Electrocardiogram Pattern Recognition and Analysis Based on Artificial Neural Networks and Support Vector Machines: A Review

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ABSTRACT
Computer systems for Electrocardiogram (ECG) analysis support the clinician in tedious tasks (e.g., Holter ECG monitored in Intensive Care Units) or in prompt detection of dangerous events (e.g., ventricular fibrillation). Together with clinical applications (arrhythmia detection and heart rate variability analysis), ECG is currently being investigated in biometrics (human identification), an emerging area receiving increasing attention. Methodologies for clinical applications can have both differences and similarities with respect to biometrics. This paper reviews methods of ECG processing from a pattern recognition perspective. In particular, we focus on features commonly used for heartbeat classification. Considering the vast literature in the field and the limited space of this review, we dedicated a detailed discussion only to a few classifiers (Artificial Neural Networks and Support Vector Machines) because of their popularity; however, other techniques such as Hidden Markov Models and Kalman Filtering will be also mentioned.

Keywords: electrocardiogram, pattern recognition, ECG features, ECG classification, arrhythmia detection, heart rate variability analysis, human identification

1. INTRODUCTION

Electrocardiogram (ECG) is the vital sign most commonly used in the clinical environment. It provides an insight into the understanding of many cardiac disorders [1, 2]. It is nowadays employed in a number of applications ranging from heart disease diagnosis follow-up [1–7], home-care monitoring [8–9], telemedicine [10–11], arrhythmia detection [12–14], heart-rate monitoring [3–4, 15–21], detection of congestive heart failure [22–27], monitoring of patients in intensive care units (ICUs) [28–30], to monitoring under imaging [31–32]. Together with these classical clinical scenarios, non-clinical applications such as human identification are

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receiving increasing attention from the scientific community [33–56]. The feasibility of ECG as an identifier of individuals has been investigated [35]. Individual identification can greatly benefit from the body of knowledge available on ECG for clinical applications [44].

All the aforementioned applications are based on the analysis of morphological and temporal characteristics of ECG waveforms. A common task in these applications is the classification of heartbeats or heart rhythm. This issue has been typically addressed in the literature using pattern recognition methodologies. The aim of this review is to provide an overview of the many proposed pattern recognition approaches to ECG analysis.

Given the huge number of studies in these areas, this review is focused on two clinical applications, i.e., arrhythmias detection, heart rate variability (HRV) analysis, and a non-clinical application, i.e., individual identification. Furthermore, the review is restricted to two pattern recognition methodologies, i.e., artificial neural networks (ANN) and support vector machines (SVM). A search of the Scopus database (http://www.sciencedirect.com/) using keywords such as 'ecg' and 'arrhythmias', 'heart rate variability', 'human identification', reveals that the number of publications concerning arrhythmias detection and HRV analysis has drastically increased in the past decades, as shown in Figure 1a; human identification, instead, can be considered an emerging application. Similarly, a search using 'ecg', 'artificial neural networks', 'support vector machine', 'linear discriminant analysis', 'k-nearest-neighbours', 'hidden markov models' reveals that the most popular pattern recognition approaches to ECG analysis are ANN and SVM, as shown in Figure 1b.

The vast existing literature on automatic ECG classification can be grouped, for the specific aim of this review, to different categories depending on the applied features and on the classification methods. The large variety of features used to represent ECG can be grouped in terms of features used for (a) arrhythmia detection [6, 14, 57–67], (b) rhythm analysis [15, 22–27, 68–70], and (c) human identification [36–56]. Classification methods range from ANN [12, 59–60, 33–34], SVM [61–62, 64–65, 67–68, 70–72], linear discriminant analysis (LDA) [73–74], k-nearest-neighbour (k-NN) [75], mixture of experts (MOE) [76], Bayesian networks [77], Kalman Filtering (KF) [78–87], Hidden Markov Models (HMM) [88–93], and decision trees (DT) [24–25]. Without providing mathematical details, this review covers sufficient basic information and references for the novice reader to approach the topic.

