrhythmia Database [26], [28], MIT-BIH Supraventricular Arrhythmia Database [26], [42] and Long Term AF Database [26], [43]. Selected two-minute sections have a high incidence of pathologies during which it is difficult to detect P waves by automatic algorithms.

Our ECG experts manually annotated P waves in all 50 records. Each record contains also an annotation of QRS complexes types and positions (obtained from the original database) and the dominant diagnosis (pathology) present in the record. The first expert provided manual annotations and the second expert checked them. Unclear parts of the records were discussed by both experts until a consensus was reached. Everything was conducted manually without the use of automated software. To facilitate the work of ECG experts, the free software tool, SignalPlant [41], was used for the manual marking of P waves.

In BUT PDB, there are 5437 P waves and 7638 QRS complexes of which 2201 are without P wave. In this database, 23 different types of pathology are present. Types of pathologies, their abbreviations, and the number of cases in the database are listed in Table 2.

The database was published on Physionet [26]. All data are provided in the WFDB format. The names (IDs) of the records are numbers from 01 to 50. The ECG signals are stored in files with suffix **.dat* and **.hea*. The annotations of P waves are stored in files with the suffix **.pwave*. The positions of QRS complexes, their types, and sampling frequency are stored in files with the suffix **.qrs*.

Table 2 Types of pathologies, their abbreviations, and the number of cases in Brno University of Technology ECG Signal Database with Annotations of P Wave (BUT PDB).

Abb.	Type of pathology	Number of cases	Abb.	Type of pathology	Number of cases
A	Atrial premature beat	14	NA	Sinus arrhythmia	1
AFIB	Atrial fibrillation	9	NOD	Nodal rhythm	3

AFL	Atrial flutter	2	P	Paced rhythm	2
B	Ventricular bigeminy	3	PREX	Pre-excitation	1
BI	Atrioventricular block 1st degree	1	R	Right bundle branch block beat	4
BII	Atrioventricular block 2nd degree	2	SVTA	Supraventricular tachyarrhythmia	3
BIII	Atrioventricular block 3rd degree	1	T	Ventricular trigeminy	2
E	Ventricular escape beat	1	V	Ventricular premature beat	20
F	Fusion of ventricular and normal beat	3	VFL	Ventricular flutter	1
IVR	Idioventricular rhythm	1	VP	Ventricular pair	1
J	Nodal beat	3	a	Aberrated atrial premature beat	1
L	Left bundle branch block beat	4			

3.3. METHODS FOR P WAVE DETECTION

Automatic detection of the P wave in ECG signal is the most complicated part of the process of ECG component analysis [22], and it is still an unsolved problem [44]. The main reasons for which algorithms fail are: a) P waves have a low voltage resulting in a low signal-to-noise ratio; b) P waves have no exclusive time and frequency characteristics; c) P waves have high interpatient variability; d) in the case of atrioventricular dissociations, P waves do not respect normal time ordering of an ECG sequence (P wave can be missing, or redundant); e) in the case of tachycardia, P waves can be hidden within T waves; f) in the case of atrial fibrillation and atrial flutter, P waves are missing or in the case of the atrial flutter are instead of P waves present F waves; g) in the case of ventricular or junctional ectopy, P waves are usually not present [22], [45]. The exact changes of ECG signal during specific pathology in the sense of P wave are mentioned in Table 1. All of these characteristics must be considered when developing a successful algorithm for P wave detection.

The main problem of commonly used algorithms for P waves detection (in literature and commercial software) is that they assume that the P wave is followed by the QRS complex. This is true in the case of a normal cardiac rhythm but not in the case of a pathological rhythm. If we incorporate such an assumption into the P wave detection algorithm, we cannot achieve reliable results on pathological records. Another reason why research in this field is not successful is that there is no publicly available database of ECG signals with pathologies and correct P waves annotations. The last reason is the ignorance of the pathophysiology function

of the hearth and its manifestation in ECG signals. Therefore, considering the above-mentioned manifestations of P wave in ECG signals during pathology, commonly used algorithms detect many false positive (FP) P waves (because of points e), f), g) mentioned in the paragraph above), false negative (FN) P waves (because of point d)) or fail (because of point a), b), c)) resulting in FN and/or FP detections.

Two commonly used algorithms [46], [47] for P waves detection, which were validated on standard ECG databases with both physiological and pathological signals were. The results are shown in Figure 3. Both algorithms were not able to deal with any type of tested pathology. In Figure 3a is shown the AV block 2nd degree, in Figure 3b atrial fibrillation (P waves are not present), in Figure 3c supraventricular tachycardia, and in Figure 3d ventricular bigeminy. The arrow indicates the correct positions of the P wave. The character "*" indicates the position of the P wave determined by the detector [46] and the character "o" the position of the P wave determined by the detector [47]. It can be seen that the detected positions are significantly different from the correct ones. It follows that other algorithms based on similar principles (which do not consider pathologies) will fail similarly in these situations.

