IEEE Access
Multidisciplinary : Rapid Review : Open Access Journal

Received May 13, 2018, accepted June 16, 2018, date of publication June 22, 2018, date of current version July 12, 2018.

Digital Object Identifier 10.1109/ACCESS.2018.2849870

Evolution, Current Challenges, and Future Possibilities in ECG Biometrics

JOÃO RIBEIRO PINTO [1,2], **(Student Member, IEEE),**
JAIME S. CARDOSO [1,2], **(Senior Member, IEEE), AND ANDRÉ LOURENÇO** [3,4,5]

[1]Faculdade de Engenharia da Universidade do Porto, 4200-465 Porto, Portugal
[2]Centre for Telecommunications and Multimedia, INESC TEC, 4200-465 Porto, Portugal
[3]CardioID Technologies LDA, Lisbon, Portugal
[4]Instituto Superior de Engenharia de Lisboa, 1600-312 Lisbon, Portugal
[5]Instituto de Telecomunicações (IT), 1049-001 Lisboa, Portugal

Corresponding author: João Ribeiro Pinto (jtpinto@fe.up.pt)

This work was supported in part by the North Portugal Regional Operational Programme through the NanoSTIMA: Macro-to-Nano Human Sensing: Towards Integrated Multimodal Health Monitoring and Analytics/NORTE-01-0145-FEDER-00001 Project under Grant NORTE 2020 and in part by the European Regional Development Fund under the PORTUGAL 2020 Partnership Agreement.

ABSTRACT Face and fingerprint are, currently, the most thoroughly explored biometric traits, promising reliable recognition in diverse applications. Commercial products using these traits for biometric identification or authentication are increasingly widespread, from smartphones to border control. However, increasingly smart techniques to counterfeit such traits raise the need for traits that are less vulnerable to stealthy trait measurement or spoofing attacks. This has sparked interest on the electrocardiogram (ECG), most commonly associated with medical diagnosis, whose hidden nature and inherent liveness information make it highly resistant to attacks. In the last years, the topic of ECG-based biometrics has quickly evolved toward the commercial applications, mainly by addressing the reduced acceptability and comfort by proposing new off-the-person, wearable, and seamless acquisition settings. Furthermore, researchers have recently started to address the issues of spoofing prevention and data security in ECG biometrics, as well as the potential of deep learning methodologies to enhance the recognition accuracy and robustness. In this paper, we conduct a deep review and discussion of 93 state-of-the-art publications on their proposed methods, signal datasets, and publicly available ECG collections. The extracted knowledge is used to present the fundamentals and the evolution of ECG biometrics, describe the current state of the art, and draw conclusions on prior art approaches and current challenges. With this paper, we aim to delve into the current opportunities as well as inspire and guide future research in ECG biometrics.

INDEX TERMS Acquisition, authentication, biometrics, biosensors, classification algorithms, electrocardiography, feature extraction, identification of persons, machine learning, off-the-person, seamless, signal processing.

I. INTRODUCTION

Websites, smartphones, safes, cars, houses, buildings, banks, and airports are just a few of our society's amenities that rely on identification or authentication systems to protect and guard ourselves, our information, or our belongings. Several still depend on traditional systems based on extrinsic entities or knowledge like cards, keys, or passwords [1], [2]. However, in the last decades, researchers have focused on avoiding the problems of traditional systems: they can be lost, stolen, discovered, or copied [3]. Biometrics present the perfect opportunity to achieve that goal, as they are focused on intrinsic characteristics of the person, requiring their physical presence, and minimizing the probability of success of possible impostors [1], [4].

A biometric system aims to either identify or authenticate a person based on a measurement of one or several biometric traits (see Fig. 1). To achieve that goal, it is composed of an acquisition module (a sensor prepared to measure the respective trait), a storage module (to store personal data of enrolled subjects), and a biometric algorithm. The biometric algorithm uses the data from the acquisition and storage modules, and is usually composed by stages of quality assessment, feature extraction, and decision [1], [5], [6].

Many human traits have been proposed and studied for the purpose of identity recognition, especially face, fingerprints, voice, and iris [4], [7]. With the increasing number of applications that rely on these, the methods to circumvent them become stronger, resorting to photographic, 3D model

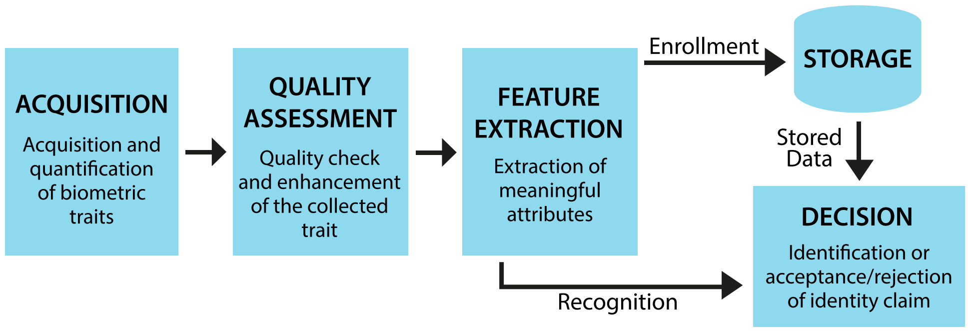

FIGURE 1. Common structure of a biometric system (based on [1], [5], [6]).

reproductions, or sound recordings of the traits [8], [9], and obliging biometric systems to include deeper security measures, such as liveness detection.

TABLE 1. Main benefits and drawbacks of the electrocardiogram when compared with other biometric traits (includes information based on [3], [4]).

Trait	Benefits	Drawbacks
Electrocardiogram (ECG)	Universality Hidden nature Simple acquisition	Requires contact Variability over time
Electroencephalogram (EEG)	Universality Hidden nature	Expensive equipment Vulnerability to noise Variability over time
Face	Easily measurable Affordable equipment	Easy circumvention Depends on face visibility and lighting
Fingerprint	High performance Permanent over time	Requires contact
Gait	Easy to measure Affordable equipment	Low performance Variability over time
Iris	High performance	Expensive equipment
Palmprint	High measurability Permanent over time	Requires contact
Photoplethysmogram (PPG)	Easy to acquire Hidden nature Affordable equipment	Low performance Variability over time
Voice	Affordable equipment	Low performance

More recently, a new set of biometric traits, called medical biometrics, has gained momentum [3], [7], [10]. The Electrocardiogram (ECG), compared with other biometric traits in Table 1, has proven to be the most promising of them, excelling in most of the characteristics that define the quality of a biometric trait [3]. Its nature makes it hard to capture and inject into the system for spoofing purposes, and the inherent liveness detection ensures the biometric system is not being attacked [11]. Furthermore, its unidimensional nature places it as a more computationally efficient alternative to image or video-based systems, especially for continuous recognition systems, highly dependent on timely decisions.

Some surveys have delved before into the topic of ECG-based biometrics or some specific and closely related aspects [9], [12]–[16]. However, this research topic has now reached a turning point that merits to be addressed and deeply discussed. Now, electrocardiogram acquisition settings are finally offering enough acceptability and comfort to be applicable to commercial biometric systems [17], [18], but have created new issues related to increased signal noise and variability [19].

Moreover, researchers have recently started to explore diverse deep learning methodologies, which bring significant improvements in robustness, but also raise new challenges regarding data availability [20]–[22]. Also, important issues regarding counterfeiting attacks in ECG biometrics have finally begun to be addressed [23], [24].

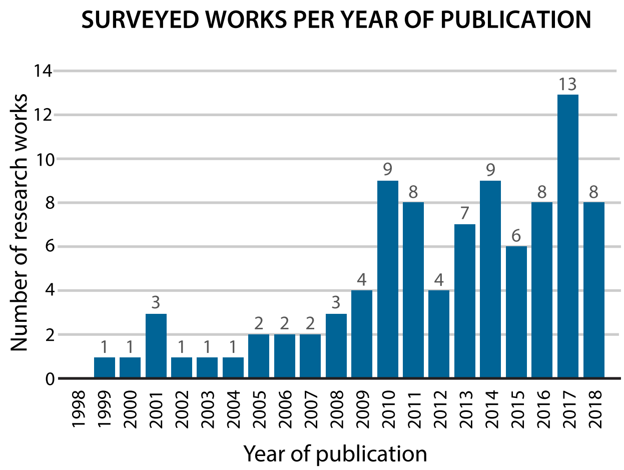

FIGURE 2. Histogram of the number of publications surveyed for this document per year of publication (this includes all papers that propose methods for unimodal and multimodal ECG biometrics).

In this turning point in ECG biometrics, this survey aims to showcase the evolution and current landscape of ECG-based biometric recognition, including a solid overview of fundamental concepts, providing a complete and deep guide to new and current researchers. After presenting the most relevant advances in ECG biometrics research, based on the review of ninety-three state-of-the-art publications (see Fig. 2), we use that deep perspective to discuss the most relevant challenges and the most promising future possibilities regarding research and development in each part of ECG biometric systems, from acquisition to decision.

Besides this introduction, this survey presents the fundamentals in anatomy, physiology, and intra and inter-subject variability, in section II; the evolution and future possibilities on acquisition of ECG signals for biometrics, in section III; guidelines on data for ECG biometrics, and a characterization of publicly available collections, in section IV; and the review and current challenges in signal denoising, in section V.

In section VI, we discuss the methods used to prepare the signals for feature extraction and decision; in section VII, we review the state-of-the-art and opportunities regarding feature extraction; and in section VIII we delve into the methods for decision in both identification and authentication. Finally, we address other developments and challenges in ECG biometrics, such as deep learning and spoofing, in section IX; and we conclude with a summary and final remarks, in section X.

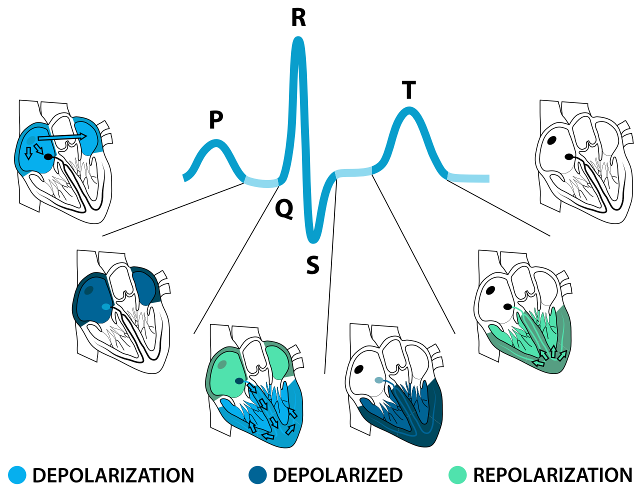

FIGURE 3. The sequence of depolarization and repolarization events in the heart, and their relationship with the different heartbeat waveforms in an ECG signal (based on [25]).

II. THE ELECTROCARDIOGRAM

More than a trending biometric trait, the electrocardiogram is a physiological signal generated from the contraction and the recovery of the heart. In this section, we aim to introduce the electrocardiogram, from generation to acquisition, discussing its inter-subject and intra-subject variability factors, how they relate to the anatomy of each person, and how they may be useful or prejudicial for biometric recognition.

A. ANATOMY AND PHYSIOLOGY OF THE ECG

In every sense of the word, the heart is a pump. Tate [26] defines three main functions of the heart: generate blood pressure, through the contraction of the myocardium, in order to keep blood moving; route blood, by sending venous blood to the lungs, in the pulmonary circulation, and arterial blood to the whole body, in the systemic circulation; and regulate blood supply, by adapting its rate and force of contraction to the current metabolic demands of the body.

The contraction of the heart is, thus, of the highest importance. The myocardial muscle cells contract in response to electrical currents, that cause the depolarization of those tissues by triggering action potentials [26], [27]. These flows of depolarization and repolarization are nothing more than electrical currents being generated and conducted through the heart. These electrical currents can be detected and measured, through electrodes placed in the body, in a process called electrocardiography.

The resulting signal is called an electrocardiogram (ECG) and, in normal conditions, is a cyclic repetition of five easily recognizable deflections: the P, Q, R, S, and T waves (see Fig. 3). Each group of these deflections composes a single heartbeat, and each can be traced back to the phase that originated it [25]–[27].

B. INTRA-SUBJECT AND INTER-SUBJECT VARIABILITY

The ECG signal, although presenting, in normal conditions, the same deflections for all subjects at all times, is characterized by a high degree of variability. Variability in the ECG can be designated as *intra-subject*, the variations between cycles (heartbeats) in the electrocardiogram of a single subject, or inter-subject, the variations between heartbeats of different subjects.

The intra-subject variability of the ECG is mainly explored for health monitoring and medical diagnosis [28]–[30], while inter-subject variability is especially useful to discriminate between subjects in biometric recognition. Both these variability types can have origin in several factors, most importantly:

- **Heart Geometry**: Heart size, cardiac muscle thickness, and the overall shape of the heart dictate the paths the electrical current will follow inside the heart, the number of muscle cells that will depolarize, and the time it takes to do it across the whole heart. Athletes, with their high physical training, commonly have larger hearts, with thicker myocardia, which affects the ECG with higher voltages in the QRS complex, and lower basal heart rates [31]–[33];
- **Individual Attributes**: Age, weight, and pregnancy, are some of the individual attributes that can cause shifts in the heart position and/or orientation. These shifts will change the orientation of the electrical current conduction vectors along the heart, meaning the electrodes will detect the signal in a different perspective, thus altering the ECG waveforms [34];
- **Physical Exercise or Meditation**: The duration of, and intervals between the different deflections of the heartbeats in an ECG signal, vary with the heart rate. These changes are especially visible on the interval between the QRS complex and the T wave in situations of tachycardia (higher heart rates) or bradycardia (lower heart rates). Changes in the heart rate caused by physical exercise or meditation do, effectively, affect the electrocardiogram [10];

- **Cardiac Conditions**: Medical conditions of the heart can also interfere in the dynamics of the electrical pulse conduction and generate variability. In the scope of biometrics, one of the most studied conditions is Arrhythmia, that causes wide variations in the heart rate across time and, as reported by several researchers, can consistently shrink the performance of ECG-based biometric systems [2], [35], [36].
- **Posture**: Postures like standing or laying down differ widely on the position and shape of internal organs. The heart is also affected by this, changing its position in the thorax, and thus its position in reference with the electrode placement, which will cause variations in the collected ECG signal [34];
- **Emotions and Fatigue**: The sympathetic and parasympathetic systems of the autonomous nervous system work to, respectively, increase or reduce the heart rate. These systems are under direct influence of psychological states and thus, under stress, fear and other strong emotions, fatigue or drowsiness, the heart rate and the ECG signal can be affected [10], [29];
- **Electrode characteristics and placement**: The type, size, and number of the electrodes, whether they are wet or dry, and the positioning on the chest or limbs, can influence the dominance of noise on the signal. The mispositioning of electrodes and reversal of leads are also sources of variability, as they change the perspective of detection of the electrocardiographic signal [31], [34].

All the previously presented factors reflect on the morphology of the electrocardiographic signals acquired from an individual. While the first two factors contribute more to inter-subject variability and to the biometric potential of the ECG signals, the remaining factors are the main origins of intra-subject variability and may undermine the process of biometric recognition. When considering the acquisition of ECG, whether for medical or biometric recognition purposes, it is of utmost importance to consider all of these and the way they can ease or difficult the task at hand.

III. ACQUISITION

Since the first research initiatives in ECG-based biometrics, the configurations used for acquisition have greatly evolved. From the early use of several wet electrodes from medical settings to the current trend of off-the-person settings, researchers mostly focused on addressing the main disadvantage of ECG as a biometric trait: acquisition acceptability.

Below, we describe the different stages of this evolution, present examples of publications that use them, and we delve into the recent developments on ECG acquisition, in order to discuss future possibilities on acquisition settings and their potential for ECG biometrics.

A. THE EVOLUTION OF ACQUISITION SETTINGS

1) MEDICAL ACQUISITIONS

For medical purposes, there are a few defined and established configurations of electrodes for the measurement of electrocardiogram signals in standard, comparable formats that ease the diagnostic of cardiac conditions (see Fig. 4). The Standard 12-Lead Configuration allows the acquisition of an ECG signal in 12 leads (or channels): three bipolar limb leads, three monopolar limb leads, and six monopolar precordial leads [37]. The corrected orthogonal configuration (Frank Leads) allows the acquisition of the ECG with seven electrodes. Processing the signals obtained from all these electrodes allows the collection of the three orthogonal leads, P_x, P_y, and P_z, thus capturing the heart dipole in three dimensions [38].

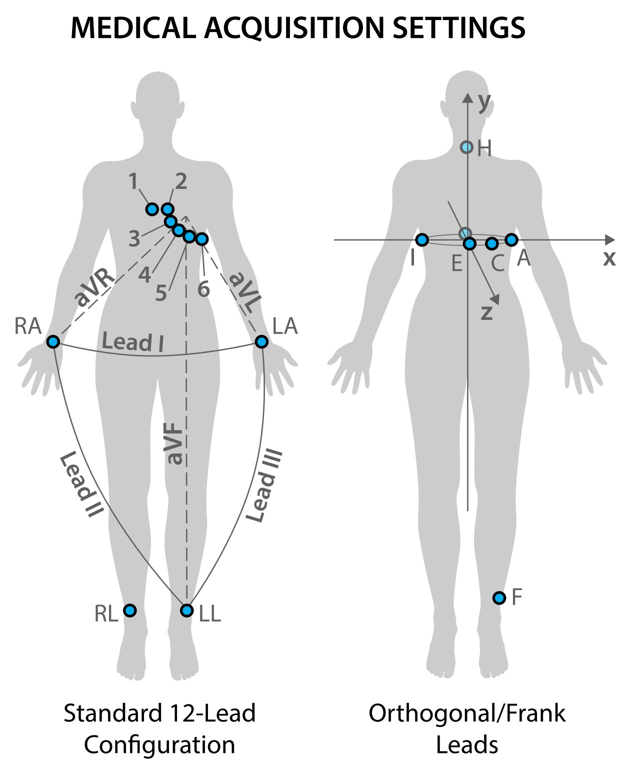

FIGURE 4. Medical acquisition settings: electrode placement and leads on the standard 12-lead configuration and Frank leads (anterior electrodes depicted in blue, posterior electrodes depicted in lighter blue).

In early ECG biometric research, recordings from standard 12-lead or Frank leads were commonly used for the development and evaluation of algorithms [39]–[41]. Even more common has been the selective use of certain leads of these configurations, especially Lead I [42]–[44], because of its higher acceptability due to the electrode placement on the wrists, but also Lead II [45]–[48], or chest leads [49], [50], [35].

Nevertheless, medical configurations present several limitations, such as large number of electrodes and their uncomfortable placement, and the limited movement and duration of the recordings, that fail to enable the development of robust biometric systems.

2) MOVEMENT FREEDOM AND HOLTER SYSTEMS

To mitigate the issues with medical acquisitions, some researchers opted for acquisitions without movement restrictions, with longer durations, and with less electrodes. One of the most prominent examples was the use of Holter systems (see Fig. 5), that are prepared to acquire ECG signals during several hours while the subjects move and perform their daily activities.

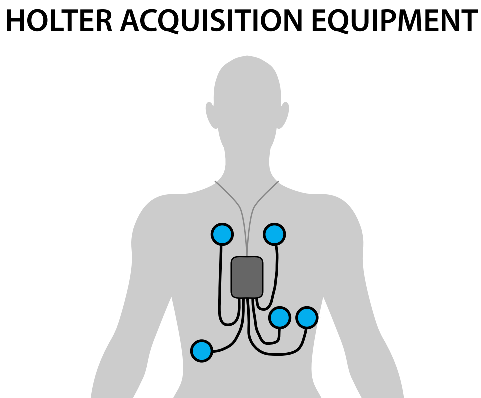

FIGURE 5. **Acquisition settings with movement: example of a five-electrode Holter system for ambulatory recordings (electrodes depicted in blue).**

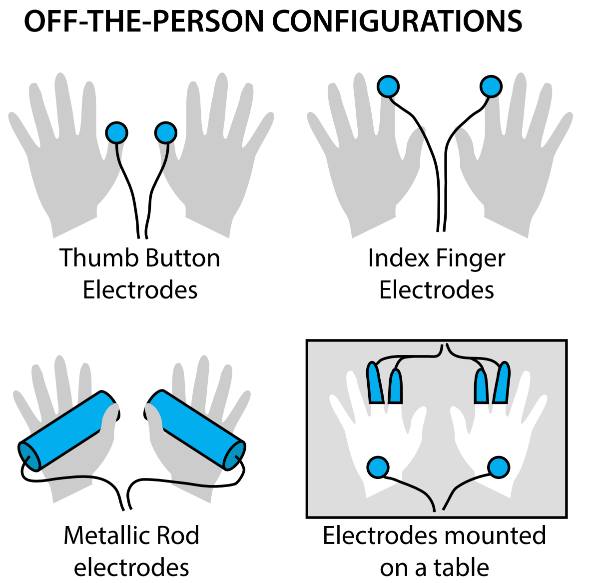

FIGURE 6. **Examples of off-the-person ECG acquisition configurations, using thumb electrodes [55], index finger electrodes [56], metallic rods grabbed by the subjects [8], [57]–[59], or electrodes mounted on a table [60] (electrodes depicted in blue).**

Acquisitions at rest were first discarded by Shen *et al.* [51], using ambulatory recordings from MIT-BIH Normal Sinus Rhythm database (described further on in this survey), acquired for thirty minutes using Holter equipment. Labati *et al.* [52], [53] user 24-hour-long Holter acquisitions, from the E-HOL 24h signal collection, and seized the opportunity to study the effect of ECG variability over time on identification performance. Similarly, Zhou *et al.* [54] used a mini-Holter system to continuously record ECG signals.