The main challenges for an ECG-based computer-aided-diagnosis system are ECG pre-processing (noise and artifacts removal), QRS detection, heartbeat classification, rhythm analysis, and disease diagnosis. This review does not consider pre-processing and QRS detection as they are very well established areas; instead, it is focussed on pattern recognition methodologies applied to heartbeat classification which is still an area of intense research [61–76, 94–97]. This review does not consider pattern recognition approaches to ECG noise removal, QRS detection, and ECG segmentation (detection of the main wave-boundaries).

In the current review, PubMed, IEEE Xplore, Scopus and Google Scholar databases were searched using the following keywords in several combinations: 'electrocardiogram',

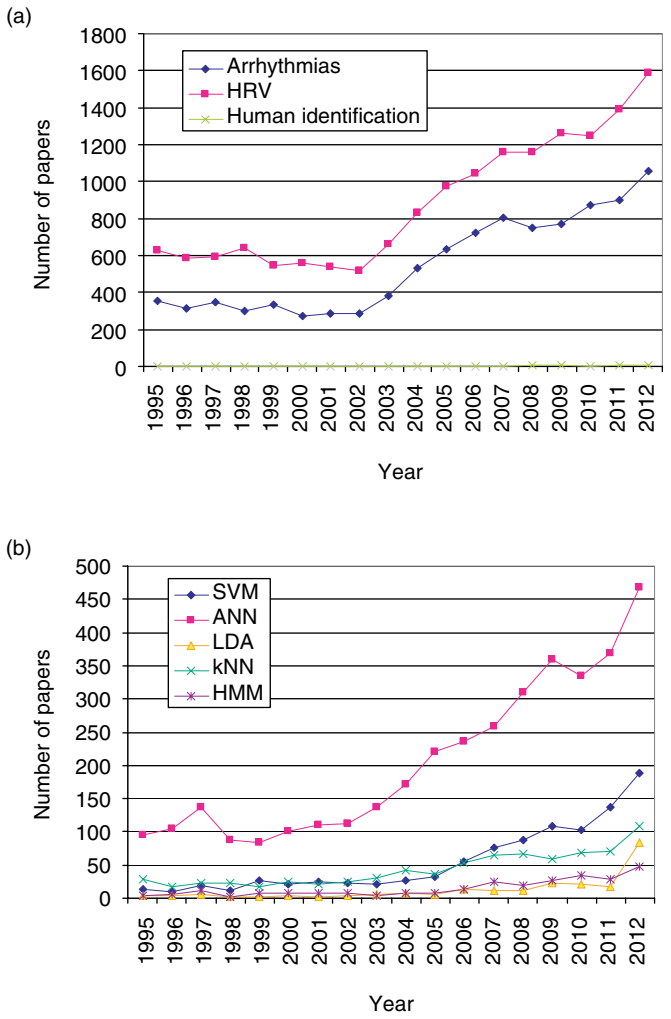

Figure 1. (a) Number of papers published per year in different ECG application areas. (b) Number of papers published per year concerning different pattern recognition methodologies applied to ECG analysis.

'support vector machine', 'artificial neural network', 'ECG', 'SVM, 'ANN', 'pattern recognition', 'arrhytmia detection', 'heart rate analysis', and 'human identification'. Papers were included in the manuscript on the basis of the ECG application and the classifier used. Papers older than about 15 years were excluded unless they reported meaningful information in the opinion of the authors. Recent papers were privileged in order to keep the review up-to-date. Many papers analysed more than one classifier and used more than

one type of features; we tried to group them as consistently as possible. A single paper could be included in more than one group.

The rest of the manuscript is organised as follows. Section 2 provides a minimal background on ECG with an emphasis on the characteristics useful for pattern recognition in ECG analysis. Section 3 is an informal presentation of the main concepts concerning pattern recognition. Section 4 reports, for completeness, some issues on ECG pre-processing. Sections 5, 6 ad 7 review the main features used for arrhythmias detection, rhythm analysis, and human identification. In section 8, some techniques for feature selection/transformation is discussed. Section 9 describes in detail the ANN, SVM and other approaches such as HMM and KF. Section 10 discusses some issues concerning ECG databases and validation. Finally, in section 11, we resume the performances of the several studies in order to compare all the features. Section 12 discusses the main unsettled issues and possible future trends in this field. Conclusions are drawn in section 13.