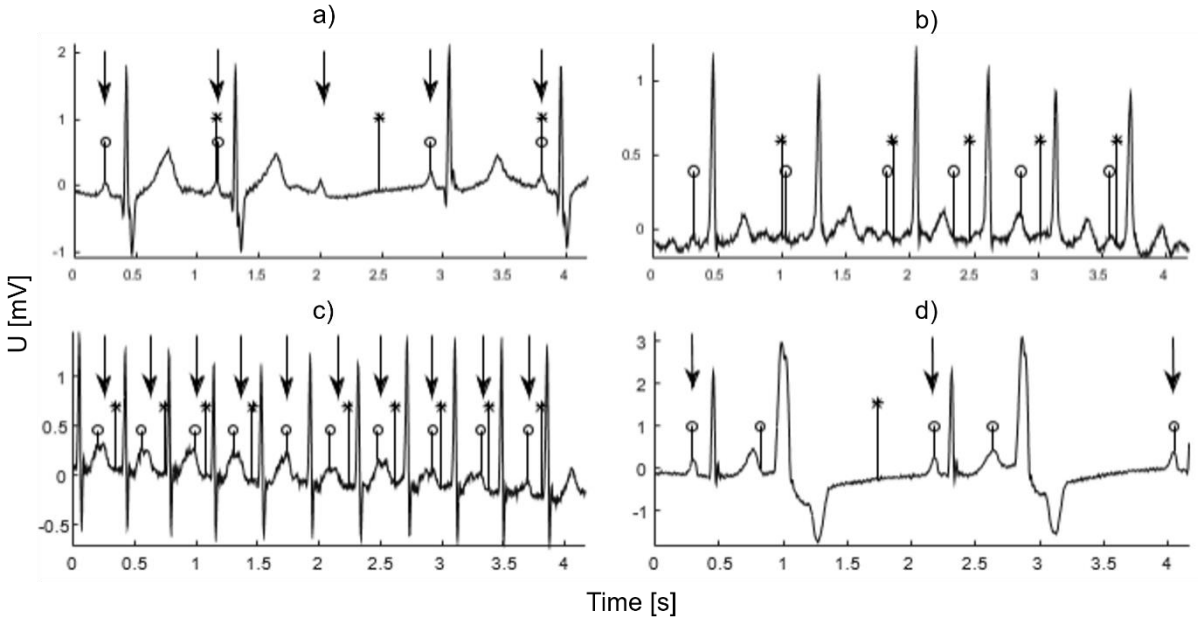

Figure 3 Demonstration of P wave detection results of two commonly used algorithms [46] and [47] in the presence of pathologies. In Figure 3a is shown the AV block 2nd degree, in Figure 3b atrial fibrillation (P waves are not present), in Figure 3c supraventricular tachycardia, and in Figure 3d ventricular bigeminy. The arrow indicates the correct position of the P-wave. The character "*" indicates the position of the P-wave determined by the detector [46] and the character "o" the position of the P-wave determined by the detector [47].

In the following sections, the most commonly used methods for P wave detection in physiological ECG signals (3.3.1) as same as pathological ECG signals (3.3.2) are described.

3.3.1. P WAVE DETECTION DURING PHYSIOLOGICAL FUNCTION OF THE HEART

There are several algorithms for P wave detection during physiological function of the heart based on different principles. The detection of QRS complexes is usually the first and essential

step of all algorithms. The successful detection of the QRS complexes is an important condition for subsequent successful detection of the P waves. If the detection of the QRS complexes fails, it usually fails the detection of the P waves as well. The most commonly used principles for the detection of the QRS complexes can be found in [5].

The methods can be grouped into five categories according to their principles:

The first class of algorithms decomposes the ECG signal into different basis functions and uses a modified signal to determine the locations of the P waves. The authors of [47], [48], [49], [50] used phasor transform with a combination of median filtering for P wave detection and delineation. A well-known wavelet transform is applied in [7], [8], [51], [52], [53] for the detection of P waves. In [7] discrete wavelet transform (DWT) is used while in [8], [51], [52], [53] is used continuous wavelet transform (CWT). In [53], after the wavelet transform, spline and morphological filtering are applied. In all methods, the WT is combined with adaptive thresholding and demarcation of the area before QRS complexes. Authors of [54] present a method based on the theory that the two poles and two zeros model can represent the discrete cosine transform (DCT) of a bell-shaped biphasic function. A system-based function of order (2,2) is used to represent a biphasic function, which is expanded into partial fractions. While each P wave requires only one biphasic function, the QRS complex needs two or three. The location of the P wave is estimated by the poles and zeros locations. In [55], DCT with a combination of the Prony method was used for the P wave detection.

The second class of approaches is based on adaptive filtering techniques. In [56], after QRS complex detection and signal filtering, part of the signal from 120 msec before to 120msec after the position of the QRS complex is removed from the signal. Moving averages are used to demarcate potential P waves and then, the detected blocks in each RR interval are counted. According to the number of detected blocks are established P waves positions. Authors of [57] proposed a method that performs bandpass filtering of the ECG signal followed by the usage of two moving average filters to detect and delineate the P waves.

The third class of approaches includes classification and pattern recognition methods. The methods directly classify the wave shapes (ECG signal) or features extracted from the ECG signal. The method [58] uses a hidden Markov tree model. This approach aims to use wavelet coefficients to characterize the different ECG waves and link these coefficients by a tree structure enabling P waves to be detected. In [59], a similar approach is applied, but as a classifier is used a neural network. In [60], the QRS complexes are detected by the method described in [61] and removed from ECG signals. Then, curve slopes are computed from the ECG signal and used as an input feature for the support vector machine (SVM) classifier. T waves are removed from the ECG signal as well and after that, the SVM classifier is used for P wave detection. The SVM classification method is also applied for P wave detection in [62]. As an input feature for the classifier, the gradient of the filtered ECG signal is used. Authors of [62] use for P wave detection K-nearest neighbor (KNN) classifier. The feature extraction is done by using the gradient of the ECG signals.

The fourth class of methods is based on fitting a model to the ECG waveform and extracting parameters of the model to determine waveform onsets and offset. In [63] is introduced a simple AR model for parameters of Gaussian functions in the ECG dynamical model. For estimating the parameters of the AR model is used an extended Kalman filter (EKF). By introducing a simple AR model for each of the dynamic parameters of Gaussian functions in the model and considering separate states for ECG waves, the new EKF structure is constructed and used for the P wave detection. EKF is also designed in [64], where the fiducial points are detected using both the parameters of Gaussian functions of the model and the state variable estimates. Methods for P waves detection present in [6] are based on Bayesian signal models that consider previous beats as prior information. To estimate the unknown parameters (P wave locations) of these Bayesian models, a block Gibbs sampler and sequential Monte Carlo method with a marginalized particle filter are used.

The fifth class of algorithms includes all remaining principles. In [9], detection and delineation of P waves are achieved by correlation analysis conducted between the ECG signal and templates of the P wave. Besides, the signal quality is evaluated, and if the quality of the analysis window is bad, then the algorithm will estimate the locations of P waves according to the previous P waves positions. Authors of [63] solve the problem of P waves detection using mixture of Gaussian function and Dynamic programming. Method [66]introduced an algorithm for the P wave detection using the optimized parameters computed by the differential evolution optimization strategy and ECG signal denoising with the help of the extended Kalman smoother framework. The authors of [67] used for the P wave identification the complete ensemble empirical mode decomposition with an adaptive noise method. In [69], there is combined several detection algorithms (morphological mathematical filtering, wavelet transform, waveform template, etc.).

The methods are usually tested on publicly available QT database [27], part of them with manually provided annotations of P waves, the others with automatically provided annotations; non-public CSE database [29], [30] with manually provided P waves annotations; signals selected from MIT-BIH Arrhythmia Database [28] with the annotations of P waves automatically made by [31] or on other not publicly available datasets. All of the above-mentioned methods (with reported results) achieved sensitivity a positive predictivity above 95 %. The complexity of the individual methods is very different, but the results are very similar whether it is the simple method or the advanced method. It means that the advanced methods do not have to be always the best choice for the P wave detection in real practice, because of their high complexity.