However, although allowing for longer acquisitions with movement and activity, Holter acquisitions still require the placement of electrodes on the torso. This significantly reduces acquisition acceptability and comfort, and damages the ECG strength as a biometric trait.

3) OFF-THE-PERSON SETTINGS

To improve acceptability and acquisition comfort, and get closer to biometric systems deployable to real settings, researchers took a number of actions regarding the acquisition of ECG signals. Wet electrodes were replaced by dry metallic electrodes, their number was reduced to two or three, and their placement was confined to the upper limbs, especially the on wrists, hands, or fingers (see Fig. 6).

These acquisition configurations were designated as off-the-person settings, as opposed to the on-the-person settings described in the two topics above. The first research works in ECG biometrics to use off-the-person signals were, to the best of our knowledge, Molina *et al.* [44], who used commercial metallic electrodes strapped to the wrists of the subjects, and Chan *et al.* [55], who acquired ECG signals using dry button electrodes held by the subjects in contact with their thumbs.

Shen *et al.* [57] recorded signals from both palms from the subjects while they held two small metallic rod electrodes. Similar configurations were used by Belgacem *et al.* [8], [58], Lin *et al.* [59], and Lourenço *et al.* [61] mounted three dry metallic electrodes on a plaque, positioned to contact with the index finger of the left hand and the thumb of the right hand. More recently, Matos *et al.* [56] used only two Ag-AgCl electrodes (with virtual ground) to acquire ECG at the index fingers.

Nevertheless, off-the-person systems still require the user to hold the electrodes or deliberately place the fingers or palms over them. This prevents us to designate them as unconstrained systems, which puts the ECG in disadvantage over other biometric traits that can already be used for unconstrained recognition. Besides this, the use of dry electrodes in farther placements makes the acquisition more vulnerable to interferences, thus affecting the quality of the signal [8], [60].

4) WEARABLES AND SEAMLESSLY INTEGRATED ACQUISITION

Recently, a few initiatives have been conducted to improve off-the-person configurations and approach unconstrained settings in ECG biometrics, and close the gap to real, commercial applications, by developing wearable technologies for ECG acquisition or embedding the sensors into common objects (see Fig. 7).

In research, the first example of this type of highly acceptable acquisition was proposed by Coutinho *et al.* [62], [63], who developed a sensor pad to be used alongside a computer keyboard. While the users use the keyboard, their palms rest on the sensor pad that continuously acquires their ECG signal to be used for authentication. This configuration was also used by Silva *et al.* [64]. More recently, Zhang *et al.* [65] have shown it is possible to acquire ECG signals from a single arm, and successfully use them for biometric recognition.

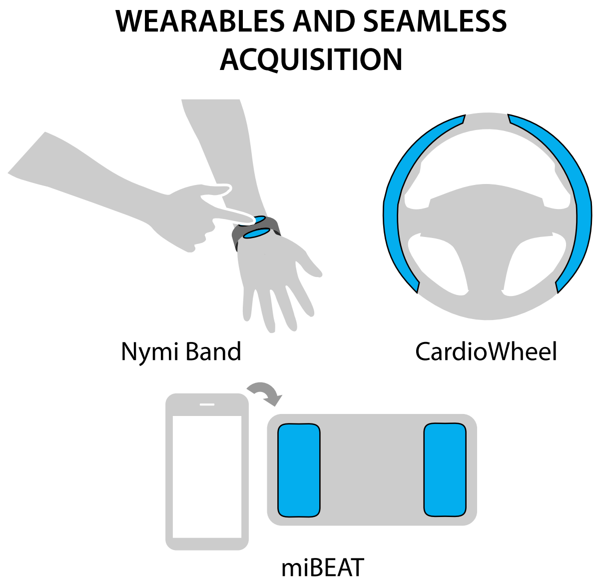

FIGURE 7. **Wearable and seamless acquisition: examples of surveyed configurations (electrodes depicted in blue).**

As for commercial applications, the Nymi Band [18] is one of the resulting products. It is a wearable wristband that acquires the ECG using two metallic electrodes on its inner and outer surface. Authentication is performed when the band is put on, requiring the user to place a finger of the opposite hand on the outer electrode of the band. After this, the session remains open until the band is taken off, and the Nymi Band broadcasts an identity signal to authenticate the user in other nearby systems.

The CardioWheel [17], like other products by CardioID Technologies LDA, is based on the incorporation of acquisition electrodes and hardware into common objects for seamless ECG measurement. It is a steering wheel cover using conductive leather for seamless and continuous biometric recognition and health monitoring of drivers, aiming towards automatic personalization of driving settings and remote fleet supervision.

Also, Yathav *et al.* [66] have recently proposed the miBEAT, a versatile platform for simultaneous acquisition of ECG and photopletismography (PPG) signals. According to the authors, the platform can be used for several custom applications, including the seamlessly integrated signal acquisition in smartphones or tablets for personal identification or authentication.

These efforts have brought ECG biometrics closer to viable, unconstrained applications. However, wearables like the Nymi Band still require the users to wear the product for long periods of time, and touch the outer electrode with the opposite hand every time they put it on to open the session. Integrated acquisition settings like the CardioWheel may suffer from unprecedented noise dominance and frequent signal loss, as the users move or take their hands off the electrodes. Hence, these issues must be addressed and adequately solved in order to obtain viable commercial ECG biometric systems.

B. REFLECTIONS ON FUTURE SETTINGS

Since the first research initiatives in ECG biometrics, many problems have been addressed regarding the acquisition, as presented in the previous subsection. However, as discussed for wearables and seamlessly integrated settings, there is still work to do. They still require contact with both limbs during acquisition, and the loose contact with the user's skin is the origin of signal loss and frequent movement artifacts.

Nevertheless, some researchers have addressed these issues. The single-arm acquisition settings studied by Zhang *et al.* [65] raise new and inspiring possibilities for wearable ECG devices. Furthermore, Chi *et al.* [67] have developed and evaluated electrodes that dismiss the need for contact, successfully acquiring ECG through layers of plastic or clothes. For applications that do not require as much information as carried by the ECG, techniques have been proposed to measure the heart rate, at a distance, using microwave Doppler sensors [68]–[70].

This paves the way for better future technologies, that could consist in seamlessly integrated biometric systems that can acquire ECG signals at short distances from one hand of the user, without requiring contact and thus suffering from signal loss. For wearables, the future could reside in products that can continuously monitor the users' ECG while only contacting with one of their wrists, or when inside their pockets separated from the body by clothes.

IV. DATA IN ECG BIOMETRICS

Numerous researchers, when working with ECG signals, for biometric recognition purposes or for automatic diagnosis of medical cardiac conditions, opt for private acquisitions of data. However, as the needs grow for more complete datasets, with more subjects, including medical conditions, on more sessions, spread across wider time frames, and under different posture and activity conditions, researchers became more aware of the importance of public signal collections [60].

Moreover, public ECG databases are needed to enable comparison and benchmarking of algorithms in challenging conditions, across different publications, without requiring researchers to replicate algorithms and evaluate them again. Below, we delve into the important aspects behind a well-structured ECG signal collection to aid the development of biometric systems, and we present the most relevant publicly available collections, and we discuss the current needs and future possibilities regarding data in ECG biometrics.

A. BUILDING A COMPLETE ECG COLLECTION

A well-structured ECG signal collection is key to appropriately guide the development towards the exploitation of the best possibilities for the system, and accurately predicting its performance upon real-life application. To achieve such a complete collection, a few aspects have to be considered:

- **Number of electrodes**: Less electrodes and leads have been shown to provide more challenging settings for biometrics [50], [71];

- **Electrode placement**: As shown by [43], the use of chest leads is less challenging than limb leads, and the distance of the electrodes to the heart has a significant negative impact on the system's performance;
- **Sampling frequency**: Sampling causes the loss of fine details that influence the recognition process [71]. The lower the sampling frequency, the larger the amount of details that can be lost, and the higher the risk of aliasing of high-frequency noise (such as electromyogram interference);
- **Subject posture, activity, and fatigue**: Several studies have shown that fatigue, exercise, or different postures have a negative effect on recognition performance, if the systems have not been trained accordingly [48], [71], [72];
- **Subject health**: Some health issues, mainly arrhythmia, can generate intra-subject signal variability that encumber the recognition process [36], [73], [74]. Thus, systems should be made robust against this, by including subjects with heart conditions in the datasets used during development and validation of the methods;
- **Number of subjects**: The diversity of individuals and their own characteristics may ease or difficult the job of the biometric systems [75], [76], and successful state-of-the-art algorithms have been shown to be significantly worse when evaluated on larger datasets [12]. The use of a collection with large number of subjects ensures the presence of subject diversity, increasing the thoroughness of the performance assessment. As visible in Fig. 8, the vast majority of surveyed publications reported the use of data from less than 100 subjects;
- **Acquisition sessions**: The ECG signal varies enough to cause recognition errors in most biometric systems, even over a short 24-hour period [52], [53]. Systems should be prepared with data from several sessions, weeks or months apart, to ensure their robustness [64], [71].

All these factors can have an impact on the performance of an ECG-based biometric system. In order to correctly assess the capabilities of such systems, it is of the highest relevance to not only build a database that fits the system's expected application context, but also one that reflects all possibilities mentioned above, in order to study the use of the same biometric system in a wider set of contexts.

B. CURRENT PUBLICLY AVAILABLE COLLECTIONS

Currently, there are several collections, publicly available for ECG biometrics research,[1] that try to cover some or all these factors to create a challenging environment for the development of robust biometric systems. Many are stored by Physionet,[2] while others are ceded by their owners. Below, we present and characterize the most relevant of the currently available ECG collections (see Fig. 9 for the number of publications that have used them), and Table 2 summarizes the characteristics of each.

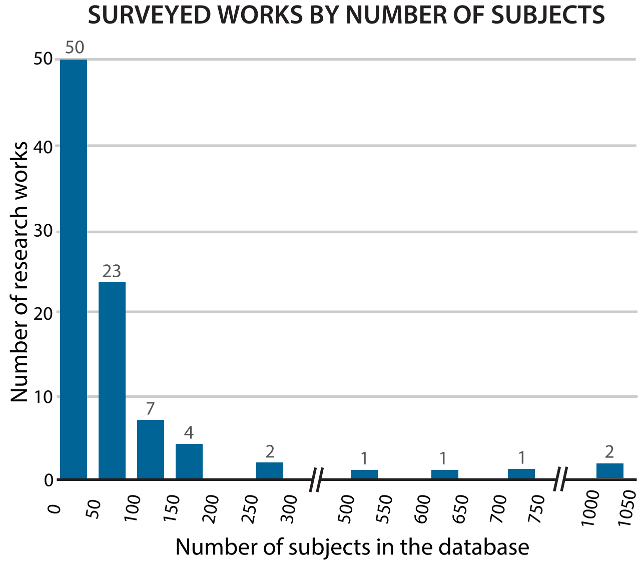

FIGURE 8. Histogram of surveyed publications per number of subjects in the datasets used (it is worthy of notice that two surveyed publications did not specify the number of subjects considered; for works that used more than one database separately, only the largest was considered; and for those that used a joint group of signals from more than one database, the total number of subjects was considered).

- **AHA**: The AHA ECG database[3] was created by the American Heart Association to guide the training of health professionals on the diagnosis of arrhythmias. It includes 154 ECG recordings from real patients, donated by various institutions, each three hours long and composed of 2 lead signals. The last 30 minutes of each recording are annotated for seven types of arrhythmia;
- **CYBHi**: The Check Your Biosignals Here initiative[4] [60] is a collection of off-the-person ECG signals acquired with two dry electrodes at the palms, and two electrolycras at the middle and index fingers. It consists of a short-term dataset, with single-session recordings of 65 volunteers; and a long-term dataset, where 63 subjects were recorded in two-sessions, three months apart. In each session, for 5 minutes, the subjects were exposed to videos designed to cause emotional reactions;
- **DriveDB**: Resulting from the Stress Recognition in Automobile Drivers initiative, this database was created with the purpose of monitoring of stress in drivers [77].

[1] Some of these databases may require prospective users to contact the respective administrators to request access to the data and/or sign agreements beforehand. Nevertheless, all presented databases are made available by the creators for research purposes.

[2] Physionet ECG databases. Available on: https://www.physionet.org/physiobank/database/#ecg.

[3] American Heart Association ECG database. Available on: https://www.ecri.org/components/Pages/AHA_ECG_USB.aspx.

[4] CYBHi dataset for off-the-person ECG biometrics. Available on: https://www.researchgate.net/publication/323543069_Check_Your_Biosignals_Here_Initiative_CYBHi_dataset_for_off-the-person_ECG_biometrics.

TABLE 2. Summary of the technical specificities of the most relevant publicly available ECG collections (OP – off-the-person; NS – number of subjects; Fs – sampling frequency (Hz); L./E. – number of leads/electrodes).

Collection	OP	NS	Fs	Electrode Placement	L./E.	Health Conditions	Activity/Posture	Sessions
AHA	No	154	250	Chest	2 / -	Various	-	3 h
CYBHi [60]	Yes	128	1000	Palms + Fingers	2 / 4	None	Reactions triggered by sound and video	Up to two 5 min. sessions, 3 months apart
DriveDB [77]	No	9	456	Chest	1 / -	-	Rest, highway, and city driving	50 min. to 1.5 h
ECG-ID [78], [79]	No	90	500	Wrists	1 / -	-	Sitting, unrestrained movement	Various 20 s rec. per subject over 6 months
E-HOL 24h	No	203	200	Chest	3 / 4	None	Ambulatory recordings	24 h
European ST-T [80]	No	79	250	Chest	2 / -	Various	Ambulatory recordings	2 h sessions
LTST [81]	No	80	250	Chest	2-3 / -	Arrhythmia and ischaemia	Ambulatory recordings	21-24 h
MIT-BIH Arrhythmia [82], [83]	No	47	360	Chest	2 / -	None	Ambulatory recordings	30 min.
MIT-BIH NSR [82], [83]	No	18	360	Chest	2 / -	None	Ambulatory recordings	30 min.
PTB [84]	No	290	1000	Chest + Limbs	15 / -	Various	At rest only	1-5 per subject, 38.4-104.2 s
QT [85]	No	105	250	Chest	- / -	Various	Rest and exercise	15 min.
UofTDB [72]	Yes	1019	200	Fingers	1 / 2	None	Sit, stand, supine, exercise, and tripod	Up to six 2-5 min. recordings over 6 months

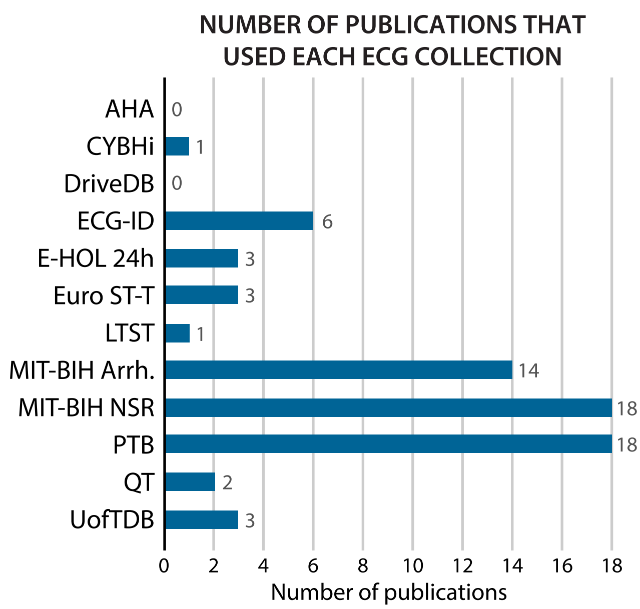

FIGURE 9. Currently available ECG collections and the number of surveyed publications that have used them.

Various physiological parameters (electrocardiogram, electromyogram, and skin conductivity) were recorded from 9 subjects over a total of 18 driving sessions, including periods of rest (lower stress levels), highway driving, and city driving (higher stress levels);

- **ECG-ID**: The ECG-ID is a database entirely focused on biometrics [78], [79]. 20-second ECG recordings were collected from 90 subjects, and are currently available on Physionet. For each subject, the database has between 2 and 20 recordings (a total of 310) collected over a six month period. The signals were acquired from Lead I using limb-clamp electrodes at the wrists;
- **E-HOL 24h Holter**: This is an ECG database, focused on biometrics, from the University of Rochester.[5] A total of 203 healthy subjects were recorded using a Holter monitor during 24 hours, with four electrodes placed on the chest, from 3 leads following a pseudo-orthogonal configuration;
- **European ST-T**: The European ST-T database [80] was originally intended for the analysis of ST and T-wave changes. The database is composed by 90 two-hour excerpts of recordings from 79 subjects, from 2 leads, and include abnormalities with origin in myocardial ischaemia, hypertension, ventricular dyskinesia, and effects of medication;

[5]University of Rochester Medical Center, Telemetric and Holter ECG Warehouse. Database E-HOL-03-0202-003. Available on: http://thew-project.org/Database/E-HOL-03-0202-003.html.

- **Long-Term ST**: The LTST database [81], available on Physionet, includes a variety of ST segment changes for the development of algorithms for the diagnosis of myocardial ischaemia. This database includes 86 records from 80 subjects, from ambulatory recordings between 21 and 24 hours, from two and three leads;
- **MIT-BIH Arrhythmia**: The MIT-BIH Arrhythmia database [82], [83], one of the most used in ECG-based biometrics research, is available at the Physionet repository. The database is composed by a total of 48 signals, 30 minutes long excerpts from ambulatory two-lead recordings. The 47 subjects were selected to obtain a representation of a wide variety of arrhythmias;
- **MIT-BIH Normal Sinus Rhythm**: This database is composed of excerpts from 18 subjects, from the MIT-BIH Arrhythmia database [82], [83], presented above, deemed to be free from arrhythmias or other abnormalities;
- **PTB**: The PTB Diagnostic ECG database [84], [86] includes 549 recordings from 290 healthy subjects and individuals with various cardiac conditions (such as myocardial infarction, dysrhythmia, hypertrophy, or heart failure). It has 1 to 5 recordings per subject, ranging between 38.4 and 104.2 seconds, from all 12 standard and 3 Frank leads;
- **QT**: The QT database aims to aid the development of automatic methods of measurement of QT waveforms [85]. This collection is a compilation of 105 15-minute relevant recording extracts from other public databases;
- **UofTDB**: The University of Toronto ECG Database [72] was specifically created for biometrics and addresses several important criteria for a thorough evaluation of biometric performance. The off-the-person ECG signals were captured using dry electrodes at the thumbs of a total of 1019 subjects. For each subject, the database includes up to six recordings over a period of six months, in various postures: supine, tripod, exercise, sitting, and standing.

C. FUTURE POSSIBILITIES REGARDING PUBLIC DATA

While many researchers opt to use private acquisitions of data for their studies on ECG biometrics, public datasets have been crucial in allowing the appropriate comparison of results across publications. Nevertheless, if our goal is to increase competitiveness between ECG-based biometrics and more developed traits, we should address some concerns regarding public collections.

Currently, countries like India, China, or the United States, are starting to invest in nation-wide identification systems for their large populations [87], which awakens the need for biometric systems that can robustly discriminate between several million enrolled subjects. To keep up with this trend, we need to work towards the creation of public ECG collections with larger number of subjects.

Moreover, researchers can currently choose from small on-the-person datasets that include health conditions and long acquisition times (such as the AHA, European ST-T, and the MIT-BIH Arrhythmia databases), or the off-the-person UofTDB collection with short recordings from several healthy subjects. This calls for the creation of a public database with number of subjects similar or superior to UofTDB, with several longer off-the-person recordings (ideally over one hour), taken over long time periods (months to years), during different activities and postures.