2. ECG BACKGROUND

ECG is one of the most studied and clinically used vital signs. ECG is the electrical activity of the heart recorded by means of electrodes on the body surface. Although intra-cardiac ECG is feasible (e.g., in pacemakers), this manuscript is focussed on surface ECG. The typical waves (P-Q-R-S-T complexes, as shown in Figure 2) of a normal ECG are originated by electrical phenomena in different parts of the heart and are synchronised by the electrical activity in the sinus node cells within the right atrium. These waves can be related to the regular conduction path within the heart (Figure 3); however, they might be present even in case of irregular conduction but with changed morphology and timing [1–2]. It should be noted that the shape of ECG waveforms may vary with the location of the electrodes; therefore, those locations have been standardised [98]. Cells within the sinus node are able to autonomously depolarise (P-wave) giving action potentials (i.e., variation of the membrane voltage) that excite the other electrically-active cells in the atrio-ventricular node and subsequently in the His

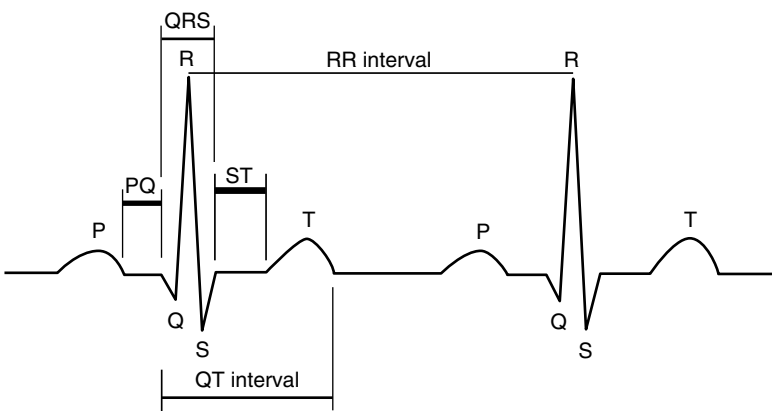

Figure 2. A typical ECG of a healthy human heart.

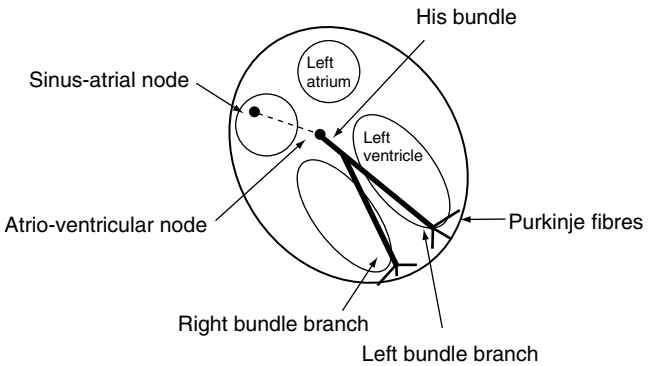

Figure 3. A schematic representation of the electrical paths within the heart. A detailed explanation of the electrical activity of the heart is given in the text.

bundle and Purkinje fibres (QRS complex), and finally stimulate the contraction of the myocardium. The T-wave is associated with ventricles repolarisation. The interval between two R complexes (heart rate) is controlled by the autonomous nervous system together with the several integrated sensory feedback systems, in order to adjust the sinus rhythm to body requirements.

Several diseases manifest peculiar ECG shapes which allow the diagnosis. For example, the elevation of the ST segment is associated to myocardial infarction (MI) [99–100]. Another important ECG characteristic is the QT interval which is the electrocardiographic manifestation of ventricular depolarisation and repolarisation. In normal heart, QT interval has been observed to shorten with the heart rate [101]; prolongation of the QT interval (e.g., induced by drugs) can be related to ventricular arrhythmia (torsades de pointes) [102], but the QT interval must be corrected for the heart rate in order to study this issue [103–104].