Although the reported accuracy of the existing P wave and T wave detection algorithms may seem high during physiological function of the hearth, in real practice it is still inefficient. One of the reasons is that there are databases with P wave annotations containing mistakes (e.g. P waves annotations of MIT-BIH Arrhythmia database [28] from Elgendi [31], Lobachevsky University Electrocardiography Database (LUDB) [32], both manually annotated, and manually annotated part of the QT database [27]), so the results of methods tested on these

databases are unreliable. The next common problem in real practice is the quality of recorded ECG signals. If the quality of signals is bad (due to the presence of noise and artifacts caused by motion, poor quality of the recording system, etc.), the accuracy of the P wave detection is bad. There is a need for a database with annotated P waves and the presence of various types of noise. One of the possibilities how to detect P waves and the other components of ECG signals in records with the presence of noise is to use methods for ECG quality assessment which were developed by our group [69], [70]. Finaly, the methods must be able to handle records with the presence of a wide range of cardiac disorders, as mentioned above. For this purpose, two ECG databases with annotated P waves were created by our group.

3.3.2. P WAVE DETECTION DURING PATHOLOGICAL FUNCTION OF THE HEART

There are only a few methods for P waves detection which were designed and tested on signals with recorded cardiac disturbances. A significant part of these methods was designed for the detection of one specific pathology [23], [24] or differentiation between two types of pathologies [25]. The method described in [71] works similar to methods designed for P wave detection in physiological signals, but in addition, it is capable to identify AF and adapt the algorithm procedure accordingly. The most sophisticated is a method [22], which can deal with various types of pathologies. All mentioned methods are described below in more detail.

A NEW METHOD OF FILTERING T WAVES TO DETECT HIDDEN P WAVES IN ELECTROCARDIOGRAM SIGNALS [23]

This method is designed to facilitate differential diagnosis of junctional reentrant tachycardias, between AV nodal reentry tachycardia (AVNRT) and AV reentry tachycardia (AVRT). The method allows detecting P wave hidden within the T wave (e.g. in the case of ECG signals with tachycardia). In the first stage, the signal is filtered using a band-pass filter with a 15-300 Hz bandwidth to attenuate T waves. In the second stage, the wavelet transform denoising procedure is performed. The result of the preprocessing contains high QRS complexes and small but still detectable P waves. These signals can be easily detected by an eye or by a simple automatic detection procedure. The method was not tested in the sense of the accuracy of P wave detection. This method can be potentially good for P wave detection but according to our experience, it is very sensitive to the noise and artifacts. Noise frequency characteristics can overlap with the P wave frequency characteristics. The second problem of this approach is impossible P wave detection in cases, where the P wave is hidden within the QRS complex. It does not even allow differential diagnosis of junctional reentrant tachycardias which is why the algorithm was designed.

P AND R WAVE DETECTION IN COMPLETE CONGENITAL ATRIOVENTRICULAR BLOCK [24]

This method is designed for the detection of P waves during AVB 2rd degree when P waves are dissociated from the QRS complexes. This method is based on the separation of the atrial activity from the ventricular activity (canceling of ventricular activity from the analyzed signal).

The procedure for QT pattern cancellation is called adaptive impulse correlated filter, which is based on the least mean square algorithm (LMS).

The AICF algorithm is based on the quasi-periodic nature of ECG. The adaptive filter coefficients store an averaged version of the signal. The output of the filter is subtracted from the original signal to cancel the contribution of the QT segments. The residual signal is mainly composed of the P waves and remnants of the QT segments. In the end, smoothed nonlinear energy operator (SNEO) is used for P waves detection.

This method provides good results of P wave detection in signals with AVB 3rd degree, but it has not been tested on the physiological signals or signals with other types of pathologies. It can be assumed that if the algorithm will be used on real data without AVB 3rd degree, many false-positive P waves will be detected.

COMPUTER DETECTION OF ATRIOVENTRICULAR DISSOCIATION FROM SURFACE ELECTROCARDIOGRAMS DURING WIDE QRS COMPLEX TACHYCARDIAS [25]

In this work, results of P waves detection are used for differentiation of wide QRS complex tachycardias, exactly between AV-associated tachycardia (e.g. AVRT, AVNRT) and ventricular tachycardia. The differentiation is not easy due to the inability to identify atrial activity, specifically atrioventricular dissociation. This method, like the study [24], is based on the separation of atrial activity from ventricular activity. The algorithm consists of subtraction of a mean beat from all beats in leads II and V1 to generate remainder electrocardiograms. The remainder ECGs were autocorrelated. After this processing, AV dissociated P wave candidates were visible in the reminder ECG along with the original ECG. The method was tested on 37 signals of 10 seconds duration. The sensitivity of the method was 65 %, specificity 100 %, positive predictive accuracy 100 %, and negative predictive accuracy 77 %. Visual inspection of the remainder electrocardiograms along with the original electrocardiograms may increase the ease of identification of AV dissociation and thus the diagnosis of ventricular tachycardia.

The big problem of the methods [23] and [24] (based on subtraction of a QRS-T template) is a high sensitivity to the variability of normal beats and the presence of abnormal beats. It can lead to the incomplete canceling of QRS-T segments and the genesis of artifacts. The artifacts can be detected as a false positive P wave. Another problem lies in successful P wave detection only in the case of pathologies, where the P wave occurrence is irregular (AV block 3rd degree, atrial fibrillation, multifocal supraventricular tachycardia, and some cases of AV block 2nd degree). In cases, where the P wave occurs in the QRS-T segment always at the same place (AV block 2nd degree, atrioventricular (nodal) reentry tachycardia, or atrial flutter), the pathological P waves will be included in the QRS-T template and removed with it.

P WAVE DETECTOR WITH PP RHYTHM TRACKING: EVALUATION IN DIFFERENT ARRHYTHMIA CONTEXTS [22]

This is the only method, found in literature, that performs and evaluate the detection of P waves within ECG signal with normal sinus rhythm and various types of pathologies: ventricular

bigeminy, ventricular trigeminy, ventricular flutter, ventricular tachycardia, idioventricular rhythm, AV block 2nd degree type Mobitz II, junctional rhythm, atrial bigeminy, atrial fibrillation, atrial flutter, and supra-ventricular tachyarrhythmia. The proposed P wave detector relies on a QRS detection coupled with a PP rhythm estimation to support the P wave detection in the case of AV dissociations. The whole process is composed of five parts. At first, two median filters remove the main noise. Then, QRS complex detection is performed. For the first three beats, P wave detection relies only on the QRS detection. After that, there is a sufficient number of P wave positions in the buffer to estimate the next P wave occurrence. According to the previous P waves positions it is selected area, where the next P wave will be searched. Finally, the selected segment is smoothed with a median filter, and the maximum is detected. The positions of maxima are checked and then considered as P waves positions.