Finally, it would also be very beneficial to have a publicly available collection of signals acquired using recent wearable and seamless technologies, such as the aforementioned CardioWheel and Nymi Band. The highly acceptable acquisition settings offered by such products places, undoubtedly, new challenges on signal noise and variability, that would be very useful for the development of robust biometric algorithms.

V. SIGNAL DENOISING

A. OVERVIEW AND OBJECTIVES

During the previously discussed stage of acquisition, the electrocardiographic signals are highly susceptible to be corrupted by noise [88]. The amplitude of their waveforms can vary depending on the electrode characteristics and placement but, in ideal conditions (using chest leads in medical settings), the QRS complex only reaches $2-3$ mV, the largest amplitude of the whole cyclic beat [89].

This means that the farthest the location of the electrodes, the weaker the signal and the more dominant the noise, that can originate in many sources, most commonly:

- **Powerline interference** (PLI): The sinusoidal alternating current, used as energy source by the acquisition equipment, reflects on the acquired signal as a high-frequency noise (60 Hz in the United States and other American countries, and 50 Hz in Europe, Asia, and most other countries) [13], [89];
- **Baseline wander** (BW): Baseline wander is caused by breathing movements and it reflects on the acquired signal as a low-frequency undulation of the signal baseline, normally below 1 Hz [13], [89];
- **Electromyographic (EMG) interference**: Like the cardiac muscle, other muscles in the body also use electric impulses to contract. While capturing ECG, electromyographic signals can interfere in the signal resulting in high-frequency, high-amplitude, short-term bursts [13], [89];
- **Electrode movement**: Skin impedance changes around the electrode, caused by the movements of the subject, can reflect as high amplitude artifacts in the signal [89];
- **Lead reversal**: The reversal of leads through misplacement of electrodes causes the incorrect measurement of potentials, reversing in amplitude some or all of the heartbeats waveforms [13];
- **Pacemaker interference**: Signals from artificial pacemakers can be captured along with the ECG signal, commonly appearing as short spikes before the S wave [13].

The stage of signal denoising is, thus, of utmost importance for a ECG biometric system. Generally, this stage is grouped with the one that follows, signal preparation, on a single phase designated as Quality Assessment (see Fig. 1) or, more commonly, Signal Preprocessing. However, as systems evolve towards more acceptable acquisition settings, as discussed before, each of these stages becomes increasingly important and detailed, and thus will be presented and discussed separately.

A summary of information on the most relevant aspects of the surveyed unimodal methods in ECG biometrics, to allow for a unprecedentedly complete analysis and comparison of state-of-the-art algorithms and their results, can be analyzed in Tables 3, 4, 5, 6, and 7.

B. APPROACHES FOR ON-THE-PERSON SIGNALS

On the first initiatives in ECG biometrics, using on-the-person acquisitions, signal-to-noise ratio was higher, and noise sources were mainly limited to powerline interference and baseline wander from breathing movements. Hence, filters, such as bandpass (BPF), lowpass (LPF), highpass (HPF), or notch (NF), were the first and have been the most frequent option, due to their simplicity and lower computational cost. Bandpass filters have been most common, with bands between $1-40$ Hz [8], [10], [28], [90], $2-40$ Hz [36], [88], [91], or $2-30$ Hz [62], [63], [92], aiming to keep most useful individual information of the ECG while attenuating low and high-frequency noise.

Recently, Choudhary and Manikandan [93] proposed the use of the Discrete Cosine Transform (DCT) for simultaneous removal of baseline wander and powerline interference, which proved more successful than bandpass filters, when compared on simulated scenarios. The Discrete Wavelet Transform (DWT) has also been proposed for denoising of on-the-person signals [89], [94], [95], as it allows to decompose the signal into several levels, which may be separately processed to eliminate noise in certain frequency ranges.

C. APPROACHES FOR OFF-THE-PERSON SIGNALS

When considering off-the-person approaches, wearables, or seamlessly integrated acquisition settings, it is reasonable to expect a considerable increase in the noise influence, with lower signal-to-noise ratio. The ability to capture the ECG signal weakens, so the amplitude of the ECG components is smaller, when compared with chest leads, and movement artifacts are much more frequent and dominant [96], [56], [60].

For these, filters have also been widely applied [56], [90], as well as DWT [97]. However, the enhanced noise content motivated the proposal of new approaches based on line fitting algorithms, such as fitting of polynomial curves and the Savitzky-Golay algorithm [98]. Their use or combination with moving average or median filters has been shown more successful than filters or transform denoising [19], [44], likely because noise is widely present across the ECG frequency range, and such methods avoid restricting their operation to narrow frequency ranges.

D. TRENDS AND CHALLENGES

Looking back, we can conclude that the trend in signal denoising has been the evolution towards methods that can adapt to increasingly unexpected and dominant noise. Considering the efforts devoted to more acceptable and comfortable acquisition settings, with increasing focus on wearables and seamless settings, it is unreasonable to expect this trend would be reversed in the near future.

While filters appear to be a wise option if the noise is confined to known frequency ranges outside the ECG frequency range, for on-the-person signals, transforms (especially DCT) have been shown to be a good alternative for denoising without causing distortions [93]. However, when the noise is widespread and/or its frequency range is unpredictable (such as with off-the-person signals), line fitting algorithms such as the Savitzky-Golay filter may be a better option, as they smooth the signal without making strong assumptions on its noise content.

Nevertheless, research must continue to work towards increasingly robust and adaptable denoising methods. Researchers have recently started to use deep learning methodologies (as discussed further on in subsection IX-A), that have shown remarkable robustness to noise and variability in several pattern recognition applications [99], [65]. These, along with a deep study of data augmentation, may result in better alternatives to current and future methods devoted to signal denoising, and should certainly be explored in depth.

VI. SIGNAL PREPARATION

A. OVERVIEW AND OBJECTIVES

ECG biometric algorithms frequently resort to the application of several processing operations over the acquired ECG signal, between denoising and feature extraction. These have the main goal to prepare the signal for the feature extraction phase, in order to maximize the performance of the system, by reducing persistent noise and variability, segmenting specific useful parts of the acquired signal, and/or discarding its undesirable or prejudicial parts [19], [96], [123].

The noise and variability that may remain after the signal denoising stage, which this stage will aim to attenuate, are generally:

- **Length inconsistencies**: The acquisition may start at the middle of an heartbeat or waveform, and its duration may vary, which may conflict with feature extraction methods that require equal length and/or aligned waveforms across acquisitions;
- **Amplitude variations**: The variation of electrode placement and contact strength over time or between sessions may cause amplitude variations in the signal, scaling differently the various heartbeats and their waveforms [102];
- **Heart rate variability**: Varying heart rate, over time or across acquisition sessions, causes variations in the duration of the heartbeat waveforms, especially the

TABLE 3. Summary of the surveyed state-of-the-art unimodal methods proposed for ECG biometrics – Part I (ordered by year of publication and first author name, DR – Dimensionality Reduction, NS – Number of Subjects, OP – Off-the-Person).

Author	Year	Denoising	Preparation	Features/DR	Decision	Dataset	NS	OP	Results
Biel *et al.* [37], [100]	1999 2001	-	Siemens Megacart ECG Processing	10 Lead I fiducial features / PCA	SIMCA	Private	20	No	IDR 100%
Kyoso *et al.* [49]	2000	HPF 0.06 Hz + LPF 60 Hz + NF 50 Hz	Beat segment. and fiducial detection	PQ and QT times	Mahalanobis distance + LDA	Private	3	No	IDR 99.5%
Kyoso *et al.* [45], [46]	2001	HPF 0.06 Hz + LPF 60 Hz + NF 50 Hz	Second-order derivative fiducial detect.	QRS duration and QT time	Mahalanobis distance + LDA	Private	9	No	IDR 94.2%
Shen *et al.* [51]	2002	-	-	RQ, RS, ST, QS time, QT time, RS slope, QRS area	Correlation + DBNN	MIT NSR	20	No	IDR 100%
Palaniappan *et al.* [42]	2004	LPF 30 Hz	Adapted Pan-Tompkins fiducial detect.	R, QR, RS, QRS width, R-R, beat form factor	MLP; SFA	MIT NSR	10	No	IDR: MLP 96.2% SFA 83.6%
Israel *et al.* [91]	2005	BPF 2–40 Hz	R detection, heartbeat segmentation and alignment by R-peaks	RQ, RS, RP, RL, RP', RT, RS', RT', P and T widths, ST, PQ, PT, LQ, ST' / LDA	Contingency matrix majority voting	Private	49	No	IDR: Anxty. 97% Norm. 98%
Saechia *et al.* [101]	2005	-	PQRST heart rate normaliz., P, QRS, and T segmentation	Fourier transform of PQRST (whole), P, QRS, and T	Neural Networks	-	-	No	FRR: Whole 17.1% Apart 2.85%
Plataniotis *et al.* [39]	2006	BPF 0.5–40 Hz	Fixed-length window blind segmentation	Autocorrelation coefficients / DCT	Norm. Euclidean dist. + Gaussian LLR	PTB	14	No	IDR 100% FAR 0.02%
Zhang *et al.* [43]	2006	-	R-peak and QRS detection, heartbeat segmentation	Amplitudes, durations, intervals, levels, & areas / PCA	Bayes-minimum-error-rate	Private (leads I, II, V1, and V2)	502	No	IDR L.I 85.3% L.II 92.0% L.V1 95.2% L.V2 97.4%
Molina *et al.* [44]	2007	Savitzky-Golay	Trahanias R detection, R-R segmentation	R-R segments	DTW path + kNN	Private	10	Yes	EER 2%
Wuebbeler *et al.* [40]	2007	Moving Median + LPF 75 Hz	R-peak detection by thresholding	2D QRS (combination of leads I, II, and III)	Temporal derivatives dist. + kNN	PTB	74	No	IDR 98.1% EER 2.8%
Agrafioti *et al.* [28]	2008	BPF 1–40 Hz	Fixed-length window blind segmentation	Normalized autocorrelation / DCT or LDA	Correlation + kNN	PTB + MIT NSR	27	No	IDR: DCT 96.3% LDA 100%
Chan *et al.* [55]	2008	NF 60 Hz	Fid. detection with backward diff., alignment and outlier rej. by cross-corr.	Signal-averaged ECG	PRD, CC, WDIST + kNN	Private	50	Yes	IDR: PRD 70% CC 80% WD 89%
Irvine *et al.* [102]	2008	BPF 0.05–60 Hz	Beat segm. and alignment by R-peaks using AC, amplitude normalization	Covariance matrix eigenvectors / PCA	kNN	Private	39	No	IDR 100%
Boumbarov *et al.* [103]	2009	HPF 0.05 Hz + DWT soft thresholding	HMM-GMM PQRST segmentation	Cardiac cycle vector matrix / PCA and LDA	RBF NN	Private	9	No	IDR 83.3%

TABLE 4. Summary of the surveyed state-of-the-art unimodal methods proposed for ECG biometrics – Part II (ordered by year of publication and first author name, DR – Dimensionality Reduction, NS – Number of Subjects, OP – Off-the-Person).

Author	Year	Denoising	Preparation	Features/DR	Decision	Dataset	NS	OP	Results
Fang *et al.* [50]	2009	BPF 2–50 Hz	R detection, 5-beat average, amplitude normalization	Avg. beat phase space portrait	Correlation; Mutual nearest pt. dist. + kNN	Private (one or three leads)	100	No	IDR: 1 l. 93% 3 l. 99%
Fatemian *et al.* [89]	2009	DWT 3rd scale + Mov. Average	Discarding outlier beats, DWT QRS, T, & P delineation	Heart-rate normalized heartbeat construction	Correlation + kNN	PTB + MIT NSR	27	No	IDR 99.6%
Guennoun *et al.* [104]	2009	LPF 30 Hz	-	Fiducial amplitude and time feat. / Physiological-state-indepen. feature select.	Mahalanobis dist. + Thresh. and Voting	Private	16	No	FRR 0.01% FAR 0%
Coutinho *et al.* [62]	2010	BPF 2–30 Hz	Beat segment. and alignment, 10-beat avg.	Uniformly quantized avg. beats	Ziv-Merhav relative entropy + kNN	Private	19	Yes	IDR 99.5%
Fatemian *et al.* [105]	2010	DWT 3rd scale	DWT beat delineation, P-wave time norm.	Avg. ensemble heartbeat	Correlation + kNN	Private	21	No	IDR 95.4% EER 3.3%
Ghofrani *et al.* [41]	2010	BPF 0.5–150 Hz + NF 50 Hz	-	AR; PSD; Lyapunov; Approximation Entropy; Higuchi Fractal Dim.; Shannon Entropy	kNN; MLP; PNN	PTB	12	No	IDR: AR 98.6% ApEn 94.3% Hig. 87.4% Lya. 96.7% Sha. 92.8%
Li *et al.* [11]	2010	-	Beat segment., amplitude and time norm.	Hermite poly. expansion; Cepstral features / HLDA	SVM + GMM-UBM fusion	MIT NSR	18	No	IDR 98.3% EER 0.5%
Murthy *et al.* [47]	2010	BPF	Pan-Tompkins	P, T, ST, PR, QRS and QT intervals / FLDA	DTW + kNN	MIT NSR	15	No	IDR 96%
Odinaka *et al.* [106]	2010	HPF 0.5 Hz + LPF 500 Hz + NF 60 Hz	R detect., beat normaliz. and Hamming seg.	Log-STFT spectrogram / Bin selection	Gaussian models LLR	Private	269	No	IDR 99% EER 0.37%
Sasikala *et al.* [94]	2010	Median Filters + DWT	QRS detection w/ Daubechies DWT, P and T detection	Fiducial amplitudes and differences	Correlation	MIT Arrh.	10	No	IDR 62.7%
Tawfiq *et al.* [107]	2010	HPF 1 Hz + LPF 40 Hz	R-alignment, amplit. norm., QRS segment.	QRS DCT coefficients	Neural Networks	Private	22	No	IDR 99.1%
Ye *et al.* [35]	2010	BPF	Beat segment. with R location annotations	Daubechies DWT / ICA	RBF SVM	MIT Arrh. MIT NSR1 MIT LT MIT NSR2	47 18 65 18	No No No No	IDR 99.6% IDR 99.3% IDR 98.1% IDR 97.5%
Coutinho *et al.* [63]	2011	BPF 2–30 Hz	Beat segment., alignment, 10-beat avg.	User-tuned Lloyd-Max quantised avg. beat	Ziv-Merhav cross parsing similarity + kNN	Private	19	Yes	EER 0.36%
Lourenço *et al.* [108]	2011	BPF 0.5–30 Hz	Engelse-Zeelenberg, beat segment., amplitude and time normaliz.	Avg. normalized beat	Euclidean dist. + kNN	Private	16	Yes	IDR 94.3% EER 13%

TABLE 5. Summary of the surveyed state-of-the-art unimodal methods proposed for ECG biometrics – Part III (ordered by year of publication and first author name, DR – Dimensionality Reduction, NS – Number of Subjects, OP – Off-the-Person).

Author	Year	Denoising	Preparation	Features/DR	Decision	Dataset	NS	OP	Results
Matta *et al.* [109]	2011	BPF	Fixed-length window blind segmentation	Autocorrelation coeff. / LDA	Euclidean dist. + kNN	Private	10	No	IDR 75% TPIR3 99%
Safie *et al.* [36]	2011	BPF 2–40 Hz	ECGPUWAVE fiducial detect., P-R & P-T quality check, 5-beat avg.	Pulse Active Ratio	Euclidean dist. + kNN	PTB (healthy or w/ arrhythmias)	112	No	EER: Heal. 9.98% Arrh. 19.2%
Shen *et al.* [57]	2011	BPF 1–50 Hz	Pan-Tompkins, heartbeat segmentation	Amplitudes, durations, slopes, angles, and QRS area / LDA	Correlation + kNN	Private	168	Yes	IDR 98%
Sufi *et al.* [110]	2011	-	P, QRS, and T segmentation, cardioid 2D loop generation	Cardioid graph centroid, extremas, area, and perimeter	Straight line and percentage dist. + kNN	MIT Arrh.	-	No	MIDR 1% FAR 0.5% FRR 0.5%
Agrafioti *et al.* [10]	2012	BPF 1–40 Hz	Fixed-length window blind segmentation	Autocorrelation coeff. / LDA	Euclidean dist. + kNN	Private	42	No	EER 3.96%
Belgacem *et al.* [8]	2012	BPF 1–40 Hz	Amplitude normal., beat segmentation and R-peak alignment	Avg. beat Daubechies DWT	Random Forest	MIT Arrh. + ST-T + MIT NSR + PTB + Private	80	No	FAR 0.60% FRR 0.58%
Lourenço *et al.* [111]	2012	BPF 1–30 Hz	Steep-slope R detection, beat segment.	Segmented heartbeats	kNN	Private	32	Yes	EER 9.39%
Singh *et al.* [112]	2012	-	QRS, P, and T delineation	Interval, angle, and amplitude fid. feat.	Euclidean dist. + kNN	MIT Arrh. + ST-T + MIT NSR + QT	73	No	EER 10.8%
Belgacem *et al.* [58]	2013	BPF 1–40 Hz	Beat segment., amplitude normalization, 100-beat avg.	Avg. beat Daubechies DWT	Random Forest	MIT Arrh. + ST-T + MIT NSR + PTB + Private	80	No	IDR 100% FAR 0.63% FRR 0.66%
Coutinho *et al.* [92]	2013	BPF 2–30 Hz	Beat segm. and alignment, 10-beat mean wave	Fid. latency and amplitude from mean waveform subsampling	Euclidean dist. + kNN	PTB Private	51 26	No	IDR 99.9% EER 0.01% IDR 99.6% EER 0.70%
Coutinho *et al.* [92]	2013	BPF 2–30 Hz	Beat segm. and alignment, 10-beat mean wave	User-tuned Lloyd-Max quantized heartbeats	Ziv-Merhav cross-pars. similarity + kNN	PTB Private	51 26	No	IDR 99.4% EER 0.13% IDR 99.9% EER 0.29%
Labati *et al.* [52]	2013	HPF 0.5 Hz + NF 50 Hz	R detection and QRS segment., rejection of low-correl. seg.	QRS segment set templates	Cross-corr. similarity mat. + kNN	E-HOL 24h	185	No	EER 5.36%
Matos *et al.* [113]	2013	HPF 0.5 Hz + NF 50 and 150 Hz	R detection, beat segment., Hamming segmentation	STFT spectrogram + Spectral zoom / Bin selection	Gaussian models LLR	Private	27	No	EER 10%
Silva *et al.* [64]	2013	BPF 5–20 Hz	R detection and beat segmentation	Mean and median ensemble beats	Euclidean and cosine dist. + kNN and SVM	Private	63	Yes	EER: kNN 0.99% SVM 9.10%
Wang *et al.* [114]	2013	-	Sliding-window segmentation	Max-pooling representation elements	kNN	PTB	100	No	IDR 99.5%

TABLE 6. Summary of the surveyed state-of-the-art unimodal methods proposed for ECG biometrics – Part IV (ordered by year of publication and first author name, DR – Dimensionality Reduction, NS – Number of Subjects, OP – Off-the-Person).