Many heart diseases can be traced back to abnormal sinus rhythm. In some cases, abnormal heartbeats occur infrequently and long observation (Holter ECG) is required to detect those events. Screening of long ECG tracks is a tedious task and can greatly benefit from computer aid. In other cases, it is required that the abnormal rhythm is automatically detected and acted upon (e.g., via defibrillation) as soon as possible, for example in intensive care units (ICU). Moreover, a reduced HRV has been reported in several cardiac and non cardiac diseases such as MI, diabetic neuropathy, cardiac failure [15]. Previous considerations explain the tremendous efforts made by the scientific community on automatic ECG analysis; as a result, computerised analysis of ECG plays a paramount role in clinical practice of cardiology today.

As already observed, together with these classical clinical applications, the emerging application of individual identification via ECG has shown promising results and has potential advantages over traditional biometric techniques such as fingerprint or iris recognition.

This review is focussed on the detection of heart arrhythmias, HRV analysis, and human identification by ECG processing. The former two applications have been intensively reported in the literature, while the third topic is relatively new with only one decade of studies.

2.1. Arrhythmias

Cardiac arrhythmias are defined as disturbances in the regularity of the normal sinus rhythm (NSR) due to problems in the electrical conduction system of the heart. Arrhythmias can be divided into two groups. One group of arrhythmias includes ventricular fibrillation (VF) and tachycardia (VT). They are both life-threatening conditions and require high–energy defibrillation (for VF) or low-energy cardioversion (for VT). It is paramount that automatic external defibrillator and implantable cardioverter defibrillator are able to distinguish reliably and accurately VT and VF from NSR and other non life-threatening arrhythmias [6, 13, 14, 57, 59, 60, 73, 105, 106].

The other group of arrhythmias includes non-life-threatening conditions that require therapy to prevent further diseases. Some arrhythmias appear infrequently and a long-term ECG recording (Holter) is needed to successfully diagnose them. Examples of arrhythmias include premature ventricular contraction (PVC, a heartbeat not originating from the sinus node, and easily recognisable on ECG because of different shape and timing from normal QRS complex), ventricular bigeminy (repeated sequence of one PVCs, followed by one normal beat), and ventricular couplets (two adjacent PVCs). Many arrhythmias manifest as a sequence of heartbeats with abnormal timings or morphology (e.g., PVC). Consequently, the first step in arrhythmias detection is heartbeat classification and rhythm analysis. Therefore, automatic ECG analysis is important in supporting the cardiologist in the detection of arrhythmias. Heartbeats have been classified by the Association for the Advancement of Medical Instrumentation (AAMI) into five classes [107]: class N contains normal and bundle branch beats; class S contains supra-ventricular ectopic beats (SVEBs); class V contains ventricular ectopic beats (VEBs); class F contains beats resulting form the fusion of normal and VEBs; and class Q contains unknown beats (see also the List of Abbreviations for abnormal beats and their acronyms used in the MIT database). Features for arrhythmia detection will be discussed in Section 5.

2.2. Heart Rate Variability

Another area of extensive study is the analysis of HRV [15]. HRV refers to the variations in RR intervals (see Figue 2) or, correspondingly, in the instantaneous heart rate (HR). The normal variability in HR is due to autonomic neural regulation of the heart and the circulatory system [15]. The balancing action of the sympathetic nervous system (SNS) and the parasympathetic nervous system (PNS) branches of the autonomic nervous system (ANS) controls the HR. Increased SNS or diminished PNS activity results in cardio-acceleration. Conversely, low SNS activity or high PNS activity causes cardio-deceleration. The degree of variability in the HR provides information about the functioning of the nervous control on the HR and heart's ability to respond.