For physiological rhythm, sensitivity Se = 99.57 % and positive predictivity PP = 99.83 % were achieved (records from MIT-BIH arrhythmia database [28]no. 100, 101, 103, 117, and 122). The Se and PP obtained for pathological signals (selected from segments of signals no. 106, 119, 207, 214, 222, 223, and 231, the exact segments are not defined in the paper) are given in Tab. 3. It can be seen that in the case of pathological signals, the detection success is significantly lower. In the article, the results are compared with another frequently used algorithm [44], which is not adapted to detect pathological P waves and its results are even worse.

Table 3 The results of P wave detection in pathological ECG achieved in the study [22].

Pathology	**Number of P waves**	**Se [%*]**	**P+ [%*]**	**Acc [%*]**
Ventricular bigeminy	610	98,85	84,45	91,08
AVB 2nd degree	838	72,79	99,51	84,08
Junctional rhythm	40	42,50	18,09	25,38
Sinus tachycardia	247	98,98	90,30	99,98
Ventricular tachycardia	2	100,00	3,57	6,89
Idioventricular rhythm	14	14,29	3,08	5,07
Atrial bigeminy	60	81,67	76,56	79,03
Supraventricular tachycardia	3	33,33	33,33	33,33

A CRUCIAL WAVE DETECTION AND DELINEATION METHOD FOR TWELVE-LEAD ECG SIGNALS [71]

The method works for P wave detection in physiological ECG signals but in addition, it can identify AF and adapt the algorithm procedure accordingly. Firstly, the positions of QRS complexes are identified. Then, based on the QRS positions, adaptive search windows are set to detect the locations of the P waves. After the detection of P waves, it is determined whether

the atrial fibrillation is present. To refuse the atrial fibrillation signal, the ECG signals are normalized to the zero-one range. Then, the algorithm determines whether signal segments satisfy the following two conditions: first, there are two adjacent signal segments, one is ascending and the other is descending; second, the amplitude of the potential P waves is higher than the threshold. If these two conditions are not met, the tested segment is considered AF, and P waves positions are rejected. The method was tested on LUDB [32] and achieved Se=98,43 % and PP=96,44 %. However, this database contains incomplete annotations and thus, the achieved results are questionable.

3.3.3. METHOD FOR ANALYSIS OF PATHOLOGIES

The literature and experience show that reliable detection of the P wave during different types of pathologies is possible only if we consider these pathologies and their characteristics. The final algorithm for P wave detection presented in this doctoral uses the identification of the possibility of the presence of some types of pathologies - atrial fibrillation, ventricular premature beats, and rules based on knowledge about the heart function for the P wave detection. The development of reliable methods for atrial fibrillation and premature ventricular beats detection was one of the most difficult and time-consuming part of the work.

For this purpose, the methods for atrial fibrillation and premature ventricular beats detection, commonly used in literature, are described in this chapter. The rules, which ensure proper P wave detection in presence of other types of pathologies (such as AV block 1st degree and 2nd degree, wandering pacemaker, supraventricular arrhythmias, tachycardia, bradycardia, etc.) are derived from knowledge about the heart function and manifestation of its pathologies, whose basics are set out in Chapter 3.1.

DETECTION OF ATRIAL FIBRILLATION

AF is a supraventricular tachyarrhythmia which is represented by inconstant atrial activation and therefore, dysregulation of atrial contractions. In atrial tissue, chaotic asynchronous electrical activity at a rate of 400 to 600 times/minute is present and only some impulses are conducted to the ventricles [72]. R peak appears at irregular intervals because the heart rate variability is very high. In ECG, P waves are not present. Instead of them, erratic baseline waves called fibrillatory waves are present. In Figure 2 b), the signal with AF is shown. Commonly used P wave detection algorithms usually detect many false-positive P waves during atrial fibrillation (they detect P waves before many complexes where P waves are not present) [73].

There are a lot of works focused on atrial fibrillation detection present in the literature. The vast majority of the methods are based on the extraction of features and using machine learning technics or thresholding for the classification of the type of the rhythm. The methods can be divided into two groups. In the first group of algorithms, the ECG signal itself is an input to the algorithm. In the second group, the sequence of RR intervals is the input. In this Chapter, the often-used algorithms are listed and briefly described.

For instance, the authors of [74] used DWT and dual-tree complex wavelet transform with four morphological features for the AF episodes classification by a shallow artificial neural network (ANN). In [75], the authors used four statistical features determined from RR intervals and the linear classifier to automatically classify AF and normal sinus rhythm segments. The authors of [76] combined the coefficients of DCT, empirical mode decomposition, and DWT with the KNN classifier for AF signals classification. The authors of [77] proposed a multi-objective optimization based on a non-dominated sorting genetic algorithm for optimizing the baseline AF prediction system. It consists of preprocessing, HRV features extraction, and support vector machine classifier. In our study [78], the method for automatic AF detection based on symbolic dynamics and Shannon entropy was introduced. The method consists of three parts. Firstly, the QRS complex detection is provided. Then, the raw RR sequence is transformed into a sequence of specific symbols and subsequently into a word sequence. Finally, the Shannon entropy of the word sequence is calculated. According to the value of Shannon entropy and the threshold, it is decided, whether AF is present in the current cardiac beat. The authors of [79] used the Lagrangian SVM classifier in a combination with an input vector consisting of sixteen features, including four features, taken from the fetal heart rate analysis in perinatal medicine, very sensitive to the heart rate changes. In [80] and [81], our group used SVM in a combination with morphological features, cluster analysis, multilevel noise estimation, decision tree, and threshold-based rules. In [82], the wavelet packet transform multivariate statistical features based on the correlation among wavelet coefficients are extracted from the corresponding histogram. The feature set is the input to the artificial neural network classifier for the AF detection. In work [83], the approach for the automated AF detection based on an 11-layers neural network was developed. The network structure is primarily stacked by a convolutional neural network and modified by Elman neural network, while automatically performing end-to-end signals classification. To classify AF, the author of [84] proposed an end-to-end model by combining the convolutional and recurrent neural networks to extract high-level features from segments of RR intervals.