Author	Year	Denoising	Preparation	Features/DR	Decision	Dataset	NS	OP	Results
Zhao *et al.* [115]	2013	HPF and DWT soft-thresh.	Beat segment. and normaliz., quality check	EEMD main IMFs and their PSD / PCA	kNN	ST-Change LTST PTB	15 18 12	No No No	IDR 98.0% IDR 95.8% IDR 96.0%
Ergin *et al.* [116]	2014	-	Segm. 2 s sliding windows	QRS fid., time domain, wavelet trans. and PSD	C4.5 and Bayesian Network	MIT NSR	18	No	F-s. C4.5 0.97% Bay. 0.96%
Iqbal *et al.* [117]	2014	-	QRS detection and segment.	QRS cardioid graph coord.	MLP	Private	30	No	IDR 96.4%
Labati *et al.* [53]	2014	HPF 0.5 Hz + NF 50 Hz	R detection, QRS segment.	QRS segments	Cross-corr. simil. kNN	E-HOL 24h	185	No	EER 5.36%
Lin *et al.* [59]	2014	-	Time-delay space reconst., Chaos theory feature extract.	Corr. dimension Lyapunov exp.	SVM	Private	26	Yes	IDR 81.7%
Lourenço *et al.* [96]	2014	-	QRS detection, DMEAN	Mean ensemble beats	SVM	Private	63	Yes	EER 2.5%
Matos *et al.* [56]	2014	LPF 50 Hz	Slope sum + thresh. for R det., beat segm.	STFT window features / Kullback-Leibler	LLR + kNN	Private	10	Yes	IDR 100% EER 14%
Pathoum-vanh *et al.* [48]	2014	BPF 0.4–40 Hz	R detection and hearbeat segmentation	CWT / FLDA	Euclidean dist. + kNN	Private (normal + increased HRV)	10	No	IDR: Norm. 97% HRV 80%
Zhou *et al.* [54]	2014	BPF 0.5–40 Hz	R detection, interval vs. amplitude plot	Signal between 3 consec. R peaks	DTW path + kNN	Private	20	No	HTER 1.45%
Brás *et al.* [118]	2015	NF 50 Hz + Moving Avg. + LPF 40 Hz	Amplitude norm., SAX conversion	Kolmogorov-based normalised rel. compression	kNN	PTB	52	No	IDR 99.9%
Choudhary *et al.* [93]	2015	DCT	FOGD peak det., peak correction, heartbeat segmentation	Avg. ensemble beat	RMSE, PRD, NCC, WWPRD, WDIST + kNN	MIT Arrh. + STC + QT + MIT NSR + SLP	127	No	FAR 5.8% FRR 11.6%
Dar *et al.* [73]	2015	Poly. line fitting	Local-maxima R det., QRS segmentation	Haar Transform / GBFS	kNN	MIT Arrh. MIT NSR ECG-ID	47 18 90	No No No	IDR 93.1% IDR 99.4% IDR 83.2%
Dar *et al.* [74]	2015	Poly. line fitting	Local-maxima R det., QRS segmentation	Haar Transform and HRV / GBFS	Random Forest	MIT Arrh. MIT NSR ECG-ID	47 18 90	No No No	IDR 95.9% FAR 4.1% IDR 100% EER 0% IDR 83.9% FAR 16.1%
Jahiruzza-man *et al.* [119]	2015	BPF 0.5–45 Hz	None	CWT and Chaotic Encryption	Identification of unique CE sequen.	MIT Arrh.	11	No	IDR 96.9%
Carreiras *et al.* [120]	2016	BPF 5–20 Hz	QRS det., beat seg. and align., DMEAN	Segmented heartbeats	kNN	Private	618	No	EER 9.01% MIDR 15.6%
Chun *et al.* [95]	2016	DWT 3rd scale	Pan-Tompkins, heartbeat segmentation	Guided filtering avg. beat / PCA	DTW or Euclidean dist. + kNN	ECG-ID	89	No	EER: DTW 5.2% Eucl. 2.4%
Hejazi *et al.* [97]	2016	DWT 3rd scale	Fixed-length window blind segmentation	Autocorrelation coeff. / KPCA	SVM	Private	52	Yes	IDR 76.3% FAR 3.5% FRR 4.83%
Louis *et al.* [90]	2016	BPF 1–40 Hz	Pan-Tompkins, beat segment. & alignment	1D multi-res. LBP	Bagging	UofTDB	1012	Yes	EER 7.89%
Porée *et al.* [71]	2016	LPF 45 Hz	Pan-Tompkins, beat segment.	10 beat avg. ensemble	Discrimination coeff./kNN	Private	14	No	IDR 100%

TABLE 7. Summary of the surveyed state-of-the-art unimodal methods proposed for ECG biometrics – Part V (ordered by year of publication and first author name, DR – Dimensionality Reduction, NS – Number of Subjects, OP – Off-the-Person).

Author	Year	Denoising	Preparation	Features/DR	Decision	Dataset	NS	OP	Results
Rezgui *et al.* [88]	2016	BPF 2–40 Hz	ECGPUWAVE QRS detection, segmentation	Amplitudes, areas, intervals and fid. slopes	SVM	MIT NSR + Arrh.	No	48	IDR 98.8%
Waili *et al.* [121]	2016	HPF 0.05 Hz + LPF 40 Hz	Pan-Tompkins, signal mean subtract. norm.	12 QRS fid. amplitudes	MLP	PTB	14	No	IDR 96%
Camara *et al.* [122]	2017	BPF 0.67–45 Hz	None	Walsh-Hadamard features, outliers rejected	kNN	MIT NSR	10	No	IDR 94.8%
Islam *et al.* [123]	2017	BPF 0.25–40 Hz	Curvature QRS detect., beat segm., time norm., AC outlier reject.	Avg. ensemble heartbeats / PCA	Euclidean dist.	Private	112	Yes	EER 10.5%
Karimian *et al.* [124]	2017	BPF 1–40 Hz	Pan-Tompkins, heartbeat segm., heart rate QT time normalization	DWT, Maximal Overlap DWT, DCT, Normalize Convolute Norm. encrypted by IOMBA	Key matching	PTB BioSec	290 13	No Yes	Rel. 97.4% Rel. 94.7%
Komeili *et al.* [125]	2017	BPF 0.5–40 Hz	Heartbeat segm. and outlier removal, z-score norm.	CWT, STFT, AC, max., st. dev., kurtosis and skewness / MSFS	SVM	UofTDB (different session or posture)	82	Yes	EER: Sess. 6.9% Post. 3.7%
Paiva *et al.* [126]	2017	-	Pan-Tompkins, LPF for Q, S, T detection	Fiducial distances ST, RT, and QT	SVM	PTB	10	No	IDR 97.5% FAR 5.71% FRR 3.44%
Pinto *et al.* [19]	2017	Savitzky-Golay + moving avg.	Trahanias, heartbeat segmentation, z-score, NCCC	DCT coefficients	SVM	Private	6	Yes	IDR 94.9% EER 2.66%
Tan *et al.* [127]	2017	BPF 2–50 Hz	Pan-Tompkins, P–QRS–T segmentation	Temporal, amplitude, and angle fid. + DWT coefficients	Random Forests + WDIST kNN	Private ECG-ID MIT Arrh. MIT NSR Combined	30 89 47 18 184	Yes No No No No	IDR 99.4% IDR 100% IDR 100% IDR 98.8% IDR 99.5%
Wieclaw *et al.* [128]	2017	BPF 4–35 Hz	Hamilton R detect., outlier rejection	Individual heartbeats	MLP	Private	18	Yes	IDR 89%
Zaghouani *et al.* [129]	2017	Median filter	Fixed-length window segm.	AC / DCT, feature security locking	Norm. Euclidean dist.	ECG-ID	90	No	EER 15%
Dong *et al.* [130]	2018	-	Construction of 3D VCG with 12-lead ECG	Banks of state and errors from 2D VCG	Minimum L1 norm of bank of errors	PTB (healthy and ill subjects)	 14 99 113	No	IDR: Healt. 98.3% Ill 93.3% All 92.8%
Guven *et al.* [131]	2018	HPF 0.5 Hz + LPF 150 Hz + mov. avg.	Z-score norm., 5 s window segmentation	AC, DCT, cepstral, and QRS features	Euclidean dist. + kNN	Private	30 45 60	Yes	IDR 100% IDR 100% IDR 98.3%
Kim *et al.* [132]	2018	-	Min-max norm. Pan-Tompkins, beat ensemble	Haar Wavelet Transform	Fuzzy membership ANN	-	73	No	FRR 1.68% FAR 5.84%
Lee *et al.* [133]	2018	BPF 0.3–35 Hz, 6th order polynomial line fitting	R & T detection, R-R segmentation, resampling	R-R segments, including two or three heartbeats (hb.)	Cosine, euclidean, manhattan dists., & CC	Private	55	No	IDR: 2 hb. 89.9% 3 hb. 93.3%
Pal *et al.* [134]	2018	HPF 1 Hz, NF 50 Hz, LPF 40 Hz	DWT fiducial det., P-QRS-T segmentation	Interval, amplitude, angle, and area fiducial features / KPCA	Euclidean distance	PTB	100	No	IDR 97.1%

ST and PQ waves, the duration of the heartbeat itself, and the time between heartbeats [123];

- **Movement artifacts**: Sudden movements, especially those caused by user activity, may cause spikes on the acquired signal that may mimic R-peaks, distort heartbeats, and influence the subsequent processes [123];
- **Contact loss or impedance artifacts**: Especially in seamlessly acquired signals or off-the-person acquisitions, contact with the electrodes may vary in strength or be momentarily interrupted, and thus cause saturation periods or signal loss [19].

To fulfill its objective, this stage generally consists of reference point detection, signal segmentation, amplitude normalization, time normalization, and/or outlier detection processes. On the other hand, some researchers have opted to discard completely the processes included in this stage [39], [28], [97], with the goal of making their algorithms completely non-fiducial.

Reference point detection and signal segmentation are common in the state-of-the-art, followed by amplitude normalization. Time normalization and outlier detection have been much less frequently applied. Below, some of the most relevant examples of each are presented and, then, some future opportunities are discussed regarding this stage.

B. COMMON PROCESSES

1) FIDUCIAL DETECTION

In order to aid posterior processes, such as signal segmentation, the preparation of the signal for recognition can include a step of detection of heartbeat reference points, designated as fiducials. The majority of the surveyed research works have used this technique, varying in the methods used.

The Pan-Tompkins algorithm [135] was the most frequent choice for fiducial detection [42], [47], [57], [90], [121], and was developed specifically for real-time QRS detection in ECG signals. The method starts by reducing noise with a bandpass filter, and a derivative is used to provide QRS slope information. A squaring function emphasizes high frequencies, and moving-window integration offers waveform feature information, after which adaptive thresholding is used to select the R-peak locations.

Some researchers [89], [94], [105], [134] have opted to use the Discrete Wavelet Transform (DWT) to pinpoint the locations of the fiducials on ECG signals and delineate the heartbeat waveforms. Fatemian and Hatzinakos [89] described this process. After appropriate noise filtering, the DWT is used to isolate the details of the QRS, of which most energy is contained on the frequency range 3–40 Hz [94]. The R peaks are detected by finding modulus maxima on the resulting signal, and the Q and S fiducials are located by searching for opposite-sign modulus maxima within a window centered in R. After the QRS is located, the P and T waves are delineated following similar processes of local maxima finding and thresholding.

The Trahanias algorithm [136] is another common algorithm [19], [44], and is based in successive morphological open and close operations over the signal that compose filtering and peak-valley extraction phases. These aim to emphasize sharp amplitude peaks (generally the R-peaks) in the signal, that are selected through adaptive thresholding.

The Engelse-Zeelenberg algorithm [137], adapted by Lourenço *et al*. [138], works with a differentiated and filtered version of the input signal. The R-peaks are located by analyzing the negative lobes on the signal, and are confirmed through an adaptive thresholding process. Other methods chosen for detection of R-peaks were Steep-slope thresholding [111], a First Order Gaussian Differentiator (FOGD) technique followed by peak correction stages [93], and thresholding of local maxima [73], [74].

The Engelse-Zeelenberg and Pan-Tompkins algorithms, based on signal differentiation, have been consistently successful in on-the-person and off-the-person signals [138], [90]. However, Pinto *et al*. [19] have recently applied them to signals acquired seamlessly with CardioWheel during driving, and Trahanias performed significantly better than the alternatives, probably because of the filtering properties of the morphological operations that highly reduce noise.

2) SIGNAL SEGMENTATION

Signal segmentation is the most commonly used signal preparation technique among the surveyed approaches. It is used to limit the signal span for feature extraction, or to set a fixed size to ease template matching when the feature is the signal itself.

In some cases, the segmentation follows the reference point location and consists on the cropping of the QRS complex and/or other waveforms [107], [110], [121], or is meant to include the whole heartbeat (or a majority of it), and is thus performed at fixed distances before and after detected R-peaks or QRS complexes [54], [90], [120]. Other research works included segmentation of the signal using sliding windows, with or without overlap, regardless of the completeness of the heartbeat cycles inside it [106], [109], [116].

The alignment and averaging of various signal segments is closely related to the signal segmentation process. The alignment is generally performed using the R-peak as reference after its location, or it is performed through correlation. It usually serves as a way to guarantee the template and the collected signal are not affected by variability, that distorts the personal information the signal contains, and could threaten the recognition task. This approach accompanied the signal segmentation in several of the analyzed research works [8], [92], [93], [96].

3) AMPLITUDE AND TIME NORMALIZATION

As previously discussed, the electrocardiogram varies over time with several factors. Specifically, differences in acquisition equipment or the interaction of the subject with it may cause differences in signal amplitude and DC offset [102]. Moreover, heart rate variability causes significant changes in the duration of the heartbeats and their waveforms. To maintain high performance regardless of this, some researchers include amplitude and time normalization techniques in the ECG biometric algorithms.

Regarding amplitude normalization, Irvine *et al.* [102] proposed min-max normalization, setting the maximum value to 1 and the minimum to 0 (y and x denote, respectively, the normalized and the original segments):

$$y[n] = \frac{x[n] - \min(x[n])}{\max(x[n]) - \min(x[n])}. \quad (1)$$

This same expression was used by some posterior approaches that applied amplitude normalization [50], [11], [36]. Odinaka *et al.* [106] opted to normalize heartbeat segments through the z-score method, by subtracting the signal mean and dividing by the standard deviation:

$$y[n] = \frac{x[n] - \mu(x[n])}{\sigma(x[n])}. \quad (2)$$

Tawfiq *et al.* [107] and Lourenço *et al.* [108] used the max-div method, that simply divides the entire beats by the R-peak amplitude value:

$$y[n] = \frac{x[n]}{\max(x[n])}. \quad (3)$$

Time normalization techniques aim to reduce the impact of heart rate variability on the electrocardiogram's heartbeats. The most noticeable impact is the total length of the heartbeat. So, some researchers performed normalization by simply shrinking the segmented signal to a predefined length, usually through signal resampling [11], [101], [108]. This technique has its limitations, as the heartbeat does not expand uniformly with lower heart rates, but it presents the advantage of only requiring the system to know the start and end points of the heartbeat.

To address the different way the heartbeat responds to heart rate, Tawfiq *et al.* [107] normalized only the QT waveform, more prone to variations from the heart rate. The researchers used the Framingham study formula to shrink or enlarge the heartbeat, computing the linearly corrected QT duration (QT_{LC}) using the time between the nearest R-peaks (RR), and the original duration of the waveform (QT), through:

$$QT_{LC} = QT + 0.154(1 - RR). \quad (4)$$

Fatemian and Hatzinakos [89] went further, segmenting each ECG heartbeat into its key waveforms (P, QRS, and T), and individually resampling them, before joining them back together, with regulated intervals between them. By reducing the effects of heart rate variability and avoiding the typical distortion of the individual waveforms, this is likely the best technique for time normalization. However, it requires the detection of several waveforms' onset and offset fiducial points, making it potentially unreliable for off-the-person or seamlessly acquired signals.

4) OUTLIER DETECTION

Outlier detection is generally applied to discard false or deflected heartbeats, segmented from unacceptably noisy signal portions affected from movement or impedance artifacts or contact loss [19].

A suitable outlier detection method should also be able to appropriately deal with heartbeats whose morphology has been affected by other factors, such as cardiac conditions. If a health condition reflects similarly in the morphology of all heartbeats, the outlier detection should consider it as a normal subject signal feature as it will not menace the recognition process. But if the condition only causes deflections occasionally, the outlier detection method should act appropriately on the affected segments, and discard them if the morphological changes are enough to menace the recognition process.

Nevertheless, the outlier detection process should be applied equally to both enrollment and test templates, in order to avoid harming the recognition performance. With the same goal in mind, the subject's stored templates/model should be updated whenever they no longer adequately describe the subject's current trait.

DMEAN, proposed by Lourenço *et al.* [139], was specifically created to reject heartbeat outliers. It checks, for each candidate heartbeat, the veracity of four rules, regarding the distance to the average template, the minimum and maximum amplitudes, and the position of the maximum heartbeat amplitude (which must correspond to the R-peak location). If it verifies the four rules, it is considered a true heartbeat, otherwise it is rejected. This method presented significant improvements when compared with DBSCAN, a common density-based clustering algorithm, but the rule-based decision may be unreliable when applied to more noisy or variable signals.

Louis *et al.* [90] opted to study Gaussian Mixture Models (GMM) as a supervised method for outlier detection. Trained on a set of known clean and desirable heartbeats, the GMM is able to then separate normal heartbeats from abnormal ones. The authors have tested it with off-the-person signals acquired at the fingertips, and reported significant improvements over the state-of-the-art approaches. Nevertheless, the method raises issues over the labeled data used to train the GMM, as the model can easily be biased towards certain subjects or patterns. These must be adequately addressed in order to successfully apply the proposed method.

More recently, Pinto *et al.* [19] proposed a clustering algorithm, NCCC, based on normalized cross-correlation between candidate heartbeats. Those that presented lower values of average cross-correlation between themselves were considered true heartbeats, as they are more similar between themselves. When evaluated with highly noisy seamlessly acquired signals, using the CardioWheel, this method presented better performance than DMEAN. However, by using clustering, it potentially becomes unreliable for sets of few candidate heartbeats.

C. THE FUTURE OF THE PREPARATION STAGE

With the rise of off-the-person, wearable, and seamlessly integrated acquisition settings, denoising is becoming increasingly flawed, and more noise is capable to survive it.

Fiducial detection will need to be improved for acceptable reliability in such signals, and amplitude and time normalization will need to be reformulated into more robust and adaptable techniques, to avoid harming the subsequent stages.

However, we expect signal segmentation and outlier detection to be increasingly applied, as the only way to reject unacceptable parts of the signal, which will become more frequent. Deep learning, as discussed further on, will probably be a robust alternative to this stage, but comes at the price of increased computational cost. Thus, this stage is expected to be increasingly important, and should certainly be addressed in depth in future research efforts.

VII. FEATURE EXTRACTION

A. OVERVIEW AND OBJECTIVES

After the first two stages, the acquisition should now be ready for the extraction of features. This stage aims to translate the acquired signal into a representation that further reduces the effects of remaining noise and intra-subject variability, while emphasizing differences between subjects, to ease the decision process.

Several feature extraction methods have been proposed for ECG biometrics, and are generally grouped by their type: fiducial, non-fiducial, or hybrid approaches [109], [113]. Furthermore, these can be clustered according to the domain in which the features are extracted – time domain, frequency domain, or others [140]. Extracted features may, additionally, suffer dimensionality reduction to improve performance [72]. In the following subsections, we discuss these topics in detail, while presenting relevant state-of-the-art examples.

The designation of approaches as fiducial or non-fiducial, in the literature, is dissonant. Some reserve the non-fiducial term to approaches that do not perform fiducial detection at any stage of the entire biometric recognition method [39], [28]. Others focus on the feature extraction stage, considering as non-fiducial other methods that require the previous location of fiducial points for segmentation of heartbeats or their waveforms.

This section addresses solely the feature extraction stage. Thus, feature extraction approaches that use fiducial measurements as features are considered fiducial, and those that do not use them are designated as non-fiducial, regardless of the signal preparation processes that may precede them.

B. FEATURE EXTRACTION MODALITIES

1) FIDUCIAL APPROACHES

Fiducial approaches are thus designated because they exclusively use as features the measurements of fiducial landmarks of the ECG signal in the time domain. These measurements vary widely throughout the state-of-the-art. Israel *et al.* [91] used several time intervals between the heartbeat waveforms P, Q, R, S, and T, as well as their onset and offset points, and the width of the P and T waveforms. Zhang and Wei [43] proposed the use of several amplitude, duration, interval, level, and area measurements of the heartbeat fiducials.

Similarly, Shen *et al.* [57] used several normalized time domain features, including the RS and ST slopes, and the QRS triangular area. More recently, Rezgui and Lachiri [88] used fifteen temporal attributes, six amplitude features, and ten morphological parameters for identification. Waili *et al.* [121] used the Q, R, and S amplitudes of twelve consecutive QRS complexes, to obtain higher robustness to variability and noise.

Nevertheless, these approaches present the significant drawback of requiring the previous localization of several fiducial points in the ECG heartbeats (see subsection VI-B1). This requirement proves difficult to satisfy when using off-the-person or seamless signals, as noise and variability distort the heartbeat waveforms and render the measurements unreliable. Thus, fiducial feature extraction approaches were significantly more frequent among the first research works, and are currently solely chosen when working with on-the-person signals.

2) NON-FIDUCIAL APPROACHES

As research evolved towards off-the-person signals and fiducial detection became unreliable, new feature sets were studied and proposed. Non-fiducial approaches are those that use the entirety of the signal (or segments of it), holistically, to extract features related to the waveform morphology [108], [109], [113].

Saechia *et al.* [101] pioneered by applying a Fourier transform to the whole PQRST segments, and to the P, QRS, and T waveforms, separately. Since then, Fourier or Wavelet transforms have been used in several occasions [8], [35], [56], [106], [107], [113]. Plataniotis *et al.* [39] and, later, Agrafioti *et al.* [10], Agrafioti and Hatzinakos [28], and Hejazi *et al.* [97], successfully accomplished their goal to dismiss completely the need for fiducial detection, by using autocorrelation coefficients from sliding-window signal segments.