Depressed HRV, i.e., a low variability of heart rate, can indicate an impairment of ANS and can be used as a predictor of risk after acute MI and as a warning sign of diabetic neuropathy [15]. Other studies have used HRV as an indicator of coronary heart disease (CHD) and dilated cardiomyopathy (DCM) [3]. A large body of studies hasused HRV for congestive heart failure (CHF) assessment [24–27]. CHF is a condition which typically develops after heart attack, long-term high blood pressure or abnormality of the heart valves [100]. In CHF. the heart muscle weakens and needs to work harder to pump the blood in the body. Early detection of CHF in elderly people could be important in reducing clinical costs due to complications of clinical conditions [24–25]. Moreover, HRV can be useful in other areas such as the study of patients with obstructive sleep apnoea syndrome (OSAS) [16–17], increased risk of developing hypertension [18-19], and other pathological conditions [20–21].

In view of the importance of HRV analysis, in 1996, the Task Force of the ESC/NASPE published guidelines for HRV analysis proposing several time and frequency parameters based on short-term (5-min) and long-term (24–h) HRV data [15]. Time-domain parameters are simple statistical indices to be calculated from both long- and short-term raw HRV data. Time-frequency parameters involve more complex calculations and analysis. They will be both briefly explained in Section 6.

2.3. Human Identification

As regards ECG for human identification, the last application discussed in this review, a few pioneering studies [35–36] suggested that the electrical paths within the heart (see Figure 3) and, consequently, the temporal relationships and shapes of the different waves (see Figure 2), should be unique for each individual, at least within a restricted population, and therefore ECG could be a powerful tool for human identification/verification. This is an emerging area of research where pattern recognition methodologies play a leadership role and that can tremendously benefit from the immense knowledge accumulated on the ECG features in other applications. Features for these applications will be covered in Section 7.

3. PATTERN RECOGNITION APPROACHES

As many textbooks are available on this subject [108–111], only a brief description of the main concepts is presented below to facilitate proper understanding of the present review.

The aim of pattern recognition methods is to assign each individual heartbeat to its specific class (e.g., VEB) or to detect a patient's pathology (e.g., CHD, MI) using the information contained in features that can be measured (for example, age, gender, standard deviation of R-R intervals, etc.). The implicit hypothesis is that the features of individuals belonging to the same class have similar values, therefore occupying a region in the multidimensional feature space separated from the other classes (see Figure 4).

It is commonly recognised that pattern recognition methods are based on three main concepts: feature extraction/selection/transformation, classification and training. While classification and training can be considered well defined areas and many algorithms

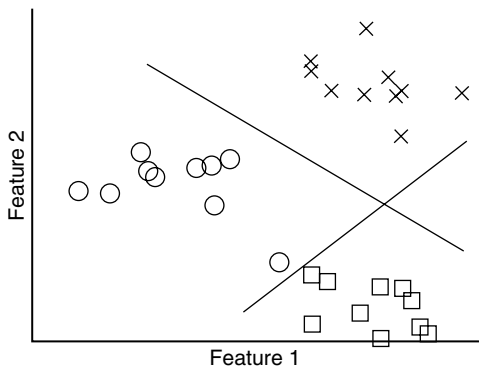

Figure 4. Illustration of pattern recognition hypothesis. Each individual is represented by a point in the feature space. Individuals forming different classes (represented by circles, crosses, or squares) occupy separate regions in the feature space.

have been proposed for selection/transformation of features, extraction of features more appropriate for a specific field of research cannot be given a general formulation independent of the specific application area.

3.1. Feature Extraction/Selection/Transformation

In the literature, the terms "feature extraction" and "feature selection" are not consistently defined. In this paper, we will use the term "feature extraction" to indicate a generic procedure for computing a set of features from a given input signal for a given application. In general, there are no universal approaches to this issue, and for each application, one has to individuate the most suitable processing techniques. On the other hand, we will use the term "feature selection" to indicate a procedure for selecting a subset of non-redundant features among the original or transformed ones (mainly for efficiency purposes). The term "feature transformation" indicates a procedure for transforming a set of features in a linear/non-linear manner (e.g., Principal Component Analysis, Linear Discriminant Analysis).