The algorithms are usually tested mainly on MIT-BIH Atrial Fibrillation Database [85], Long Term Atrial Fibrillation Database [43], and PTB-XL ECG Dataset [86].

DETECTION OF VENTRICULAR PREMATURE BEATS

A ventricular premature beat is an extra heartbeat originating in the ventricles below the bundle of His. They may occur singly, in clusters of two or more, or bigeminy or trigeminy. In ECG, these changes are present: P wave is usually missing; retrograde P waves may be present (usually hidden in the QRS complex); the QRS complex occurs early, it is broader, malformed and its duration lasts more than 120 msec; T wave has an opposite direction than the QRS biggest wave and after PVC, the compensatory pause usually appears [52]. In Figure 2 d), the signal with PVC is shown. Commonly used algorithms for P wave detection, e.g. [56], [59], [62], usually fail in this situation. They detect the T wave belonging to the heartbeat preceding PVC as the P wave belonging to PVC.

In the literature, several methods have been proposed for the automatic detection of premature ventricular contraction. The vast majority of the developed techniques are based on the extraction of features and machine learning technics for the classification of the beat type. In this Chapter, the often-used algorithms are listed and briefly described.

In a study [87], the ECG signal is decomposed into the corresponding DWT scales and segmented. Then, curve length and high order moment-based features are calculated for each beat. After generation of feature source and segmentation, multi-layer perceptron back-propagation neural network, probabilistic neural network, and support vector machine methods are designed and used for PVC detection. The paper [88] presents a method based on parameters obtained from modeling of the ECG signal cumulants. Cumulants have many properties that make them effective tools for describing morphological changes in non-stationary signals. The properties are the ability to suppress morphological variations of different beats of ECG signals belonging to a specific class of heart arrhythmia and reduce the effect of noise on the classification. The method combines it with the Hermitian model and performs an efficient classification. In a study [89], matching template beats are determined and each beat of the ECG signal is correlated with them. PVC detection is performed by analyzing the maximum and minimum values of the correlation coefficient for PVC and normal beats. In our studies [90] and [91] there were calculate 71 morphological and spectral features from detected QRS complexes. A filter method was applied to select only the most informative features. The selected features were combined with four models for automatic classification - discriminant function analysis, naive Bayes classifier, SVM, and KNN with different settings. In [92], wavelet-transformed ECG signal beats are used as a set of features for PVCs classification by a neural network. The study [93] introduced a model-based dynamic algorithm for tracking the ECG characteristic waveforms using an extended Kalman filter. A “polarogram”, polar representation of the signal, which is constructed using the Bayesian estimation of the state variables is introduced. The polarogram allows to specify a polar envelope for normal rhythms. In a study [94], PVCs are detected by the neural network with weighted fuzzy membership functions using wavelet transformed coefficients. In [95], a method based on DWT is used. Three different feature spaces based on wavelet coefficients are tested. The principal component analysis is applied to reduce the dimension of the feature spaces. KNN and SVM methods are developed for differentiation between the types of heartbeats. In the paper [96], Pruned Fuzzy KNN classifier is proposed. It is a time-efficient pruning algorithm that can maintain good classification accuracy with an appropriate retained ratio of training data.

The vast majority of the algorithms were tested on the MIT-BIH arrhythmia database.

4. SELECTED PAPERS

The results of the research leading to the achievement of the aims of this thesis (specified in Chapter 2) were published at conferences and in scientific journals. The most important papers written during the Ph.D. study and contributing to solving the established aims are attached to this thesis.

Paper 1 describes the QRS complex detector (Aim 2) and method for P wave detection during physiological function of the heart (Aim 3). Paper 2 examines the possibilities of detection of premature contraction in ECG signals (Aim 4). The classification of PVC based on knowledge analyzed in Paper 2 is provided in Paper 3 (Aim 4). Paper 4 presents a method for atrial fibrillation detection (Aim 4). In Paper 5, the first version of the algorithm able to deal with the detection of P waves in pathological signals as same as first database of physiological and pathological ECG records with annotated P waves is proposed (Aim 5 and 6). Paper 6 introduces the final version of the algorithm for P waves detection during pathology and second database with annotated P waves (Aim 5 and 6).

A more detailed description of each paper and its contribution to solving the specific aims of this thesis precedes each paper.

PAPER 1 - DETECTION OF P, QRS AND T COMPONENTS OF ECG USING PHASOR TRANSFORM

CITATION

Maršánová L. Detection of P, QRS and T Components of ECG Using Phasor Transform. Proceedings of the Student Conference Blansko 2016;55-58

PAPER CONTRIBUTION

Paper 1 introduces a method for detection of P, QRS and T components in physiological ECG signals. Firstly, a reliable QRS complex detector is designed, because it is necessary to detect QRS complexes in advance for accurate detection of P and T waves. The algorithm is based on phasor transform (PT). PT converts each ECG sample into a phasor and therefore, it enhances changes in the ECG signal. Waves with small voltage are then easily detectable. The method was tested on standard ECG databases (MIT-BIH arrhythmia database, QT database, and CSE database). Further, a robust detector of P and T waves is created. As same as in the case of QRS complexes detector, phasor transform is the fundamental principle. Considering instantaneous phase variations in consecutive samples of the transformed ECG, the slight variations produced by P waves and T waves in the original signal are maximized. In PT signal, the area before the QRS complex position is demarcated and the P wave is searched there. In the case of the T wave, the area is defined after the QRS complex position. In the defined areas are found maxima and these positions are considered as positions of the P wave and T wave, respectively. The method was tested on the QT database and CSE database. The results of the detection are better, or comparable with the results presented by other authors. It confirms that the presented method is suitable for ECG component detection. This fulfilled Aims 2 and 3.

AUTHOR'S CONTRIBUTION

The author surveyed related literature, developed a new methodology for detection of P, QRS and T components in physiological ECG signals, designed and performed the analysis and testing of the algorithm and wrote the whole manuscript.

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PAPER 2 - ECG FEATURES AND METHODS FOR AUTOMATIC CLASSIFICATION OF VENTRICULAR PREMATURE AND ISCHEMIC HEARTBEATS: A COMPREHENSIVE EXPERIMENTAL STUDY.