Sufi *et al.* [110] aimed to apply two-dimensional feature extraction from image analysis applications to ECG biometric recognition, and accomplished this by transforming 1D ECG heartbeats into 2D cardioid graphs. Then, the researchers used the cardioid centroid, area, perimeter, and extrema as features. Iqbal *et al.* [117] also used cardioid graphs, selecting their x and y coordinates as features. Dong *et al.* [130] opted for the combination of 12 ECG leads to build tridimensional vectorcardiograms (3D VCG or TVCG), taking advantage of this to formulate a novel deterministic recognition approach.

From the perspectives of lossy compression or quantization, Coutinho *et al.* [63], [92] devised a user-specific method of feature extraction based on Lloyd-Max quantization, and Brás and Pinho [118] inspired on Kolmogorov complexity to propose a Kolmogorov-based relative heartbeat compression algorithm for feature extraction. More recently, Louis *et al.* [90] aimed to avoid the effects of noise by applying one-dimensional multi-resolution local binary patterns (1DMRLBP) for extraction of local and global signal characteristics.

Furthermore, several state-of-the-art methods use segmented heartbeats or average ensemble heartbeats [53], [111], [120], or segments between R peaks [44], [54], resulting from the signal preparation stage, as feature sets for decision, effectively skipping the feature extraction stage.

As presented, some non-fiducial approaches have successfully dismissed the need for robust fiducial detection, while others only require the detection of the R-peak (generally needed for heartbeat segmentation). While more applicable to noisier signals, these have still to reach the near-perfect performance reported by works using fiducial features.

3) HYBRID APPROACHES

Hybrid approaches are those that use features from both fiducial and non-fiducial origins. Following the state-of-the-art analysis performed for this survey, these proved to be significantly more uncommon than the other two types of approaches.

Palaniappan and Krishnan [42] combined the common fiducial features R amplitude, QR interval, RS interval, QRS width, and RR interval, with a non-fiducial QRS complex form factor, computed using the segment and its first and second derivatives. Ergin *et al.* [116] proposed the fusion of QRS fiducials, with several time domain, Wavelet transform, and Power Spectral Density (PSD) features, computed across two-second sliding windows. Dar *et al.* [74] opted for the extraction of a total of 46 features from Haar transform and heart-rate-variable RR intervals.

By requiring the extraction of features through both fiducial and non-fiducial techniques, hybrid approaches present more complexity. This would, in some applications, be tolerable if accompanied by a significant improvement in recognition performance. However, following the results reported by publications using similar evaluation settings, this has not been verified. Thus, the best option would be to select either fiducial or non-fiducial, considering the signal quality and system requirements on the expected application settings.

C. DIMENSIONALITY REDUCTION

Although frequently overlooked, dimensionality reduction has a very important goal in biometric systems and pattern recognition algorithms in general. In the quest to entirely capture the wide variety of individual information stored by the electrocardiographic signal, the number of features extracted by biometric systems can easily become too high for a time-efficient and reliable recognition process [9]. Thus, dimensionality reduction aims to select or transform the extracted features, in order to reduce its number to a more computationally viable number, while keeping the maximum discriminant power to improve the system's recognition performance [72].

Biel *et al.* [37], [100], the pioneers in ECG biometric recognition, applied dimensionality reduction using correlation matrices, to select 10 of 30 features from Lead I, of a grand total of 360 features extracted from all 12 leads. Israel *et al.* [91] selected 12 of 15 extracted fiducial features using Wilkes' lambda stepwise correlation. Matos *et al.* [113], [56] used the symmetric Kullback-Leibler divergence for bin selection, after fitting Gaussian models to STFT spectrograms of heartbeat segments. Dar *et al.* [73], [74] applied the Greedy Best First Search (GBFS) algorithm for selection of Haar transform features.

Plataniotis *et al.* [39] used the Discrete Cosine Transform (DCT) to reduce the features extracted from windowed autocorrelation. Later, Agrafioti and Hatzinakos [28] obtained better performance with dimensionality reduction using Linear Discriminant Analysis (LDA) than with DCT, also for autocorrelation features. LDA was also the choice of [10], [103], [109]. Li and Narayanan [11] opted for an extension of LDA, the Heteroscedastic Linear Discriminant Analysis (HLDA), while Pathoumvanh *et al.* [48] used the less general Fisher Linear Discriminant Analysis (FLDA). Hejazi *et al.* [97] used, besides LDA, Principal Component Analysis (PCA) and Kernel Principal Component Analysis (KPCA) for dimensionality reduction, concluding that KPCA rendered the best performance results.

In fact, the work performed by Agrafioti and Hatzinakos [28], Plataniotis *et al.* [39], and, more recently, Hejazi *et al.* [97], on the use of non-fiducial autocorrelation feature extraction, provides an adequate platform for comparison of dimensionality reduction algorithms. According to their findings, LDA enabled higher decision performance than unsupervised techniques, such as PCA and DCT coefficients, the first to be explored by these researchers, despite LDA's supervised nature that requires knowledge of the subjects prior to the deployment of the biometric system [109].

More recently, other supervised techniques, such as the non-linear KPCA method [97], [134], were shown to be better alternatives to LDA, which indicates that research should probably focus on more sophisticated dimensionality reduction methods. Also, deep learning methodologies, such as convolutional neural networks or autoencoders, can be tuned to provide optimized non-linear dimensionality reduction, which justifies further and deeper studies.

D. FUTURE WORK IN FEATURE EXTRACTION

Through the analysis of the surveyed research works, it is possible to conclude that fiducial approaches generally contribute more towards a high performance biometric system, as the use of specific measurements reduces useless information to a minimum, and allows for feature sets with less dimensions.

However, as noise increases, the relevance of robustness overcomes that of accuracy, and the former can only be offered by non-fiducial methods. The ideal feature extraction method would be one that combines the conditions for high performance offered by fiducial approaches with the robustness to noise and variability offered by non-fiducial approaches.

Unfortunately, such method is still to be devised. It is possible that, with the onset of deep learning methodologies in ECG biometrics (to be discussed further on,

TABLE 8. Definition of the commonly used metrics for performance evaluation in identification and authentication tasks.

Task	Metric	Definition
Identification	True Positive Acceptance Rate	$TPIR(R) = \frac{\text{No. of trials where one of the strongest R predictions is correct}}{\text{Total number of trials}}$
	Identification Rate	$IDR = TPIR(1) = \frac{\text{No. of trials where the strongest prediction is correct}}{\text{Total number of trials}}$
	Misidentification Rate	$MIDR = 1 - IDR = \frac{\text{No. of trials where the strongest prediction is incorrect}}{\text{Total number of trials}}$
Authentication	False Acceptance Rate	$FAR(T) = \frac{\text{Number of impostor trials where the prediction score is above } T}{\text{Total number of impostor trials}}$
	False Rejection Rate	$FRR(T) = \frac{\text{Number of legitimate trials where the prediction score is below } T}{\text{Total number of legitimate trials}}$
	Equal Error Rate (see Fig. 10)	$EER = FAR(T)$, for T that gives $FAR(T) = FRR(T)$
	Area Under the Curve (see Fig. 10)	$AUC = \int_0^1 1 - FRR(FAR(T))\, dT$

in subsection IX-A), with their characteristic robustness to noise and versatile feature extraction capabilities, we can approach such ideal.

VIII. DECISION

A. OVERVIEW AND OBJECTIVES

Based on the representation of the ECG acquisition, obtained through processes of feature extraction and dimensionality reduction, the decision stage aims to accurately attribute one of the enrolled identities to the user, in the case of identification tasks, or to accept or reject and identity claim, for authentication tasks [2], [6], [141].

In the case of identification, the decision stage usually consists of a classification process while, for authentication, the acceptance or rejection of the identity claim is generally based on a reference threshold T that is applied to the prediction score. Adequately assessing performance in both tasks is of the utmost importance, and thus a few metrics have become common for the evaluation of biometric algorithms. The most frequent are presented in Table 8 and in Fig. 10.

Below, we present the decision methods used for ECG biometric algorithms, we analyze them in depth, and we delve into future possibilities for enhanced decision in both identification and authentication tasks. To help the comparison of state-of-the-art methods in terms of reported performance, we group the results of the surveyed publications that have used the four most common collections (see Fig. 9) – PTB, ECG-ID, MIT-BIH Normal Sinus Rhythm, and MIT-BIH Arrhythmia – in Tables 9, 10, 11, and 12, respectively.

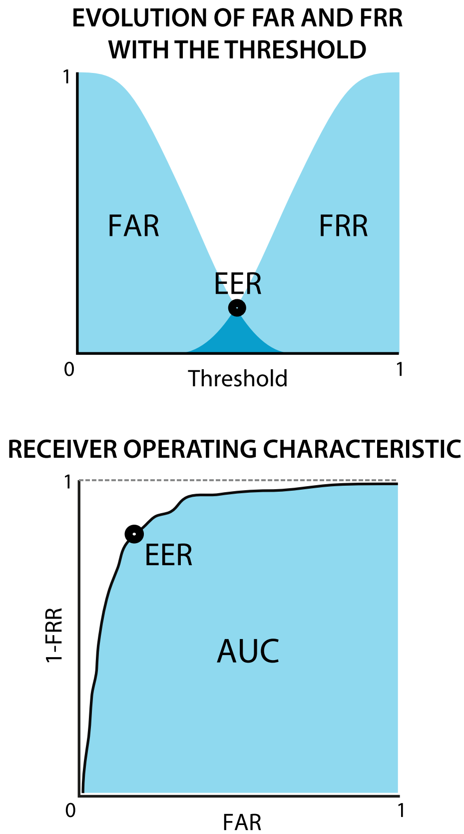

FIGURE 10. The evolution of False Acceptance Rate and False Rejection Rate with the threshold T (top), and an example of a Receiver Operating Characteristic curve (bottom).

B. STATE-OF-THE-ART DECISION METHODS

1) CLASSIFIERS

The decision stage of the ECG biometric algorithms can consist on a classifier, trained on the stored templates from the set of subjects enrolled in the biometric system, which will discrimination between the subjects, in order to output an accurate decision when needed. Classifiers are more commonly used for identification tasks, and are generally either Support Vector Machines, Nearest Neighbor classifiers, or Artificial Neural Networks.

Support Vector Machines (SVM) are classifiers that, based on a given set of training data, compute an optimal hyperplane that divides two classes, ensuring maximum margin between the boundary and the nearest samples [88]. Kernel functions allow to map non-linearly separable datasets into alternative feature spaces, where an optimal hyperplane boundary can be found. SVM have been extensively used in ECG-based recognition [11], [35], [59], [64], [88], [96], [97], [111]. In what concerns the kernel functions, Gaussian Radial Basis Function (RBF) and non-linear polynomial kernels have been the most studied.

Nearest Neighbor classifiers, commonly k-Nearest-Neighbors (kNN), take the feature vector being classified and those of the stored templates and, in the feature space,

TABLE 9. Results of surveyed approaches evaluated with the PTB database (ordered by number of subjects – NS; works that joined PTB with other databases [8], [28], [58], [89] are not included).

Author	Year	NS	Results	
Karimian *et al.* [124]	2017	290	Reliab.	97.4%
Dong *et al.* [130]	2018	113	IDR	92.8%
		99	IDR	93.3%
		14	IDR	98.3%
Safie *et al.* [36]	2011	112	EER	19.2%
Wang *et al.* [114]	2013	100	IDR	99.5%
Pal and Singh [134]	2018	100	IDR	97.1%
Wuebbeler *et al.* [40]	2007	74	IDR	98.1%
			EER	2.8%
Labati *et al.* [145]	2018	52	IDR	100%
Brás and Pinho [118]	2015	52	IDR	99.9%
Coutinho *et al.* [92]	2013	51	IDR	99.9%
			EER	0.01%
Plataniotis *et al.* [39]	2006	14	IDR	100%
			FAR	0.02%
Waili *et al.* [121]	2016	14	IDR	96%
Zhao *et al.* [115]	2013	12	IDR	96.0%
Ghofrani and Bostani [41]	2010	12	IDR	98.6%
Paiva *et al.* [126]	2017	10	IDR	97.5%
			FAR	5.71%
			FRR	3.44%

TABLE 10. Results of surveyed approaches evaluated with the ECG-ID database (ordered by number of subjects – NS).

Author	Year	NS	Results	
Salloum and Kuo [22]	2017	90	IDR	100%
Zaghouani *et al.* [129]	2017	90	EER	15%
Dar *et al.* [73]	2015	90	IDR	82.3%
Dar *et al.* [74]	2015	90	IDR	83.88%
			FAR	16.1%
			FRR	0.3%
Tan *et al.* [127]	2017	89	IDR	100%
Chun *et al.* [95]	2016	89	EER	5.2%

TABLE 11. Results of surveyed approaches evaluated with the MIT-BIH Normal Sinus Rhythm database (ordered by number of subjects – NS; works that joined MIT NSR with other databases [8], [28], [58], [88], [89], [93], [112] are not included).

Author	Year	NS	Results	
Shen *et al.* [51]	2002	20	IDR	100%
Li and Narayanan [11]	2010	18	IDR	98.3%
			EER	0.5%
Ye *et al.* [35]	2010	18	IDR	99.3%
			FPIR	26.9%
Ergin *et al.* [116]	2014	18	F-score	0.97%
Dar *et al.* [73]	2015	18	IDR	99.4%
Dar *et al.* [74]	2015	18	IDR	100%
			EER	0%
Tan *et al.* [127]	2017	18	IDR	98.8%
Zhang *et al.* [20]	2017	18	IDR	95.1%
Murthy and Jayaraman [47]	2010	15	IDR	96%
Palaniappan *et al.* [42]	2004	10	IDR	96.2%
Camara *et al.* [122]	2017	10	IDR	94.8%

TABLE 12. Results of surveyed approaches evaluated with the MIT-BIH Arrhythmia database (ordered by number of subjects – NS; works that joined MIT Arrhythmia with other databases [8], [58], [88], [93], [112] are not included).

Author	Year	NS	Results	
Ye *et al.* [35]	2010	47	IDR	99.6%
			FPIR	12.3%
Dar *et al.* [73]	2015	47	IDR	93.1%
Dar *et al.* [74]	2015	47	IDR	95.9%
			FAR	4.1%
			FRR	0.1%
Salloum and Kuo [22]	2017	47	IDR	100%
			EER	3.4%
Tan *et al.* [127]	2017	47	IDR	100%
Zhang *et al.* [20]	2017	47	IDR	91.1%
Jahiruzzaman *et al.* [119]	2015	11	IDR	96.9%
Sasikala *et al.* [94]	2010	10	IDR	62.7%
Sufi *et al.* [143]	2010	-	MIDR	1%
			EER	0.5%

compute the distance between the former and each one of the others. The feature vector is then attributed the most verified class among the k closest template vectors. Nearest Neighbor classifiers have been extensively used in ECG biometrics [10], [40], [41], [71], [111], [114], [118], [120], mainly because they offer the advantage of being easily updated when new samples become available, by just storing them on the database, while most other techniques would require the repetition of the training process [95].

As for Artificial Neural Networks (ANNs), they mimic the function of their biologic homonyms, that consist of webs of interconnected neurons that receive inputs, analyze and modify them, and pass them along until they reach a target organ or tissue [27]. These classifiers are also composed by neurons (or nodes), arranged in a varying number of layers, and connected between them. The first layer receives the inputs (feature vectors), the nodes have activation functions, and their connections are weighted to guide the final classification, output by the last node layer [9], [117].

ANNs are especially useful in non-linear classification problems [9]. Various types of these classifiers were used in the surveyed approaches, especially the Multilayer Perceptron (MLP) [41], [42], [117], [142], but also the Decision-based Neural Network (DBNN) [51], the Simplified Fuzzy ARTMAP (SFA) [42], the Radial Basis Function Neural Network (RBFNN) [103], and the Probabilistic Neural Network (PNN) [41]. Most of these are trained with similar loss functions, optimized with gradient-descent-based methods, differing in the node activation functions.

Besides the most common methods, there have been proposals of decision based on discriminant and component analysis. These methods are more commonly used for dimensionality reduction, as they allow the transformation of the feature space in order to minimize intraclass variance and increase discrimination between classes [37]. However, these transformations of the feature space have also been used for the classification of new samples, for the first works in ECG biometric recognition, with LDA [45], [46], [49] or SIMCA [37], [100], a commercial PCA-based data analysis algorithm.

2) METRIC-BASED MATCHING

Other methods are based on the comparison between the currently acquired trait and the previously acquired templates, stored in the system database. The comparison is performed based on similarity or dissimilarity metrics: for identification, the comparison with the best result will decide the identity to be chosen; for authentication, the metric value is compared with a defined threshold to decide whether to accept or reject the identity claim. Hence, the processes of metric-based matching can be seen as adaptations of nearest neighbor algorithms. The use of metrics for decision has been significantly more common for authentication than for identification tasks.

A substantial fraction of the research works that apply matching methods have opted to use distance metrics. The most popular distance metric was, by far, the Euclidean distance [36], [39], [48], [64], [95], [108], [109], [112]. However, Euclidean distance is regarded by some researchers as unreliable in high dimensional spaces, leading to the use of other distance metrics, such as the cosine distance [64], and the Mahalanobis distance [45], [46], [49], [104].

The correlation coefficient, unlike distance metrics, serves to measure the statistical similarity between two signals or feature vectors [28]. It was first used for matching method by Shen *et al*. [51], and was since used in several other works [28], [55], [57], [89], [94], [105]. Choudhary and Manikandan [93] studied the Normalized Cross-Correlation (NCC), comparing it to four different distance metrics: the Root Mean Square Error (RMSE), the Percent Residual Difference (PRD), the Wavelet Weighted-based Percent Residual Difference (WWPRD), and the Wavelet Distance (WDIST). Based on the results, the researchers concluded that NCC offered the best performance for authentication tasks.

Besides distance metrics and similarity metrics based on correlation, other techniques can be found in the state-of-the-art. Examples include Gaussian log-likelihood [56], [106], [113], and Dynamic Time Warping (DTW) paths [44], [47], [54]. About DTW, we should remark its applicability on out of time scale or unsynchronized signals, without needing signal alignment, which, despite increased computational cost, proves very useful when working with signals suffering from increased variability.

Another matching method worthy of mention is the Ziv-Merhav cross parsing algorithm [62], [63], [92], originally used with symbol sequences for data compression, modified to compare two quantized heartbeat segments and output two measures, similarity and relative entropy. In general, metric-based methods offer less accuracy than methods based on classifiers, but they gain some robustness by not having to be trained on a specific dataset, and thus do not depend much on the set of enrolled subjects, nor need to be re-trained every time a new subject is enrolled in the system.

3) OTHER METHODS AND TECHNIQUES

A few researchers have opted for more unusual methods or techniques for decision. Zhang and Wei [43] built a classification method based on Bayes theory error minimization, while Ergin *et al*. [116] used Bayesian Networks along with C4.5 Decision Trees. Some have proposed ensemble decision methods, like Random Forests [8], [58], [74], and Bagging [90]. Jahiruzzaman and Hossain [119], after computing Chaotic Encryption (CE) features, based its decision approach on the identification of unique CE sequences for each subject.

Moreover, combined with several aforementioned methods, Pinto *et al*. [19] proposed the use of User-Tuned Authentication, applying different specific thresholds depending on the identity claimed for each authentication task. The researchers found that the use of specific, subject-specific thresholds reduces overall false acceptances and rejections, improving the performance of the authentication system.

C. CHALLENGES AND FUTURE WORK

SVM and kNN, two of the most common decision algorithms, have proven their superiority in performance, even in situations with increased noise and variability. It is safe to assume that these would be wise options for new ECG biometric algorithms. However, it would be useful to find an equally accurate alternative that would not require re-training with every subject enrollment or update (as SVM does) or the memory-heavy storage of all subject's templates (as kNN does). Artificial Neural Networks, or even Deep Neural Networks, could potentially solve these issues, but researchers will need to dedicate efforts to reach (or surpass) the performance level offered by SVM and kNN.

IX. OTHER DEVELOPMENTS AND CHALLENGES

The bulk of research initiatives in electrocardiogram-based biometrics has been focused on the development of biometric recognition algorithms, generally dividing the algorithms in the aforementioned stages of signal denoising, preparation, feature extraction, and decision. Nevertheless, some authors have devoted efforts to address other important issues, challenges, and opportunities regarding this biometric trait.

Here, we will delve into the those most relevant, namely the recent study of deep learning for ECG biometrics, template and model updates, continuous biometrics, multimodal ECG biometrics, and spoofing and data security.

Besides these increasingly trending issues, there are other relevant open questions that should be addressed. While off-the-person, wearable, and seamlessly integrated

TABLE 13. Summary of the deep learning state-of-the-art methods proposed for ECG biometrics (ordered by year of publication and first author name, DR - Dimensionality Reduction, NS - Number of Subjects, OP - Off-the-Person).