One of the main disadvantages of feature transformation is that the physiological meaning of the original feature is typically lost in the transformation. Existing feature selection/transformation approaches typically fall into one of two categories: wrapper and filter. Wrappers include a specific classifier as a part of their performance evaluation, while filters employ evaluation criteria independent of the classifier. Wrappers tend to give superior performance as they find features better suited for the predetermined classifier; however, they are computationally expensive. Instead, filters are widely used due to their computational efficiency when the number of features is very large.

Clearly, the more 'discriminative power' have the chosen features, the more accurate will be the whole system.

3.2. Classification

As a general rule, a classifier divides the feature space into non-overlapping regions corresponding to different classes. The algorithms can be based on a variety of approaches including Bayesian classifiers, neural networks, SVMs, K-nearest-neighbour, fuzzy logic, etc. ANN and SVM will be discussed in section 8.

An important classification strategy is the mixture of classifiers (MOC) or mixture of experts (MOE) scheme in which it is possible to take advantage of the performance of various classifiers based on different approaches or on different features. There are generally two approaches to MOC: classifier selection and classifier fusion. In classifier selection, each classifier is an expert in some area of the feature space. Therefore, it has a highest weight if the feature vector is in the vicinity of that area. In classifier fusion, each classifier is trained over the whole feature space. The combination is obtained with several methods such as majority voting, maximum posterior probabilities, weighted outputs, etc.

MOC may have some advantages over a single classifier. First, a set of classifiers with similar training performance may have different generalisation performances. Therefore, combining the decisions of several classifiers can reduce the risk of selection of a poor classifier. Second, an MOC can manage large amount of data because each classifier can be trained on a different portion of data. Third, an MOC can learn very complex decision boundaries. For example, a decision based on majority voting of a sufficient number of linear classifier can learn a complex non-linear boundary. Fourth, MOC can manage heterogeneous features (data fusion) where each classifier is trained on a specific type of features.

In order for the MOC to operate well, it is important that the single classifiers be 'diverse'; i.e., they have decision boundaries different from each other. This can be accomplished using different training sets, typically obtained with random re-sampling of the available training set, or using different training parameters. Moreover, an MOC may be constituted by classifiers of different types (ANN, SVM, etc.) or may use heterogeneous features.

3.3. Training and Validation

After the features have been extracted/selected/transformed from the original ones, the classifier should be designed. Typically, the available data set is divided into a training set and a test set. The design of the classifier is carried out using the training set; the latter is supposed to be composed of data, with the typical characteristics of the population that is under investigation (e.g., the proportion of healthy and ill subjects should be well represented within the training set). Two approaches can be taken for classifier design: supervised and unsupervised learnings. In supervised learning, each training element has a label indicating the correct class. The classifier thus 'learns' how to recognise the class comparing the output with the correct label. In the unsupervised approach, the classifier has no information about the correct class of each individual, and it needs to be learnt in a data-driven way (clustering).

Subsequently, the generalisation properties of the classifier (i.e., its capability to correctly classify an object it has never seen before) must be validated against a test set

of data which is different from the training set. To this end, cross-validation is an efficient technique. To evaluate the performance of the classifier and its sensitivity to the training and test sets, two methods are commonly employed: (a) the leave-one-out method is used if the data set is small, where each element is removed one by one from the data set, and the classifier is designed on the remaining elements and is tested on the removed one); (b) the 10-fold technique is used for larger databases, where the data set is divided into 10 subsets and a procedure similar to leave-one-out is applied considering one subset at a time. Cross-validation can facilitate optimal design of the classifier parameters in terms of, for example, the number of neurons in a neural network yielding the best performances. In this case, further validation is required to assess the generalisation performances.