CITATION

Maršánová L, Ronzhina M, Smisek R, Vitek M, Nemcova A, Smital L, et al. ECG features and methods for automatic classification of ventricular premature and ischemic heartbeats: A comprehensive experimental study. Scientific Reports 2017;7.

PAPER CONTRIBUTION

In paper 2, there were examined possibilities of premature contraction detection. Various aspects of automatic classification of various heartbeat types have been addressed. Particularly, non-ischemic, moderate ischemic, severe ischemic, and ventricular premature beats were classified. ECG signals recorded on isolated rabbit hearts under non-ischemic and ischemic conditions were used for the analysis. Various morphological and spectral features (voltage and interval-related features, features based on area under various parts of ECG and its spectral features obtained by four different approaches - fast Fourier transform, short-time Fourier transform, continuous wavelet transform, and Wigner-Ville distribution) and classification models (discriminant function analysis, naive Bayes classifier, support vector machine, and k-nearest neighbors – all with several different settings) were proposed and tested on the same data set. It was found that: a) morphological features are generally more suitable than spectral features; b) quality results can be achieved using features calculated without time-consuming delineation of the QRS-T segment; c) the use of a reduced number of features for model training allows achieving similar or even better results in comparison with the whole feature set; d) k-nearest neighbors and support vector machine seems to be the most appropriate models. These findings are important for designing simple, fast, and accurate algorithms suitable for timely diagnosis. The results presented in Paper 2 and Paper 3 are used in Paper 5 and Paper 6 for the detection of P waves. This fulfilled Aim 4 and particularly Aim 3.

AUTHOR'S CONTRIBUTION

The author surveyed related works, developed a new methodology for ventricular and ischemic beats detection, performed testing on the annotated dataset, wrote a major part of the manuscript, and participated in the finalization of the whole manuscript.

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PAPER 3 - AUTOMATIC DETECTION OF P WAVE IN ECG DURING VENTRICULAR EXTRASYSTOLES

Maršánová L, Nemcova A, Smisek R, Goldmann T, Vitek M, Smital L. Automatic Detection of P Wave in ECG During Ventricular Extrasystoles. World Congress on Medical Physics snd Biomedical Engineering 2018, 2019:381-385.

PAPER CONTRIBUTION

In Paper 3, a method for P wave detection in ECG signals containing ventricular extrasystoles is proposed. The detection of PVC is based on the extraction of morphological features from QRS complexes and T waves which were selected from the features described and analyzed in Paper 2. The results of detection are used for demarcation of areas where P waves are searched using the method introduced in Paper 1. The proposed algorithm was tested on a part of MIT-BIH Arrhythmia Database P-Wave Annotations [35] where the ECG signals with ventricular extrasystoles or normal rhythm are present. The results of P wave detection in ECG during ventricular extrasystoles using the proposed algorithm are significantly better than the results presented in other works. It was found that the approach based on the combination of PVC identification and consequent P wave detection algorithm is the right way for accurate P wave detection in signals with ventricular pathologies. This fulfilled Aim 4 and particularly Aim 5.

AUTHOR'S CONTRIBUTION

The author developed a new methodology for P wave detection in ECG signals with ventricular extrasystoles, performed testing of the algorithm, wrote a major part of the manuscript, and participated in the finalization of the whole manuscript.

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PAPER 4 - SINGLE-FEATURE METHOD FOR FAST ATRIAL FIBRILLATION DETECTION IN ECG SIGNALS

CITATION

Maršánová L, Smital L, Smisek R, Nemcova A, Vitek M. Single-Feature Method for Fast Atrial Fibrillation Detection in ECG Signals. Computing in Cardiology 2020.

PAPER CONTRIBUTION

The detection of atrial fibrillation, another pathology that affects the detection of P waves, was examined in Paper 4. This simple and efficient method for automatic AF detection is based on symbolic dynamics and Shannon entropy. The method consists of three parts. Firstly, QRS complex detection is provided. Then, the raw RR sequence is transformed into a sequence of specific symbols and subsequently into a word sequence. Finally, the Shannon entropy of the word sequence is calculated. According to the value of Shannon entropy, it is decided, whether AF is present in the current heartbeat. The method was tested on the MIT-BIH Atrial Fibrillation database [85], MIT-BIH Arrhythmia database [28], Long Term Atrial Fibrillation database [86], and CinC Challenge database 2020. The achieved results are comparable with other authors of more complicated and computationally demanding methods. The method is used by the method for P wave detection presented in Paper 6. This fulfilled Aim 4 and particularly Aim 5.

AUTHOR'S CONTRIBUTION

The author surveyed related works, developed a new methodology for atrial fibrillation detection in ECG signals, performed testing of the algorithm, wrote a major part of the manuscript, and participated in the finalization of the whole manuscript.

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PAPER 5 - ADVANCED P WAVE DETECTION IN ECG SIGNALS DURING PATHOLOGY: EVALUATION IN DIFFERENT ARRHYTHMIA CONTEXTS

CITATION

Maršánová L, Nemcova A, Smisek R, Vitek M, Smital L. Advanced P Wave Detection in ECG Signals During Pathology: Evaluation in Different Arrhythmia Contexts. Scientific Reports 2019;9.

PAPER CONTRIBUTION

In Paper 5, a method for P wave detection in ECG signals during more than one pathology is proposed. The entire algorithm consists of eight parts: filtration, QRS complex detection, T wave detection, feature extraction, QRS complex classification, application of decision rules (decision whether a P wave can be expected and what its specific type is, i.e. normal or dissociated), demarcation of the segment for P wave searching, and P wave detection. The algorithm is based on the P wave detection method presented in Paper 1. The detection of PVC consists of two steps: extraction of six morphological features (chosen from those presented in Paper 2 and Paper 3) and heartbeat classification by the kNN method. The decision rules and PVC detection enable finding the P wave in the correct location, or not to search for it at all. To test the algorithm on pathological signals, there were no publicly available standard ECG databases with a sufficient number of correctly annotated P wave positions. Thus, 12 signals selected from the MIT-BIH Arrhythmia Database [28] were manually annotated in terms of P waves. These annotations are publicly available on Physionet [26], [33] as MIT-BIH Arrhythmia Database – P waves annotation (MIT PDB). The same signals were used in Paper 3. Moreover, the algorithm was validated using physiological records from the QT database. The proposed algorithm can detect the P wave in both physiological ECG signals, as well as in signals with a pathology, namely, AV block 2nd degree and premature ventricular contraction. For the physiological signals, the achieved results are comparable with the results of other methods. For the pathological signals, the results highly outperform the other methods. This improvement represents a significant step towards fully automated analysis systems respected by ECG experts. This fulfilled Aim 5 and Aim 6.