Author	Year	Denoising	Preparation	Features/DR	Decision	Dataset	NS	OP	Results
Eduardo *et al.* [21]	2017	FIR Bandpass 5–20 Hz	Pan-Tompkins, heartbeat segmentation, DMEAN	Deep Autoencoder	kNN	Private	709	No	MIDR 0.91%
Salloum and Kuo [22]	2017	-	Pan-Tompkins, heartbeat segmentation, z-score norm.	(Included in decision)	LSTM/GRU RNN	ECG-ID MIT Arrh.	90 47	No No	IDR 100% IDR 100%
Zhang *et al.* [20]	2017	Bandpass filter 2–50 Hz	Min-max normalization, 2-second blind segmentation	Autocorrelation of wavelet transform coefficients, component selection	Multiscale 1D CNN	CEBSDB WECG Fantasia MIT NSR STDB MIT Arrh. AFDB VFDB	20 22 40 18 28 47 23 22	No No No No No No No No	IDR 99.0% IDR 94.5% IDR 97.2% IDR 95.1% IDR 90.3% IDR 91.1% IDR 93.9% IDR 86.6%
Zhang *et al.* [65]	2017	-	2D representation generation	(Included in decision)	2D CNN	Private	10	Yes	IDR 98.4%
Labati *et al.* [145]	2018	HPF 0.5 Hz, NF 50 Hz	R detection, QRS segmentation, vector of 8 selected QRS	(Included in decision)	1D CNN, softmax (iden.), Hamming distance (auth.)	PTB E-HOL 24	52 92	No No	IDR 100% EER 2.75%
Luz *et al.* [144]	2018	-	Heartbeat segmentation, spectrogram	(Included in decision)	1D + 2D CNN	UofTDB CYBHi	1019 128	Yes Yes	EER 14.3% EER 12.8%

acquisition technologies have been studied with the goal of increasing real-life applicability of ECG biometric systems, mobile and cloud-based systems are two topics that have been overlooked, but could provide useful approaches towards highly competitive ECG biometric systems.

A. DEEP LEARNING IN ECG BIOMETRICS

Deep Learning methodologies are quickly revolutionizing several fields in pattern recognition, galvanizing the machine learning community with outstanding results and unforeseen robustness to input noise and variability in diverse tasks [146].

It achieves these milestones mainly due to the flexibility and robustness of convolutional layers for feature learning, the selective memory of recurrent layers connected to their previous instances, and the versatility of fully-connected layers [20], [146]. Their adaptability to scarce data through techniques such as data augmentation, fine tuning, transfer learning, and weakly supervised learning, just add to their power for pattern recognition applications.

This has been verified in several recent research works. Using a Recurrent Neural Network (RNN), Hannun *et al.* [99] built an end-to-end speech recognition algorithm that offered increased robustness to speaker variation and background noise. With a 34-layer Convolutional Neural Network (CNN), Rajpurkar *et al.* [30] achieved superior performance in detection of several arrhythmias in ECG signals, when compared with professional cardiologists. Using one-dimensional data augmentation, Um *et al.* [147] reached improved performance with a CNN for classification of motor state of Parkinson's patients.

In the topic of ECG biometrics (see Table 13), the study of deep learning is still a pioneering affair. Initially, Zhang *et al.* [20] proposed a multi-scale CNN that receives, in parallel, selected autocorrelation coefficients of approximation and detail Wavelet transform coefficient sets of two-second ECG segments. Eduardo *et al.* [21] replaced the feature extraction stage using an Autoencoder to learn lower dimensional representations of segmented heartbeats, which were ultimately fed to a kNN classifier.

However, most researchers aim to integrate several stages into the deep learning model. Salloum and Kuo [22], after signal preprocessing and segmentation, replaced the stages of feature extraction and decision with a RNN with Long Short-Term Memory (LSTM) and Gated Recurrent Unit (GRU). Zhang *et al.* [65] replaced the stages of feature extraction and classification, by feeding 2D representations of single-arm ECG signals to a CNN. Luz *et al.* [144] also integrated the feature extraction and decision stages, proposing the combined use of two separate CNN, one receiving segmented heartbeats as input and the other receiving the respective heartbeats' spectrograms, fused at score level.

More recently, Labati *et al*. [145] detected, segmented, and selected QRS complexes from ECG signals, and concatenated them into a QRS vector that served as input to a unidimensional CNN that fulfilled the purposes of feature extraction and decision. With a softmax output, the method attained 100% IDR on the PTB database and, with Hamming distance matching, achieved 2.75% EER with long-term signals from the E-HOL 24h collection.

As aforementioned, there is still much to study to appropriately take advantage of the great potential of deep learning for ECG biometrics. The integration of all four stages of denoising, preparation, feature extraction, and decision in a single model could allow for a much deeper and coordinated optimization for individual recognition. The flexibility offered by such models, combined with techniques of data augmentation and regularization, could lead us to new levels of robustness against noise and variability.

Analyzing the surveyed deep learning methods for ECG biometrics, the methodology with the most potential should be RNN, as used by Salloum and Kuo [22], due to the outstanding performance achieved. Furthermore, deep learning should be more deeply studied and evaluated in off-the-person settings. Despite the fact that deep learning brings significantly increased computational requirements to biometric systems, they should be compensated by a considerable boost in performance and robustness.

B. TEMPLATE OR MODEL UPDATES

Minding the goal of developing a biometric system that is both accurate and robust, it is paramount to acknowledge the variability of the ECG over time. As aforementioned, Labati *et al*. [52] have shown, using twenty-four-hour-long Holter recordings, that even in such short periods, the ECG varies enough to impact the biometric recognition performance.

It is expectable, after weeks and months of use, that a biometric system decision models and/or stored templates do not adequately represent the enrolled subjects anymore. This further emphasizes the need for data, during development and evaluation, that is acquired from the same subjects in diverse moments over long time periods, but also requires the systems to include techniques to ensure the models or templates are up-to-date and continue to adequately represent the enrolled subjects.

For this, some researchers have proposed template update methods, reliable ways to ensure the system maintains the capability of recognizing the enrolled subjects. In order to keep up with their constant variability, the proposed methods frequently update the respective templates stored in the database [10], [63], [92]. Specifically, the method proposed by Agrafioti *et al*. [10] updates the stored templates based on the detected emotional state of the subject: when the physiological state of the subject changes (and the system outputs weaker matching scores), the most recent acquisitions of the subject are used for template update.

Although template update is far more common in ECG biometrics than model update, this can only be applied to nearest neighbour classifiers or decision based in metrics. For other decision methods (e.g., the more successful SVM), there is no access to templates to update, and the update must be performed on the model. This, for SVM classifiers, requires the separate storage of the templates and means the re-training of the algorithm, and for Neural Networks, difficults the control of the influence of new samples relative to original templates. Hence, given the obvious advantages and current issues, it is clear that research should devote efforts into more effective, widely applicable, and controllable techniques for template or model update.

C. CONTINUOUS BIOMETRICS

Generally, biometric systems maintain a session open after a favorable decision, until the user terminates it. This generates security flaws, as the system becomes vulnerable to attackers when the user momentarily leaves the system unattended without closing the session. This can be avoided by setting time limits or closing the session after some idle time, but this impacts usability and productivity as it requires the user to frequently re-open the session, e.g., when reading a document or watching a video without interacting with the system for a long time [104].

Continuous biometric systems, also referred to as online or real-time biometrics, are those that quickly output a first decision and frequently update it. With this, current users are frequently recognized and the session is effortlessly kept open for them, but when attackers or impostors try to take advantage of a session left open, the system detects them and closes the session [104]. The electrocardiogram, as a continuously available biometric trait with low processing requirements, is especially fitted for such systems.

The first continuous approach was proposed by Guennoun *et al*. [104], that frequently generated a comparison score to assess if the authenticated user was, still, the one using the system. Louis *et al*. [90] devised a similar approach, by allowing for three different results in each cycle: blocking out any impostors (reject), maintaining the system open for the authenticated user (accept), or, in doubt, simply delay the decision for the next cycle (continue).

Matta *et al*. [109] was the first to focus on continuous identification, performing it every five seconds. Matos *et al*. [56] performed a real-time recognition process on 100 ms sliding windows over a continuously received ECG signal. More recently, Camara *et al*. [122] opted to consider the electrocardiographic signals as continuous data streams, focusing on ensuring the method's applicability in real-time. Additionally, the authors have remarked the enhanced capabilities of continuous systems, continuously receiving new trait data, to adapt and ensure reliability over long time periods.

Along with increased security, the frequent decision renewal by continuous biometric systems bring two other advantages. The first is the possibility to combine the most

TABLE 14. Summary of the state-of-the-art multimodal biometric methods using ECG biometrics (ordered by year of publication and first author name, NS - Number of Subjects, OP - Off-the-Person ECG acquisition).

Author	Year	Biometric Traits	Fusion	NS	OP	Results	
Israel *et al.* [148]	2003	ECG + Face	Feature level	15	No	IDR	99%
			Decision level	15	No	IDR	94%
			Score level	15	No	IDR	66%
Boumbarov *et al.* [149]	2011	ECG + Face	Score level	28	No	IDR	99.5%
Singh *et al.* [150]	2012	ECG + Face + Fingerprint	Score level	78	No	EER	0.22%
Bugdol and Mitas [151]	2014	ECG + Voice	Feature level	30	No	IDR	77%
Pouryayevali [152]	2015	ECG + Fingerprint	Score level	45	Yes	EER	0.08%
Charkraborty *et al.* [153]	2017	ECG + Face (profile)	Feature level	40	Yes	IDR	97.5%
Arteaga-Falconi *et al.* [154]	2018	ECG + Fingerprint	Decision level	73	No	EER	0.46%

recent past decisions to support the current decision, as studied by Pinto *et al.* [19], which improves performance by reducing influence of single wrong decisions. Other advantage is the greater amount of trait data available, being continuous acquired from the users, which could be useful for more frequent, thorough, and effective template or model update procedures [122].

Nevertheless, continuous ECG biometric systems currently present several limitations. Although the ECG signal is, as aforementioned, a biometric trait that presents low processing requirements, the need for quick and frequently renewed decisions in continuous systems requires the computational cost to be low and the hardware to be adequately powerful.

Furthermore, to frequently renew the decision, the system should also be able to perform accurately and robustly with short ECG segments, which can be difficult to achieve. However, continuous ECG biometric systems present significant advantages for several applications, and certainly merit the devotion of future efforts towards their development.

D. MULTIMODAL ECG BIOMETRICS

As research moves towards more acceptable ECG acquisition settings, multimodal biometric systems are placing themselves as a good alternative to unimodal ECG biometric systems. This is mainly due to noise and variability in the acquired signals, enhanced by the trending off-the-person, wearable, and seamless acquisition techniques, that impact performance and robustness. Multimodal systems generally offer significant advantages in terms of representation, certainty, accuracy, and completeness [155].

Some authors have developed ECG multimodal systems (see Table 14), acquiring one or more traits alongside the ECG, to take advantage of its desirable universality, uniqueness, and continuous availability, and diminish the undesirable effects of its variability.

To the extent of our knowledge, Israel *et al.* [148] were the first to propose an ECG multimodal system, using ECG to improve face biometric identification, fusing both traits at feature, decision, and score levels. They found that, while the sole use of face images was a better alternative than a unimodal ECG algorithm, the fusion of face with ECG at feature level brought significant improvements to the identification rate, from 91% to 99%.

Boumbarov *et al.* [149] used face images to improve ECG biometric performance, studying diverse score level fusion rules, and reported the improvement of IDR from 95.7% to 99.5%, when using product rule. Singh *et al.* [150] also fused traits at the score level, opting to use three traits regarded as least obtrusive – ECG, face, and fingerprint – for authentication. While separate, the ECG, face, and fingerprint authentication algorithms presented, respectively, 10.8%, 4.52%, and 2.12% EER. However, fusing ECG and face gave 3.02% EER, fusing ECG and fingerprint gave 1.52% EER, and fusing all three traits offered 0.22% EER.

Bugdol and Mitas [151] opted to combine the ECG with the non-invasive and socially acceptable voice trait. While ECG and voice offered, respectively, 28% and 72% IDR, the fusion of both at feature level allowed for an improvement to 77% IDR. Pouryayevali [152] was the first to use off-the-person ECG acquisitions in multimodal biometrics, resorting to the UofTDB database. With fingerprint acquisition, the author reported the improvement of EER in across-session acquisitions from 3.12% (using only ECG) to 0.08%.

Arteaga-Falconi *et al.* [154] opted to fuse fingerprint and ECG at the decision level. While their fingerprint unimodal algorithm offered 1.18% EER in authentication tasks, the fusion with ECG reduced EER to 0.46%. Regarding the fusion rule, they found it was best to give preference to the fingerprint results, considering ECG a weaker biometric trait.

It should be noted that miBEAT [66], mentioned in subsection III-A, reports being capable of multimodal biometric identification in seamlessly integrated settings, using ECG and PPG signals. Nevertheless, despite preliminary tests on heart rate variability measurements, no identification or authentication tests were performed.

Following the findings of the surveyed works, the most lucrative path in multimodal ECG biometrics could be the fusion of ECG with more than one other trait, considering, naturally, their harmonious integration and potential for unobtrusive acquisition. Face appears to be the most applicable trait, especially for seamless and continuous biometric systems, as it does not require contact, but fingerprint has reported better performance.

Moreover, it would be beneficial to study multimodal ECG biometrics with larger sets of subjects, following the current trends in unimodal ECG biometrics. To this end, efforts should be devoted towards the development of large public datasets with diverse traits, especially face and fingerprint, alongside ECG acquired from off-the-person, wearable, or seamless settings.

E. SPOOFING AND DATA SECURITY

Despite all the advantages offered by biometrics when compared with traditional authentication systems, there are two highly relevant issues that remain to be completely solved: spoofing and data security. These problems have been recently studied by researchers so, below, we delve into what has been done and what lies ahead.

1) SPOOFING AND COUNTERFEITING

In the case of keys and passwords, either they correspond or not to their stored counterparts. However, biometric traits are variable, they have a fuzzy nature that requires systems to allow some leeway when granting access. This allows attackers to be successful if they can acquire the trait from a victim and store it for later use, or mimic their trait with sufficient similarity.

Although the electrocardiogram's power against spoofing has been consistently praised in state-of-the-art publications, it has only recently been adequately tested. Eberz *et al*. [23] showcased the vulnerabilities of the commercial Nymi Band, and proved that it is possible to acquire ECG signals from a victim and inexpensively use them to attack the authentication wearable, with significant success rates. Although their spoofing technique still required contact with both hands of the victim, which is a protection other traits do not offer, it serves as a warning to researchers and developers of biometric systems to start studying and implementing strong spoofing prevention measures.

The vulnerabilities of the ECG biometric systems have been further confirmed by Karimian *et al*. [24], who studied a systematic mapping function that allows any attacker to transform his own signals into a victim's. The authors reported over 90% success rate in online spoofing attacks.

Researchers have already started to address the problem of spoofing in ECG biometrics. Specifically, Komeili *et al*. [156] has studied an algorithm to strengthen multimodal biometric systems, using the liveness information of the ECG combined with the high authentication performance offered by fingerprints. However, there is still much to do to ensure the inviolability of ECG biometric systems.

2) DATA SECURITY

Much more than a different type of key or password, a biometric trait is a piece of the user: it carries sensitive personal information that is closely connected to its identity. By requiring the storage of biometric trait measurements (templates) of the enrolled subjects, biometric systems are a vulnerability to the user privacy and security, which must be adequately addressed with advanced storage protection methods.

Although some works in ECG biometrics have included encryption or compression based techniques [119], [118], [63], these have been chosen not specifically for security but to obtain more meaningful and robust features. Nevertheless, Nandi *et al.* [157] has separately proposed a method for generation of hash codes for ECG signals, based on cellular automata. The authors state that the obtained encryption enhances trait security for human authentication systems.

When applying ECG for healthcare monitoring, some researchers have specifically devoted efforts to stored data security. Sufi *et al*. [158] were among the first to address this topic, by developing an ECG encryption technique based on chaos theory, to ensure patient privacy in time-critical telecardiology. Son *et al*. [159] proposed a signal scrambling method to secure transmitted data and anonymous identity schemes to preserve privacy in an intelligent arrhythmia detection system. However, there is still a long way to go until we secure the personal information stored in ECG biometric systems.

3) CHALLENGES AND OPPORTUNITIES

Spoofing and data security, two real and pressing issues that remain to be solved in ECG biometrics, appear even more urgent when we consider that, unlike passwords or keys, we do not have the option to change our biometric traits when they are stolen [155], [160].

As the topic of ECG biometrics evolves from research knowledge to widespread commercial products, and already with some deployed commercial systems, storing sensitive information on the enrolled users, the need to appropriately and completely address the problems of spoofing and data security is more pressing than ever.

Future research endeavors should further study ways to pinpoint and reduce vulnerabilities and prevent spoofing attacks. Also, techniques such as cancellable biometrics or cryptosystems [155], [161], already studied for other traits, should be explored and adapted for ECG signals, to ensure the security of stored data.

X. CONCLUSION

As shown by this survey, through a detailed presentation and discussion of the evolution of electrocardiogram-based biometrics, the ECG has the potential to be one of the main biometric traits. However, some challenges are still to be solved, especially regarding acquisition, deep learning, multimodal biometrics, public data, spoofing, and data security, that raise new and exciting research opportunities for the near future.

First, it is remarkable how the electrocardiogram, commonly acquired through medical-grade equipment, is now measurable by wearable gadgets and seamlessly integrated systems, significantly increasing acquisition comfort and acceptability. Research should continue exploring seamless acquisition settings, and should address the possibility of measuring ECG without contact, to further enable real ECG biometric applications.

Then, to address noise and variability, enhanced by increasingly acceptable acquisition settings, multimodal systems should be further studied. Traits to be further explored would include face, that would be easily applicable in most real settings, the fingerprint, that offers the best accuracy improvements, or the PPG, that can be easily acquired alongside the ECG. Also, efforts should be devoted to build new publicly available multimodal datasets, including ECG signals, to offer more challenging settings for research and development.

Finally, vulnerability to spoofing attacks should be a main concern in all proposed biometric systems and algorithms. The protection of the users and their privacy should always include their data, through the study of new and improved encryption techniques and storage protection methods to avoid malicious access to biometric templates.

In these changing times for biometrics, quality research is key to affirm the ECG as a viable alternative to the most famous traits. Hopefully, following the challenges discussed in this survey, research can address the open issues, taking advantage of current opportunities, and propose increasingly competitive and applicable ECG biometric systems.

REFERENCES

[1] A. K. Jain, A. A. Ross, and K. Nandakumar, *Introduction to Biometrics*. Springer, 2011.

[2] F. Agrafioti, J. Gao, and D. Hatzinakos, "Heart biometrics: Theory, methods and applications," in *Biometrics*, J. Yang, Ed. Rijeka, Croatia: InTech, 2011, pp. 199–216.

[3] M. Abo-Zahhad, S. M. Ahmed, and S. N. Abbas, "Biometric authentication based on PCG and ECG signals: Present status and future directions," *Signal, Image Video Process.*, vol. 8, no. 4, pp. 739–751, May 2014.

[4] G. Kaur, G. Singh, and V. Kumar, "A review on biometric recognition," *Int. J. Bio-Sci. Bio-Technol.*, vol. 6, no. 4, pp. 69–76, 2014.

[5] S. Prabhakar, S. Pankanti, and A. K. Jain, "Biometric recognition: Security and privacy concerns," *IEEE Security Privacy*, vol. 1, no. 2, pp. 33–42, Mar. 2003.

[6] R. M. Bolle, J. H. Connell, S. Pankanti, N. Ratha, and A. W. Senior, *Guide to Biometrics*, 1st ed. New York, NY, USA: Springer, 2004.

[7] N. Akhter, S. Tharewal, V. Kale, A. Bhalerao, and K. V. Kale, "Heart-based biometrics and possible use of heart rate variability in biometric recognition systems," in *Advanced Computing and Systems for Security*, vol. 1, R. Chaki, A. Cortesi, K. Saeed, and N. Chaki, Eds. New Delhi, India: Springer, 2016, pp. 15–29.

[8] N. Belgacem, A. Nait-Ali, R. Fournier, and F. Bereksi-Reguig, "ECG based human authentication using wavelets and random forests," *Int. J. Cryptogr. Inf. Secur.*, vol. 2, no. 2, pp. 1–11, 2012.

[9] A. Fratini, M. Sansone, P. Bifulco, and M. Cesarelli, "Individual identification via electrocardiogram analysis," *Biomed. Eng. OnLine*, vol. 14, no. 1, p. 78, 2015.

[10] F. Agrafioti, F. M. Bui, and D. Hatzinakos, "Secure telemedicine: Biometrics for remote and continuous patient verification," *J. Comput. Netw. Commun.*, vol. 2012, Oct. 2012, Art. no. 924791.