For evaluation purposes, in a supervised *N*-class problem, a confusion matrix is often constructed. Element c_{ij} of the confusion matrix contains the number of individuals belonging to class *i,* that were actually assigned to class *j*. The confusion matrix gives all information regarding the performance of the classifier; however, some synthetic indices have been developed in the case of the two-class problem (i.e., detection or non-detection of an event), including the numbers of True Positives (TP, real events detected by the classifier), False Negatives (FN, real events not detected), False Positives (FP, incorrect detection of not occurred events), and True Negatives (TN, correct detection of absence of event). For each class *i,* we can define the TP rate for a two-class problem as following:

$$TPR_i = \frac{c_{ii}}{\sum_s c_{is}} = \frac{TP}{TP + FN} \tag{1}$$

and the FP rate,

$$FPR_i = \frac{\sum_{j \neq i} c_{ji}}{\sum_{r \neq i} \sum_s c_{rs}} \tag{2}$$

In the AAMI guidelines for reporting performance of algorithms for heartbeat recognition [107], it is recognized that in the case of wave detection on ECG, TN are not well defined and the proposed metrics are: Sensitivity = Se = TP/(TP + FN) and Positive Predictivity = P+ = TP/(TP + FP). Another performance metric is the error rate (ER) defined as the ratio of the number of misclassified beats to the total number of beats.

4. ECG PRE-PROCESSING

ECG pre-processing for noise removal and QRS detection is a well established area. A comprehensive review is outside the scope of the present manuscript. However, for completeness, the main ideas are briefly reviewed here. Moreover, although concepts

from pattern recognition have been proposed for pre-processing and QRS detection [112–115], they are not covered in this review due to space limitation.

ECG pre-processing typically involves a notch filter for removal of the power-line interference, a low-pass filter to remove high-frequency noise due to muscles activity, and a high-pass filter for removal of low-frequency drift mainly due to baseline oscillation (breath, etc.) [116–120]. Recently, more sophisticated techniques, such as Kalman Filtering and Hilbert-Huang Transform (HHT), have been proposed for denoising [78–87, 121, 124].

QRS detection occurs at the end of the pre-processing phase. QRS detection relies on the very peculiar shape of the QRS peak. It is the most important phase in ECG heartbeat recognition and in HRV analysis (Figure 2). Accurate R-peak detection and location is essential also for reconstructing the RR intervals series which is fundamental for HRV analysis [15]. Many QRS detection algorithms have been proposed [116–120]; one of the most classical was proposed by Pan and Tompkins [119]. A good review of QRS detection algorithms is available in [125].

Another important issue is the location of the waveform boundaries (i.e., the onsets and offsets of P-Q-R-S-T waves), also known as heartbeat segmentation which has been addressed with traditional methods (e.g., use of derivatives) or, more recently, with sophisticated techniques (e.g., Hidden Markov Models) [91, 120, 126–128].

A schematic diagram for an ECG classification system is shown in Figure 5. After ECG pre-processing (denoising and QRS detection), a typical system includes a stage for heartbeat segmentation and/or RR interval series extraction. Moreover, stages for the computation of several features must be present. The classification stage might be based on a single classifier or a mixture of classifiers.

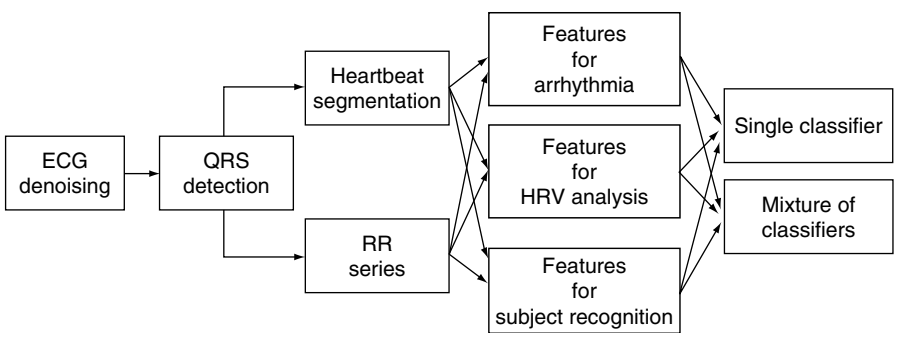

Figure 5. A typical classification scheme for ECG analysis. After ECG denoising and QRS detection, a typical algorithm includes heartbeat segmentation and RR interval series extraction, computation of various features (for arrhythmia, HRV, subject recognition), and a classification stage (typically based on a single classifier or on a mixture of classifiers).