AUTHOR'S CONTRIBUTION

The author surveyed related works, developed a new methodology for P wave detection in ECG signals during different types of pathologies, performed annotation of signals, performed testing of the algorithm, wrote a major part of the manuscript, and participated in the finalization of the whole manuscript.

PAPER 6 - RELIABLE P WAVE DETECTION IN PATHOLOGICAL ECG SIGNALS

CITATION

Šaclová L, Nemcova A, Smisek R, Smital L, Vitek M, Ronzhina M. Reliable P wave detection in pathological ECG signals. Scientific Reports 2022;12.

PAPER CONTRIBUTION

The original method presented in Paper 5 was significantly enhanced and its results are presented in Paper 6. The new method improves P wave detection during many types of pathologies. The original method was supplemented with additional rules based on knowledge about heart manifestation during other pathologies, evaluation of heart rate variability (detection of atrial fibrillation and flutter presented in Paper 4), and a modified method for PVC detection (basic method was presented in Paper 2 and Paper 3). According to this analysis, it is determined in which area the P wave will be searched and where it is probably not present. The algorithm performance was validated using physiological records from MIT-BIH Arrhythmia Database – P waves annotation (MIT PDB) [35] and QT database [27] and pathological signals from MIT PDB and Brno University P wave database (BUT PDB) [34] annotated by our team. The BUT PDB is described in the paper. For the physiological signals, the achieved results are comparable with the results of other methods. For the pathological signals, the results highly outperform the other methods. This fulfilled Aim 5 and Aim 6.

AUTHOR'S CONTRIBUTION

The author developed a new methodology for P wave detection in ECG signals with different types of pathologies, enhanced the previous version of the algorithm, described differences, performed annotation of signals, performed testing of the algorithm, wrote a major part of the manuscript, and participated in the finalization of the whole manuscript.

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5. CONCLUSION

In this thesis, it is described the theoretical background of P waves detection in ECG signals during pathologies. It is necessary for the development of an accurate and reliable P wave detection algorithm and the understanding of the contribution made and described in the presented papers. This fulfills Aim 1.

Reliable QRS complex detector and detectors of the P wave and T wave able to deal with the detection of these ECG components in physiological signals (from databases commonly used for this purpose) were introduced. The methods and their results are presented in Paper 1. The main contribution of this part of the thesis is a novel and robust detector of ECG components. This fulfilled Aims 2 and 3.

Then, the possibilities of premature contraction detection were examined. In paper 2, various morphological and spectral features and classification models were tested and analyzed to find the best way to detect PVC in ECG signals. The identification of PVC enables the accurate detection of P waves when they are present. In Paper 3, the method for P wave detection in ECG signals during ventricular extrasystoles was proposed. The first contribution of this part of the thesis is the design of a method for PVC detection and the second is the development of a method for P waves detection during ventricular pathology. Thus, part of the Aim 4 was fulfilled.

Detection of atrial fibrillation, another pathology that affects P wave detection, was investigated in Paper 4. The method and its results are presented in Paper 4. The main contribution of this part of the thesis is a simple and efficient method for the automatic detection of atrial fibrillation. The methods and results presented in Paper 2, Paper 3, and Paper 4 fulfilled Aim 4.

Two databases of ECG signals with annotated P waves were created to test the P wave detection algorithms. Both databases are publicly available on Physionet. One of them is described in Paper 5 and the other in Paper 6. These databases will contribute to the development and proper comparison of new P wave detection algorithms. This fulfilled Aim 6.

Finally, a method for P wave detection able to deal with many types of pathologies is proposed in Paper 5 and Paper 6. The proposed method successfully detected P waves in the database of ECG signals containing 17 different types of pathologies. This advanced P wave detection method represents a huge step towards reliable and fully automated analysis systems. When implemented in complex software, it can simplify cardiologists' work and increase the diagnostic yield of ECG records. This fulfilled Aim 5.

The algorithm was designed in Matlab (Mathworks, Inc., Natic, US-MA) [97]. The algorithm is applicable for ECG processing and evaluation in future research or implementation in ECG signal evaluation software used in medical practice.

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SYMBOLS AND ABBREVIATIONS

RBB	right bundle branch Tawar arm
LBB	left bundle branch Tawar arm
SR	sinus rhythm
WPW	Wolff-Parkinson-White
SA	sinoatrial
AV	atrioventricular
LUDB	Lobachevsky University Electrocardiography Database
SNR	signal-to-noise ratio
ECG	electrocardiogram
SVE	Supraventricular ectopic beat
SVT	Atrial tachycardia
AFL	Atrial flutter
AFIB	Atrial fibrillation
PJC	Premature junctional contraction
PVC	Premature ventricular contraction
IVR	Idioventricular rhythm
VTACH	Ventricular tachycardia
MIT PDB	MIT-BIH Arrhythmia Database – P waves annotation
BUT PDB	Brno University of Technology ECG Signal Database with Annotations of P Wave
WFDB	WaveForm DataBase
DCT	discrete cosine transform
SWM	support vector machine
CWT	continuous wavelet transform
DWT	discrete wavelet transform
KNN	K-nearest neighbor
EKF	extended Kalman filter
AVNRT	AV nodal reentry tachycardia
AVRT	AV reentry tachycardia
LMS	least mean square
SNEO	smoothed nonlinear energy operator
ANN	artificial neural network
PT	phasor transform

CURRICULUM VITAE

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STUDIES

2015 – 2022	Doctoral degree Biomedical Electronics and Biocybernetics, FEEC, BUT
2013 – 2015	Master's degree (Ing.) Biomedical Engineering and Bioinformatics, FEEC, BUT
2010 – 2013	Bachelor's degree (Bc.) Biomedical Technology and Bioinformatics, FEEC, BUT