[11] M. Li and S. Narayanan, "Robust ECG biometrics by fusing temporal and cepstral information," in *Proc. IEEE Int. Conf. Pattern Recognit. (ICPR)*, Aug. 2010, pp. 1326–1329.

[12] I. Odinaka, P.-H. Lai, A. D. Kaplan, J. A. O'Sullivan, E. J. Sirevaag, and J. W. Rohrbaugh, "ECG biometric recognition: A comparative analysis," *IEEE Trans. Inf. Forensics Security*, vol. 7, no. 6, pp. 1812–1824, Dec. 2012.

[13] B. Singh, P. Singh, and S. Budhiraja, "Various approaches to minimise noises in ECG signal: A survey," in *Proc. 5th Int. Conf. Adv. Comput. Commun. Technol.*, Feb. 2015, pp. 131–137.

[14] S. M. Walke and R. S. Deshpande, "On-line real time feature extraction of ECG signal: Recent advances survey," in *Proc. Int. Conf. Inf. Process. (ICIP)*, Dec. 2015, pp. 211–216.

[15] M. Bassiouni, W. Khalefa, E.-S. A. El-Dahshan, and A.-B. M. Salem, "A study on the intelligent techniques of the ECG-based biometric systems," in *Recent Advances in Electrical Engineering*. Singapore: World Scientific, 2015, pp. 26–31.

[16] M. Merone, P. Soda, M. Sansone, and C. Sansone, "ECG databases for biometric systems: A systematic review," *Expert Syst. Appl.*, vol. 67, pp. 189–202, Jan. 2017.

[17] A. Lourenço, A. P. Alves, C. Carreiras, R. P. Duarte, and A. Fred, "CardioWheel: ECG biometrics on the steering wheel," in *Proc. Joint Eur. Conf. Mach. Learn. Knowl. Discovery Databases (ECML PKDD)*, Porto, Portugal, A. Bifet *et al.*, Eds. Cham, Switzerland: Springer, 2015, pp. 267–270.

[18] F. Agrafioti, K. Martin, and S. Oung, "Preauthorized wearable biometric device, system and method for use thereof," U.S. Patent 9 472 033 B2, Oct. 18, 2016.

[19] J. R. Pinto, J. S. Cardoso, A. Lourenço, and C. Carreiras, "Towards a continuous biometric system based on ECG signals acquired on the steering wheel," *Sensors*, vol. 17, no. 10, p. 2228, 2017.

[20] Q. Zhang, D. Zhou, and X. Zeng, "HeartID: A multiresolution convolutional neural network for ECG-based biometric human identification in smart health applications," *IEEE Access*, vol. 5, pp. 11805–11816, 2017.

[21] A. Eduardo, H. Aidos, and A. Fred, "ECG-based biometrics using a deep autoencoder for feature learning: An empirical study on transferability," in *Proc. INSTICC Int. Conf. Pattern Recognit. Appl. Methods (ICPRAM)*, vol. 1, Feb. 2017, pp. 463–470.

[22] R. Salloum and C. C. J. Kuo, "ECG-based biometrics using recurrent neural networks," in *Proc. IEEE Int. Conf. Acoust., Speech Signal Process. (ICASSP)*, Mar. 2017, pp. 2062–2066.

[23] S. Eberz, N. Paoletti, M. Roeschlin, M. Kwiatkowska, and I. Martinovic, "Broken hearted: How To attack ECG biometrics," in *Proc. Netw. Distrib. Syst. Secur. Symp. (NDSS)*, 2017.

[24] N. Karimian, D. L. Woodard, and D. Forte, "On the vulnerability of ECG verification to online presentation attacks," in *Proc. IEEE Int. Joint Conf. Biometrics (IJCB)*, Oct. 2017, pp. 143–151.

[25] E. N. Marieb and K. Hoehn, *Human Anatomy & Physiology*, 9th ed. Glenview, IL, USA: Pearson, 2013.

[26] P. Tate, *Seeley's Principles of Anatomy and Physiology*, 2nd ed. New York, NY, USA: McGraw-Hill, 2009.

[27] V. C. Scanlon and T. Sanders, *Essentials of Anatomy and Physiology*, 5th ed. Philadelphia, PA, USA: F. A. Davis Company, 2007.

[28] F. Agrafioti and D. Hatzinakos, "ECG based recognition using second order statistics," in *Proc. 6th Annu. Commun. Netw. Services Res. Conf. (CNSR)*, May 2008, pp. 82–87.

[29] A. Sahayadhas, K. Sundaraj, and M. Murugappan, "Detecting driver drowsiness based on sensors: A review," *Sensors*, vol. 12, no. 12, pp. 16937–16953, 2012.

[30] P. Rajpurkar, A. Y. Hannun, M. Haghpanahi, C. Bourn, and A. Y. Ng. (2017). "Cardiologist-level arrhythmia detection with convolutional neural networks." [Online]. Available: https://arxiv.org/abs/1707.01836

[31] R. Hoekema, G. J. H. Uijen, and A. van Oosterom, "Geometrical aspects of the inter-individual variability of multilead ECG recordings," in *Proc. Comput. Cardiology*, vol. 26, Sep. 1999, pp. 499–502.

[32] A. van Oosterom, R. Hoekema, and G. J. H. Uijen, "Geometrical factors affecting the interindividual variability of the ECG and the VCG," *J. Electrocardiol.*, vol. 33, pp. 219–227, 2000.

[33] R. Hoekema, G. J. H. Uijen, and A. van Oosterom, "Geometrical aspects of the interindividual variability of multilead ECG recordings," *IEEE Trans. Biomed. Eng.*, vol. 48, no. 5, pp. 551–559, May 2001.

[34] R. J. A. Schijvenaars, "Intra-individual Variability of the Electrocardiogram: Assessment and exploitation in computerized ECG analysis," Ph.D. dissertation, Dept. Med. Inform., Erasmus Univ. Rotterdam, Rotterdam, The Netherlands, 2000.

[35] C. Ye, M. T. Coimbra, and B. V. K. V. Kumar, "Investigation of human identification using two-lead electrocardiogram (ECG) signals," in *Proc. 4th IEEE Int. Conf. Biometrics, Theory Appl. Syst. (BTAS)*, Sep. 2010, pp. 1–8.

[36] S. I. Safie, J. J. Soraghan, and L. Petropoulakis, "Electrocardiogram (ECG) biometric authentication using pulse active ratio (PAR)," *IEEE Trans. Inf. Forensics Security*, vol. 6, no. 4, pp. 1315–1322, Dec. 2011.

[37] L. Biel, O. Pettersson, L. Philipson, and P. Wide, "ECG analysis: A new approach in human identification," *IEEE Trans. Instrum. Meas.*, vol. 50, no. 3, pp. 808–812, Jun. 2001.

[38] R. MacLeod and B. Birchler. (Feb. 2014). ECG measurement and analysis. University Utah. [Online]. Available: http://www.sci.utah.edu/~macleod/bioen/be6000/labnotes/ecg/l3-ecg.pdf

[39] K. N. Plataniotis, D. Hatzinakos, and J. K. M. Lee, "ECG biometric recognition without fiducial detection," in *Proc. Biometrics Symp., Special Session Res. Biometric Consortium Conf.*, Sep. 2006, pp. 1–6.

[40] G. Wübbeler, M. Stavridis, D. Kreiseler, R.-D. Bousseljot, and C. Elster, "Verification of humans using the electrocardiogram," *Pattern Recognit. Lett.*, vol. 28, no. 10, pp. 1172–1175, Jul. 2007.

[41] N. Ghofrani and R. Bostani, "Reliable features for an ECG-based biometric system," in *Proc. 17th Iranian Conf. Biomed. Eng. (ICBME)*, Nov. 2010, pp. 1–5.

[42] R. Palaniappan and S. M. Krishnan, "Identifying individuals using ECG beats," in *Proc. Int. Conf. Signal Process. Commun. (SPCOM)*, Dec. 2004, pp. 569–572.

[43] Z. Zhang and D. Wei, "A new ECG identification method using Bayes' teorem," in *Proc. IEEE Region 10 Conf. TENCON*, Nov. 2006, pp. 1–4.

[44] G. G. Molina, F. Bruekers, C. Presura, M. Damstra, and M. van der Veen, "Morphological synthesis of ECG signals for person authentication," in *Proc. 15th Eur. Signal Process. Conf.*, Sep. 2007, pp. 738–742.

[45] M. Kyoso and A. Uchiyama, "Development of an ECG identification system," in *Proc. 23rd Annu. Int. Conf. IEEE Eng. Med. Biol. Soc.*, vol. 4, Oct. 2001, pp. 3721–3723.

[46] M. Kyoso and A. Uchiyama, "Development of ECG identification system," *Jpn. J. Med. Electron. Biol. Eng.*, vol. 39, p. 559, May 2001.

[47] V. N. Murthy and S. Jayaraman, "Human electrocardiogram for biometrics using DTW and FLDA," in *Proc. 20th Int. Conf. Pattern Recognit. (ICPR)*, Aug. 2010, pp. 3838–3841.

[48] S. Pathoumvanh, S. Airphaiboon, and K. Hamamoto, "Robustness study of ECG biometric identification in heart rate variability conditions," *IEEJ Trans. Elect. Electron. Eng.*, vol. 9, no. 3, pp. 294–301, May 2014.

[49] M. Kyoso, K. Ohishi, and A. Uchiyama, "Development of ECG identification system," *Jpn. J. Med. Electron. Biol. Eng.*, vol. 38, p. 392, May 2000.

[50] S.-C. Fang and H.-L. Chan, "Human identification by quantifying similarity and dissimilarity in electrocardiogram phase space," *Pattern Recognit.*, vol. 42, no. 9, pp. 1824–1831, 2009.

[51] T. W. Shen, W. J. Tompkins, and Y. H. Hu, "One-lead ECG for identity verification," in *Proc. 2nd Joint Eng. Med. Biol., 24th Annu. Conf. Annu. Fall Meeting Biomed. Eng. Soc. (EMBS/BMES)*, vol. 1, 2002, pp. 62–63.

[52] R. D. Labati, R. Sassi, and F. Scotti, "ECG biometric recognition: Permanence analysis of QRS signals for 24 hours continuous authentication," in *Proc. IEEE Int. Workshop Inf. Forensics Secur. (WIFS)*, Nov. 2013, pp. 31–36.

[53] R. D. Labati, V. Piuri, R. Sassi, F. Scotti, and G. Sforza, "Adaptive ECG biometric recognition: A study on re-enrollment methods for QRS signals," in *Proc. IEEE Symp. Comput. Intell. Biometrics Identity Manage. (CIBIM)*, Dec. 2014, pp. 30–37.

[54] X. Zhou, Y. Lu, M. Chen, S. D. Bao, and F. Miao, "A method of ECG template extraction for biometrics applications," in *Proc. 36th Annu. Int. Conf. IEEE Eng. Med. Biol. Soc. (EMBC)*, Aug. 2014, pp. 602–605.

[55] A. D. C. Chan, M. M. Hamdy, A. Badre, and V. Badee, "Wavelet distance measure for person identification using electrocardiograms," *IEEE Trans. Instrum. Meas.*, vol. 57, no. 2, pp. 248–253, Feb. 2008.

[56] A. C. Matos, A. Lourenço, and J. Nascimento, "Embedded system for individual recognition based on ECG biometrics," *Procedia Technol.*, vol. 17, pp. 265–272, Nov. 2014.

[57] T.-W. Shen, W. J. Tompkins, and Y. H. Hu, "Implementation of a one-lead ECG human identification system on a normal population," *J. Eng. Comput. Innov.*, vol. 2, no. 1, pp. 12–21, 2011.

[58] N. Belgacem, A. Nait-Ali, R. Fournier, and F. Bereksi-Reguig, "ECG based human identification using random forests," in *Proc. Int. Conf. E-Technol. Bus. Web (EBW)*. Bangkok, Thailand, 2013.

[59] S.-L. Lin, C.-K. Chen, C.-L. Lin, W.-C. Yang, and C.-T. Chiang, "Individual identification based on chaotic electrocardiogram signals during muscular exercise," *IET Biometrics*, vol. 3, no. 4, pp. 257–266, 2014.

[60] H. P. da Silva, A. Lourenço, A. Fred, N. Raposo, and M. Aires-de-Sousa, "Check your biosignals here: A new dataset for off-the-person ECG biometrics," *Comput. Methods Programs Biomed.*, vol. 113, no. 2, pp. 503–514, 2014.

[61] A. Lourenço, H. Silva, D. P. Santos, and A. Fred, "Towards a finger based ECG biometric system," in *Proc. Int. Conf. Bio-Inspired Syst. Signal Process. (BIOSIGNALS)*, Rome, Italy, 2011, pp. 1–6.

[62] D. P. Coutinho, A. L. N. Fred, and M. A. T. Figueiredo, "One-lead ECG-based personal identification using Ziv-Merhav cross parsing," in *Proc. 20th Int. Conf. Pattern Recognit.*, Aug. 2010, pp. 3858–3861.

[63] D. P. Coutinho, A. L. N. Fred, and M. A. T. Figueiredo, "ECG-based continuous authentication system using adaptive string matching," in *Proc. Int. Conf. Bio-Inspired Syst. Signal Process. (BIOSIGNALS)*, 2011, pp. 354–359.

[64] H. P. Silva, A. Fred, A. Lourenço, and A. K. Jain, "Finger ECG signal for user authentication: Usability and performance," in *Proc. IEEE 6th Int. Conf. Biometrics: Theory, Appl. Syst. (BTAS)*, Sep./Oct. 2013, pp. 1–8.

[65] Q. Zhang, D. Zhou, and X. Zeng, "PulsePrint: Single-arm-ECG biometric human identification using deep learning," in *Proc. IEEE 8th Annu. Ubiquitous Comput., Electron. Mobile Commun. Conf. (UEMCON)*, Oct. 2017, pp. 452–456.

[66] J. Yathav, A. Bailur, A. K. Goyal, and Abhinav, "miBEAT based continuous and robust biometric identification system for on-the-go applications," in *Proc. Int. Conf. Commun. Netw.* (Series Advances in Intelligent Systems and Computing), vol. 508, N. Modi *et al.*, Eds. Singapore: Springer, 2017, pp. 269–275, doi: 10.1007/978-981-10-2750-5_28.

[67] Y. M. Chi, T.-P. Jung, and G. Cauwenberghs, "Dry-contact and noncontact biopotential electrodes: Methodological review," *IEEE Rev. Biomed. Eng.*, vol. 3, pp. 106–119, Oct. 2010.

[68] L. Scalise, Y. Velchev, K. Tonchev, and I. Paliy, "Non contact heart monitoring," in *Advances in Electrocardiograms—Methods and Analysis*, R. M. Millis, Ed. Rijeka, Croatia: InTech, 2012.

[69] D. Obeid, G. Zaharia, S. Sadek, and G. El Zein, "Microwave Doppler radar for heartbeat detection vs electrocardiogram," *Microw. Opt. Technol. Lett.*, vol. 54, no. 11, pp. 2610–2617, 2012.

[70] S. Bounyong, M. Yoshioka, and J. Ozawa, "Monitoring of a driver's heart rate using a microwave sensor and template-matching algorithm," in *Proc. IEEE Int. Conf. Consum. Electron. (ICCE)*, Jan. 2017, pp. 43–44.

[71] F. Porée, G. Kervio, and G. Carrault, "ECG biometric analysis in different physiological recording conditions," *Signal, Image and Video Process.*, vol. 10, no. 2, pp. 267–276, 2016.

[72] S. Wahabi, S. Pouryayevali, S. Hari, and D. Hatzinakos, "On evaluating ECG biometric systems: Session-dependence and body posture," *IEEE Trans. Inf. Forensics Security*, vol. 9, no. 11, pp. 2002–2013, Nov. 2014.

[73] M. N. Dar, M. U. Akram, A. Shaukat, and M. A. Khan, "ECG based biometric identification for population with normal and cardiac anomalies using hybrid HRV and DWT features," in *Proc. 5th Int. Conf. IT Converg. Secur. (ICITCS)*, Aug. 2015, pp. 1–5.

[74] M. N. Dar, M. U. Akram, A. Usman, and S. A. Khan, "ECG biometric identification for general population using multiresolution analysis of DWT based features," in *Proc. 2nd Int. Conf. Inf. Secur. Cyber Forensics (InfoSec)*, Nov. 2015, pp. 5–10.

[75] G. Doddington, W. Liggett, A. Martin, M. Przybocki, and D. Reynolds, "SHEEP, GOATS, LAMBS and WOLVES: A statistical analysis of speaker performance in the NIST 1998 speaker recognition evaluation," in *Proc. 5th Int. Conf. Spoken Lang. Process.*, Sydney, NSW, Australia, Nov./Dec. 1998, Paper 0608.

[76] N. Yager and T. Dunstone, "The biometric menagerie," *IEEE Trans. Pattern Anal. Mach. Intell.*, vol. 32, no. 2, pp. 220–230, Feb. 2010.

[77] J. A. Healey and R. W. Picard, "Detecting stress during real-world driving tasks using physiological sensors," *IEEE Trans. Intell. Transp. Syst.*, vol. 6, no. 2, pp. 156–166, Jun. 2005.

[78] T. S. Lugovaya, "Biometric human identification based on electrocardiogram," M.S. thesis, Faculty Comput. Technol. Inform., Saint Petersburg Electrotech. Univ., Saint Petersburg, Russia, Jun. 2005.
[79] A. P. Nemirko and T. S. Lugovaya, "Biometric human identification based on electrocardiogram," in *Proc. 12th Russian Conf. Math. Methods Pattern Recognit.*, 2005, pp. 387–390.
[80] A. Taddei *et al.*, "The European ST-T database: Standard for evaluating systems for the analysis of ST-T changes in ambulatory electrocardiography," *Eur. Heart J.*, vol. 13, no. 9, pp. 1164–1172, 1992.
[81] F. Jager *et al.*, "Long-term ST database: A reference for the development and evaluation of automated ischaemia detectors and for the study of the dynamics of myocardial ischaemia," *Med. Biol. Eng. Comput.*, vol. 41, no. 2, pp. 172–183, 2003.
[82] R. G. Mark, P. S. Schluter, G. B. Moody, P. H. Devlin, and D. Chernoff, "An annotated ECG database for evaluating arrhythmia detectors," *IEEE Trans. Biomed. Eng.*, vol. 29, no. 8, p. 600, Aug. 1982.
[83] G. B. Moody and R. G. Mark, "The MIT-BIH arrhythmia database on CD-ROM and software for use with it," in *Proc. Comput. Cardiol.*, vol. 17. Sep. 1990, pp. 185–188.
[84] R. Bousseljot, D. Kreiseler, and A. Schnabel, "Nutzung der EKG-Signaldatenbank CARDIODAT der PTB über das Internet," *Biomed. Tech.*, vol. 40, no. s1, pp. 317–318, 1995.
[85] P. Laguna, R. G. Mark, A. Goldberg, and G. B. Moody, "A database for evaluation of algorithms for measurement of QT and other waveform intervals in the ECG," in *Proc. Comput. Cardiol.*, vol. 24, Sep. 1997, pp. 673–676.
[86] D. Kreiseler and R. Bousseliot, "Automatisierte EKG-Auswertung mit Hilfe der EKG-Signaldatenbank CARDIODAT der PTB," *Biomed. Tech.*, vol. 40, no. s1, pp. 319–320, 1995.
[87] A. K. Jain and A. Kumar, "Biometric recognition: An overview," in *Second Generation Biometrics: The Ethical, Legal and Social Context*, E. Mordini and D. Tzovaras, Eds. Dordrecht, Amsterdam, The Netherlands: Springer, 2012, pp. 49–79.
[88] D. Rezgui and Z. Lachiri, "ECG biometric recognition using SVM-based approach," *IEEJ Trans. Elect. Electron. Eng.*, vol. 11, no. s1, pp. S94–S100, 2016.
[89] S. Z. Fatemian and D. Hatzinakos, "A new ECG feature extractor for biometric recognition," in *Proc. IEEE Int. Conf. Digit. Signal Process.*, Jul. 2009, pp. 1–6.
[90] W. Louis, M. Komeili, and D. Hatzinakos, "Continuous authentication using one-dimensional multi-resolution local binary patterns (1DMRLBP) in ECG biometrics," *IEEE Trans. Inf. Forensics Security*, vol. 11, no. 12, pp. 2818–2832, Dec. 2016.
[91] S. A. Israel, J. M. Irvine, A. Cheng, M. D. Wiederhold, and B. K. Wiederhold, "ECG to identify individuals," *Pattern Recognit.*, vol. 38, no. 1, pp. 133–142, Jan. 2005.
[92] D. Pereira Coutinho, H. Silva, H. Gamboa, A. Fred, and M. Figueiredo, "Novel fiducial and non-fiducial approaches to electrocardiogram-based biometric systems," *IET Biometrics*, vol. 2, no. 2, pp. 64–75, Jun. 2013.
[93] T. Choudhary and M. S. Manikandan, "A novel unified framework for noise-robust ECG-based biometric authentication," in *Proc. 2nd Int. Conf. Signal Process. Integr. Netw. (SPIN)*, Feb. 2015, pp. 186–191.
[94] P. Sasikala and R. S. D. Wahidabanu, "Identification of individuals using electrocardiogram," *Int. J. Comput. Sci. Netw. Secur.*, vol. 10, no. 12, pp. 147–153, Dec. 2010.
[95] S. Y. Chun, "Single pulse ECG-based small scale user authentication using guided filtering," in *Proc. Int. Conf. Biometrics (ICB)*, Jun. 2016, pp. 1–7.
[96] A. Lourenço, C. Carreiras, H. Silva, and A. Fred, "ECG biometrics: A template selection approach," in *Proc. IEEE Int. Symp. Med. Meas. Appl. (MeMeA)*, Jun. 2014, pp. 1–6.
[97] M. Hejazi, S. A. R. Al-Haddad, Y. P. Singh, S. J. Hashim, and A. F. A. Aziz, "ECG biometric authentication based on non-fiducial approach using kernel methods," *Digit. Signal Process.*, vol. 52, pp. 72–86, May 2016.
[98] A. Savitzky and M. J. E. Golay, "Smoothing and differentiation of data by simplified least squares procedures," *Anal. Chem.*, vol. 36, no. 8, pp. 1627–1639, 1964.
[99] A. Hannun *et al.* (2014). "Deep speech: Scaling up end-to-end speech recognition." [Online]. Available: https://arxiv.org/abs/1412.5567
[100] L. Biel, O. Pettersson, L. Philipson, and P. Wide, "ECG analysis: A new approach in human identification," in *Proc. 16th IEEE Instrum. Meas. Technol. Conf. (IMTC)*, vol. 1, May 1999, pp. 557–561.
[101] S. Saechia, J. Koseeyaporn, and P. Wardkein, "Human identification system based ECG signal," in *Proc. IEEE Region 10th Conf. TENCON*, Nov. 2005, pp. 1–4.
[102] J. M. Irvine, S. A. Israel, W. T. Scruggs, and W. J. Worek, "eigenPulse: Robust human identification from cardiovascular function," *Pattern Recognit.*, vol. 41, no. 11, pp. 3427–3435, 2008.
[103] O. Boumbarov, Y. Velchev, and S. Sokolov, "ECG personal identification in subspaces using radial basis neural networks," in *Proc. IEEE Int. Workshop Intell. Data Acquisition Adv. Comput. Syst., Technol. Appl. (IDAACS)*, Sep. 2009, pp. 446–451.
[104] M. Guennoun, N. Abbad, J. Talom, S. M. M. Rahman, and K. El-Khatib, "Continuous authentication by electrocardiogram data," in *Proc. IEEE Int. Conf. Sci. Technol. Humanity (TIC-STH)*, Sep. 2009, pp. 40–42.
[105] S. Z. Fatemian, F. Agrafioti, and D. Hatzinakos, "HeartID: Cardiac biometric recognition," in *Proc. 4th IEEE Int. Conf. Biometrics, Theory Appl. Syst. (BTAS)*, Sep. 2010, pp. 1–5.
[106] I. Odinaka *et al.*, "ECG biometrics: A robust short-time frequency analysis," in *Proc. IEEE Int. Workshop Inf. Forensics Secur.*, Dec. 2010, pp. 1–6.
[107] M. M. Tawfik, H. Selim, and T. Kamal, "Human identification using time normalized QT signal and the QRS complex of the ECG," in *Proc. 7th Int. Symp. Commun. Syst. Netw. Digit. Signal Process. (CSNDSP)*, Jul. 2010, pp. 755–759.
[108] A. Lourenço, H. Silva, and A. Fred, "Unveiling the biometric potential of finger-based ECG signals," *Comput. Intell. Neurosci.*, vol. 2011, p. 5, Jan. 2011.
[109] R. Matta, J. K. H. Lau, F. Agrafioti, and D. Hatzinakos, "Real-time continuous identification system using ECG signals," in *Proc. 24th Can. Conf. Elect. Comput. Eng. (CCECE)*, May 2011, pp. 001313–001316.
[110] F. Sufi, I. Khalil, and I. Habib, "Cardioids-based faster authentication and diagnosis of remote cardiovascular patients," *Secur. Commun. Netw.*, vol. 4, no. 11, pp. 1351–1368, 2011.
[111] A. Lourenço, H. Silva, and A. Fred, "ECG-based biometrics: A real time classification approach," in *Proc. IEEE Int. Workshop Mach. Learn. Signal Process.*, Sep. 2012, pp. 1–6.
[112] Y. N. Singh and S. K. Singh, "Evaluation of electrocardiogram for biometric authentication," *J. Inf. Secur.*, vol. 3, no. 1, pp. 39–48, Jan. 2012.
[113] A. C. Matos, A. Lourenço, and J. Nascimento, "Biometric recognition system using low bandwidth ECG signals," in *Proc. IEEE 15th Int. Conf. e-Health Netw., Appl. Services (Healthcom)*, Oct. 2013, pp. 518–522.
[114] J. Wang, M. She, S. Nahavandi, and A. Kouzani, "Human identification from ECG signals via sparse representation of local segments," *IEEE Signal Process. Lett.*, vol. 20, no. 10, pp. 937–940, Oct. 2013.
[115] Z. Zhao, L. Yang, D. Chen, and Y. Luo, "A human ECG identification system based on ensemble empirical mode decomposition," *Sensors*, vol. 13, no. 5, pp. 6832–6864, 2013.
[116] S. Ergin, A. K. Uysal, E. S. Gunal, S. Gunal, and M. B. Gulmezoglu, "ECG based biometric authentication using ensemble of features," in *Proc. 9th Iberian Conf. Inf. Syst. Technol. (CISTI)*, Jun. 2014, pp. 1–6.
[117] F.-T.-Z. Iqbal, K. A. Sidek, N. A. Noah, and T. S. Gunawan, "A comparative analysis of QRS and cardioid graph based ECG biometric recognition in different physiological conditions," in *Proc. IEEE Int. Conf. Smart Instrum., Meas. Appl. (ICSIMA)*, Nov. 2014, pp. 1–5.
[118] S. Brás and A. J. Pinho, "ECG biometric identification: A compression based approach," in *Proc. 37th Annu. Int. Conf. IEEE Eng. Med. Biol. Soc. (EMBC)*, Aug. 2015, pp. 5838–5841.
[119] M. Jahiruzzaman and A. B. M. A. Hossain, "ECG based biometric human identification using chaotic encryption," in *Proc. Int. Conf. Elect. Eng. Inf. Commun. Technol. (ICEEICT)*, May 2015, pp. 1–5.
[120] C. Carreiras, A. Lourenço, H. Silva, A. Fred, and R. Ferreira, "Evaluating template uniqueness in ECG biometrics," in *Proc. 11th Int. Conf. Inf. Control, Automat. Robot. (ICINCO)*, Vienna, Austria, J. Filipe, O. Gusikhin, K. Madani, and J. Sasiadek, Eds. Cham, Switzerland: Springer, 2016, pp. 111–123.
[121] T. Waili, R. M. Nor, A. W. B. A. Rahman, K. A. Sidek, and A. A. Ibrahim, "Electrocardiogram identification: Use a simple set of features in QRS complex to identify individuals," in *Proc. 12th Int. Conf. Comput. Inf. Technol. Recent Adv. Inf. Commun. Technol. (IC2IT)*, P. Meesad, S. Boonkrong, and H. Unger, Eds. Cham, Switzerland: Springer, 2016, pp. 139–148.
[122] C. Camara, P. Peris-Lopez, L. Gonzalez-Manzano, and J. Tapiador, "Real-time electrocardiogram streams for continuous authentication," *Appl. Soft Comput.*, vol. 68, pp. 784–794, Jul. 2017.

[123] M. S. Islam and N. Alajlan, "Biometric template extraction from a heartbeat signal captured from fingers," *Multimedia Tools Appl.*, vol. 76, no. 10, pp. 12709–12733, May 2017.

[124] N. Karimian, Z. Guo, M. Tehranipoor, and D. Forte, "Highly reliable key generation from electrocardiogram (ECG)," *IEEE Trans. Biomed. Eng.*, vol. 64, no. 6, pp. 1400–1411, Jun. 2017.

[125] M. Komeili, W. Louis, N. Armanfard, and D. Hatzinakos, "Feature selection for nonstationary data: Application to human recognition using medical biometrics," *IEEE Trans. Cybern.*, vol. 48, no. 5, pp. 1446–1459, May 2018.

[126] J. S. Paiva, D. Dias, and J. P. S. Cunha, "Beat-ID: Towards a computationally low-cost single heartbeat biometric identity check system based on electrocardiogram wave morphology," *PLoS ONE*, vol. 12, no. 7, p. e0180942, Mar. 2017.

[127] R. Tan and M. Perkowski, "Toward improving electrocardiogram (ECG) biometric verification using mobile sensors: A two-stage classifier approach," *Sensors*, vol. 17, no. 2, p. 410, 2017.

[128] L. Wieclaw, Y. Khoma, P. Fałat, D. Sabodashko, and V. Herasymenko, "Biometrie identification from raw ECG signal using deep learning techniques," in *Proc. 9th IEEE Int. Conf. Intell. Data Acquisition Adv. Comput. Syst., Technol. Appl. (IDAACS)*, vol. 1, Sep. 2017, pp. 129–133.

[129] E. K. Zaghouani, A. Benzina, and R. Attia, "ECG based authentication for e-healthcare systems: Towards a secured ECG features transmission," in *Proc. 13th Int. Wireless Commun. Mobile Comput. Conf. (IWCMC)*, Jun. 2017, pp. 1777–1783.

[130] X. Dong, W. Si, and W. Huang, "ECG-based identity recognition via deterministic learning," *Biotechnol., Biotechnol. Equip.*, vol. 32, no. 3, pp. 769–777, 2018.

[131] G. Guven, H. Gürkan, and U. Guz, "Biometric identification using fingertip electrocardiogram signals," *Signal, Image Video Process.*, vol. 12, no. 5, pp. 933–940, Feb. 2018.

[132] H. J. Kim and J. S. Lim, "Study on a biometric authentication model based on ECG using a fuzzy neural network," *IOP Conf. Ser., Mater. Sci. Eng.*, vol. 317, no. 1, p. 012030, 2018.

[133] W. Lee, S. Kim, and D. Kim, "Individual biometric identification using multi-cycle electrocardiographic waveform patterns," *Sensors*, vol. 18, no. 4, p. 1005, 2018.

[134] A. Pal and Y. N. Singh, "ECG Biometric Recognition," in *Mathematics and Computing*, D. Ghosh, D. Giri, R. N. Mohapatra, E. Savas, K. Sakurai, and L. P. Singh, Eds. Singapore: Springer, 2018, pp. 61–73.

[135] J. Pan and W. J. Tompkins, "A real-time QRS detection algorithm," *IEEE Trans. Biomed. Eng.*, vol. BME-32, no. 3, pp. 230–236, Mar. 1985.

[136] P. E. Trahanias, "An approach to QRS complex detection using mathematical morphology," *IEEE Trans. Biomed. Eng.*, vol. 40, no. 2, pp. 201–205, Feb. 1993.

[137] W. A. H. Engelse and C. Zeelenberg, "A single scan algorithm for QRS-detection and feature extraction," in *Proc. Comput. Cardiol.*, Geneva, Switzerland, vol. 6, 1979, pp. 37–42.

[138] A. Lourenço, H. Silva, P. Leite, R. Lourenço, and A. Fred, "Real time electrocardiogram segmentation for finger based ECG biometrics," in *Proc. Int. Conf. Bio-Inspired Syst. Signal Process.-Biosignals (INSTICC)*, Feb. 2012, pp. 49–54.

[139] A. Lourenço, H. Silva, C. Carreiras, and A. Fred, *Outlier Detection in Non-intrusive ECG Biometric System*. Berlin, Germany: Springer, 2013, pp. 43–52.

[140] Z. Hassan, S. O. Gilani, and M. Jamil, "Review of fiducial and non-fiducial techniques of feature extraction in ECG based biometric systems," *Indian J. Sci. Technol.*, vol. 9, no. 21, 2016.

[141] P. J. Grother, G. W. Quinn, and P. J. Phillips, "Report on the evaluation of 2D still-image face recognition algorithms," NIST, Gaithersburg, MD, USA, NIST Interagency Rep. 7709, 2010.

[142] T. Waili, R. M. Nor, H. Yaacob, K. Sidek, and A. W. A. Rahman, "A hasty approach to ECG person identification," in *Proc. Int. Conf. Comput. Commun. Eng. (ICCCE)*, Jul. 2016, pp. 267–271.

[143] F. Sufi, I. Khalil, and J. Hu, "ECG-based authentication," in *Handbook of Information and Communication Security*, P. Stavroulakis and M. Stamp, Eds. Berlin, Germany: Springer, 2010, pp. 309–331.

[144] E. J. da Silva Luz, G. J. P. Moreira, L. S. Oliveira, W. R. Schwartz, and D. Menotti, "Learning deep off-the-person heart biometrics representations," *IEEE Trans. Inf. Forensics Security*, vol. 13, no. 5, pp. 1258–1270, May 2018.

[145] R. D. Labati, E. Muñoz, V. Piuri, R. Sassi, and F. Scotti, "Deep-ECG: Convolutional neural networks for ECG biometric recognition," *Pattern Recognit. Lett.*, Mar. 2018, doi: 10.1016/j.patrec.2018.03.028.

[146] Y. LeCun, Y. Bengio, and G. Hinton, "Deep learning," *Nature*, vol. 521, pp. 436–444, May 2015.

[147] T. T. Um *et al.*, "Data augmentation of wearable sensor data for Parkinson's disease monitoring using convolutional neural networks," in *Proc. 19th ACM Int. Conf. Multimodal Interaction (ICMI)*, 2017, pp. 216–220.

[148] S. A. Israel, W. T. Scruggs, W. J. Worek, and J. M. Irvine, "Fusing face and ECG for personal identification," in *Proc. 32nd Appl. Imagery Pattern Recognit. Workshop*, Oct. 2003, pp. 226–231.

[149] O. Boumbarov, Y. Velchev, K. Tonchev, and I. Paliy, "Face and ECG based multi-modal biometric authentication," in *Advanced Biometric Technologies*, G. Chetty, Ed. Rijeka, Croatia: InTech, 2011.

[150] Y. N. Singh, S. K. Singh, and P. Gupta, "Fusion of electrocardiogram with unobtrusive biometrics: An efficient individual authentication system," *Pattern Recognit. Lett.*, vol. 33, no. 14, pp. 1932–1941, 2012.

[151] M. D. Bugdol and A. W. Mitas, "Multimodal biometric system combining ECG and sound signals," *Pattern Recognit. Lett.*, vol. 38, pp. 107–112, Mar. 2014.

[152] S. Pouryayevali, "ECG biometrics: New algorithm and multimodal biometric system," M.S. thesis, Univ. Toronto, Toronto, ON, Canada, 2015.

[153] S. Chakraborty, M. Mitra, and S. Pal, "Biometric analysis using fused feature set from side face texture and electrocardiogram," *IET Sci., Meas. Technol.*, vol. 11, no. 2, pp. 226–233, Mar. 2017.

[154] J. S. Arteaga-Falconi, H. Al Osman, and A. El Saddik, "ECG and fingerprint bimodal authentication," *Sustain. Cities Soc.*, vol. 40, pp. 274–283, Jul. 2018.

[155] L. M. Dinca and G. P. Hancke, "The fall of one, the rise of many: A survey on multi-biometric fusion methods," *IEEE Access*, vol. 5, pp. 6247–6289, 2017.

[156] M. Komeili, N. Armanfard, and D. Hatzinakos, "Liveness detection and automatic template updating using fusion of ECG and fingerprint," *IEEE Trans. Inf. Forensics Security*, vol. 13, no. 7, pp. 1810–1822, Jul. 2018.

[157] S. Nandi *et al.*, "Cellular automata based encrypted ECG-hash code generation: An application in inter human biometric authentication system," *Int. J. Comput. Netw. Inf. Secur.*, vol. 6, no. 11, pp. 1–12, 2014.

[158] F. Sufi, F. Han, I. Khalil, and J. Hu, "A chaos-based encryption technique to protect ECG packets for time critical telecardiology applications," *Secur. Commun. Netw.*, vol. 4, no. 5, pp. 515–524, 2011.

[159] J. Son, J. Park, H. Oh, M. Z. A. Bhuiyan, J. Hur, and K. Kang, "Privacy-preserving electrocardiogram monitoring for intelligent arrhythmia detection," *Sensors*, vol. 17, no. 6, p. 1360, 2017.

[160] K. Siddique, Z. Akhtar, and Y. Kim, "Biometrics vs passwords: A modern version of the tortoise and the hare," *Comput. Fraud Secur.*, vol. 2017, no. 1, pp. 13–17, 2017.

[161] N. K. Ratha, S. Chikkerur, J. H. Connell, and R. M. Bolle, "Generating cancelable fingerprint templates," *IEEE Trans. Pattern Anal. Mach. Intell.*, vol. 29, no. 4, pp. 561–572, Apr. 2007.

JOÃO RIBEIRO PINTO (S'15) received the M.Sc. degree in bioengineering from the University of Porto in 2017. His academic education was focused on a wide array of subjects, such as signal and image processing, machine learning, computer-aided diagnosis, sensors, electronics, and software engineering. He served as the Founding Member and the Vice-Chair of the Engineering in Medicine and Biology Society Chapter of the IEEE Student Branch at the University of Porto, Portugal, from 2015 to 2017.

He has addressed the topic of continuous biometric recognition in driving settings, using electrocardiographic signals acquired on the steering wheel, in collaboration with the CardioID Technologies LDA. He is currently a Research Fellow with the Department of Electrical and Computer Engineering, Faculdade de Engenharia da Universidade do Porto, and a Collaborator with the Visual Computing and Machine Intelligence Group, INESC TEC, where he is involved in signal processing and machine learning for pattern recognition applications, specifically for biometric identification using highly noisy electrocardiographic signals from off-the-person and seamless acquisition settings.

JAIME S. CARDOSO (SM'11) received the Licenciatura (five year) degree in electrical and computer engineering, the M.Sc. degree in mathematical engineering, and the Ph.D. degree in computer vision from the University of Porto in 1999, 2005, and 2006, respectively. He is currently an Associate Professor with Habilitation at the Faculty of Engineering, University of Porto (FEUP), where he has been teaching machine learning and computer vision in the doctoral programs and multiple courses for the graduate studies. He is also the Leader of the Information Processing and Pattern Recognition Area in the Telecommunications and Multimedia Unit, INESC TEC. He is the Co-Founder of ClusterMedia Labs, an IT company developing automatic solutions for semantic audio-visual analysis.

He has co-authored over 150 papers, over 50 of which in international journals. His research interests include computer vision, machine learning, and decision support systems. He was a recipient of numerous awards, including the Honorable Mention in the Exame Informática Award 2011, in software category, for the project Semantic PAC and the First Place in the ICDAR 2013 Music Scores Competition: Staff Removal (task: staff removal with local noise) 2013. The research results have been recognized both by the peers, with over 2000 citations to his publications and the advertisement in the mainstream media several times.

ANDRÉ LOURENÇO received the M.Sc. and Ph.D. degrees in electrical and computer engineering from the Instituto Superior Técnico (IST), Universidade de Lisboa, Portugal. He is the Co-Founder and the CEO of the CardioID Technologies LDA. He is also a Researcher with the Instituto de Telecomunicações, where he is collaborating in numerous research projects funded by the National Science Foundation. Since 2005, he has been an Invited Professor at the Electronics, Telecommunications and Computers Department, ISEL, where he is lecturing topics in information processing and programming and supervising over 30 final year projects and six master theses for post-graduate students.

Apart from technical qualities, he has key business and entrepreneurial experience under his belt. He gained invaluable experience at the startups the Albatroz Engineering (software and hardware development 2006) and the Lusospace (space technology development from 2003 to 2005), learning key project management and commercial and technical skills. He then went on to co-found and run Minalytics, a startup for software analytics and data mining (2013), before diving headfirst into co-founding and running CardioID Technologies LDA. His scientific contributions include 12 book chapters, 8 peer-reviewed papers, 77 international conference papers, and one patent (pending)—Device and Method for Continuous Biometric Recognition Based on Electrocardiographic Signals.