SELECTED PUBLICATIONS

2022	Šaclová L, Nemcova A, Smisek R, Smital L, Vitek M, Ronzhina M. Reliable P wave detection in pathological ECG signals. Scientific Reports 2022;12:1-12.
2021	Ronzhina, M, Stračina, T Lacinová, Ondáčová K, Pavlovičová M, Maršánová L, Smíšek R, Janoušek O, Fialová K, Kolářová J, Nováková M, Provazník I. Di-4-ANEPPS modulates electrical activity and progress of myocardial ischemia in rabbit isolated heart. Frontiers in Physiology 2021;12(6):1-15. Němcová A, Vargová E, Smíšek R, Maršánová L, Smital L, Vítek M. Brno University of Technology Smartphone PPG Database (BUT PPG): Annotated Dataset for PPG Quality Assessment and Heart Rate Estimation. BioMed Research International 2021;9:1-6.
2020	Nemcova A, Jordanova I, Varecka M, Smisek R, Maršánová L, Smital L, Vitek M. Monitoring of heart rate, blood oxygen saturation, and blood pressure using a smartphone. Biomedical Signal Processing and Control 2020;59:1-10. Smital L, Haider CL, Vitek M, Leinveber P, Jurak P, Nemcova A, Smisek R, Maršánová L, Provaznik I, Felton CL, Gilbert B, Holmes D. Real-time quality assessment of long-term ECG signals recorded by wearables in free-living conditions. IEEE Transactions on Biomedical Engineering 2020;67(10):2721-34. Smisek R, Nemcova A, Maršánová L, Smital L, Vitek M, Kozumplik J. Cardiac pathologies detection and classification in 12-lead ECG. Computing in Cardiology (CinC) 2020. Maršánová L, Nemcova A, Smisek R, Smital L, Vitek M. Single-feature method for fast atrial fibrillation detection in ECG signals. Computing in Cardiology (CinC) 2020. Smital L, Maršánová L, Smisek R, Nemcova A, Vitek M. Robust QRS detection using combination of three independent methods. Computing in Cardiology (CinC). 2020.
2019	Maršánová L, Nemcova A, Smital L, Smisek R, Vitek M. Advanced P wave detection in ECG signals during pathology: evaluation in different arrhythmia contexts. Scientific Reports 2019;9:1-11.
2018	Nemcova A, Vitek M, Maršánová L, Smisek R, Smital L. Assessment of ECG signal quality after compression. World Congress on Medical Physics and Biomedical Engineering 2018:169-73. Nemcova A, Smisek R, Maršánová L, Smital L, Vitek M. A comparative analysis of methods for evaluation of ECG signal quality after compression. BioMed Research International 2018:1-26. Smisek R, Hejc J, Ronzhina M, Nemcova A, Maršánová L, Kolarova J, Smital L, Vitek M. Multi-stage SVM approach for cardiac arrhythmias detection in short single-lead ECG recorded by a wearable device. Physiological Measurement 2018;39(9):1-14. Maršánová L, Nemcova A, Smisek R, Goldmann T, Vitek M, Smital L. Automatic detection of P wave in ECG during ventricular extrasystoles. World Congress on Medical Physics and Biomedical Engineering 2018:381-385.

2017	Smisek R, Hejc J, Ronzhina M, Nemcova A, Maršánová L, Chmelik J, Kolarova J, Provaznik I, Smital L, Vitek M. SVM based ECG classification using rhythm and morphology features, cluster analysis and multilevel noise estimation. Computing in Cardiology (CinC) 2020. Maršánová L, Ronzhina M, Smisek R, Vitek M, Nemcova A, Smital L, Novakova M. ECG features and methods for automatic classification of ventricular premature and ischemic heartbeats: A comprehensive experimental study. Scientific Reports 2017;7:1-11.
2016	Smisek R, Maršánová L, Nemcova A, Vitek M, Kozumplik J, Novakova M. CSE database: extended annotations and new recommendations for ECG software testing. Medical and Biological Engineering and Computing 2016;54(12):1-10. Maršánová L, Ronzhina, M, Smisek R, Vitek M. Použití kumulantů vyšších řádů pro automatickou klasifikaci EKG. Elektrorevue 2016;(18)4:103-111. Maršánová, L. Detection of P, QRS and T Components of ECG Using Phasor Transform. Sborník příspěvků studentské konference Blansko 2016:55-58. Maršánová, L.; Vitek, M. Rules for determination of expected P wave type in ECG signals. Proceedings of the 22st Conference STUDENT EEICT 2016;400-404.
2015	Ronzhina M, Maršánová L, Smisek R, Olejníčková V, Janoušek O, Veselý P, Kolářová J, Nováková M, Provazník I. Classification of ventricular premature and ischemic beats in animal electrograms. Computing in Cardiology 2015:1137-1140. Maršánová L, Ronzhina M, Vitek M. Automatická klasifikace EKG s použitím morfologických parametrů. Elektrorevue 2015;(18)4:115-123. Maršánová L, Ronzhina M. Classification of experimental electrograms. Proceedings of the 21st Conference STUDENT EEICT 2015;237-239.

LECTURES

Digital Signal and Image Processing

Digital Signal Processing and Analysis

Analysis and Interpretation of Biological Data

WORK

2012 – 2019 - Cardiology Clinic Mudr. Petr Bouchal, Pekařská, Brno, Czech republic

2016 – 2022 – Brno University of Technology, Department of Biomedical Engineering, Brno, Czech republic

2022 – Collegue of Polytechnic Jihlava, Department of Technical Studies, Brno, Czech republic

ACHIEVEMENTS

2020 PhysioNet/Computing in Cardiology Challenge – 11th place out of 42 teams

2017 PhysioNet/Computing in Cardiology Challenge – 9th place out of 67 teams

Brno Ph.D. Talent 2015 – finalist

MEMBERSHIP

Czech Athletic Federation

Czech Athletic National Team

FELLOW RESEARCHER

2022	Database of kinematics and EMG of walking, running and elementary body movements Internal project Collegue of Polytechnic Jihlava
2019 – 2021	Health and activity monitoring by wearables in extreme conditions The Office of Naval Research (ONR)
2017	Detection of P wave in pathological ECG Internal BUT projects – inter-faculty project (cooperation with FIT)

RESEARCH TEAM

Members: Ing. Lucie Šaclová (Maršánová), Ing. Martin Vitek, Ph.D., Ing. Lukas Smital, Ph.D., Ing. Marina Ronzhina, Ph.D., Ing. Andrea Nemcova, Ph.D., Ing. Radovan Smisek

Main areas of interest: health and activity monitoring by wearables (including filtration, QRS complex detection, P wave detection, ECG delineation, ECG compression, ECG and PPG quality assessment, pathological ECG signal processing and analysing, ECG pathology classification, PPG analysis, classification of activities, step detection, fall detection, data recording using smartphone and wearables, quality annotations, P wave annotations, …)

Current projects: Health and activity monitoring by wearables in extreme conditions, funded by The Office of Naval Research (ONR), cooperation with Mayo Clinic in Rochester, Minnesota