5. FEATURES FOR ARRHYTHMIA DETECTION

Clinical observations revealed that arrhythmias involve a modification of the morphology of abnormal heartbeats with respect to normal ones (e.g., PVC). Morphological descriptors can therefore be used for effective detection of arrhythmias. Morphological information can be included in several types of feature, and we have grouped them into the following categories: time domain, frequency domain, wavelet-based, parametric modelling approaches, and multilead features. Table 1 summarises papers using this type of features. Morphological features are often used in combination with temporal information (RR interval, etc.) discussed in section 6.

5.1. Features in Time Domain

A large collection of QRS morphological descriptors have been proposed, as shown in Figure 6 [95]: width (time-interval between the onset and offset of the QRS), amplitude (maximal amplitudes of the positive and negative peak), areas (areas of the positive and negative peaks, total area), slopes (slopes of the QRS onset and offset), and vector-

Table 1. Features and classifiers used for arrhythmia detection

Reference	Arrhythmia	Features	Classifier
Hadhoud *et al*. [6]	VT, VF	Time-domain	ANN
Shyu *et al*. [12]	PVC	Wavelet	FNN
Ge *et al*. [13]	APC, PVC, SVT, VT, VF	Time-domain	GLM-based
Zhang *et al*. [14]	VT, VF	Time-domain	Threshold
Tsipouras *et al*. [57]	PVC, VT, VF, BII	Time-domain	Set of rules
De Chazal *et al*. [58]	VEB, SVEB, fusion	Time-domain	LDA
Minami *et al*. [59]	VT, VF	Frequency domain	ANN
Clayton *et al*. [60]	VT, VF	Frequency domain	ANN
Osowski *et al*. [61]	MIT-BIH arrhythmia	Parametric modelling	SVM
Mohebbi *et al*. [63]	AF	Time and frequency domain	SVM
Melgani *et al*. [64]	MIT-BIH arrhythmia	Time domain	SVM
Kostka *et al*. [66]	AF	Wavelet	SVM
Jankowski *et al*. [67]	VT	Time domain	SVM
Chua *et al*. [71]	PVC, CHB, SSS, CHF	Parametric modelling	SVM
Barquero-Perez *et al*. [129]	AF, VF	Frequency domain	LDA
Chen *et al*. [106]	VT, VF, SVT	Parametric modelling	LDA
Balasundaram *et al*. [73]	VT, VF	Wavelet	LDA
Herrero *et al*. [130]	PVC, LBBB, RBBB	Wavelet	ANN
Christov *et al*. [95]	PVC, LBBB, RBBB	Time domain, wavelet	K-NN
Owis *et al*. [105]	VT, VF	Time domain	K-NN
Martinez and Olmo [131]	TWA	Frequency domain	Threshold
Koide *et al*. [132]	AF	Multilead	Threshold
Chen *et al*. [133]	VF	Frequency domain	Threshold
Everett *et al*. [134]	AF	Frequency domain	Threshold

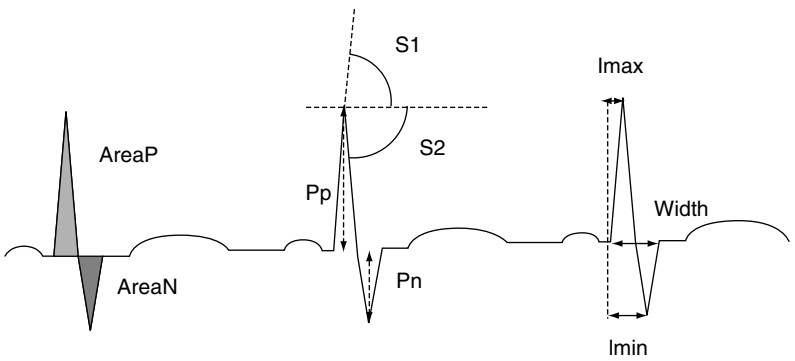

Figure 6. Morphological features proposed by Christov *et al*. [95]. Areas under positive and negative peaks (AreaP and AreaN, respectively), slope of the QRS onset to maximal peak (S1) and from the first to the second peak (S2), amplitude of the maximal positive peak (Pp) and of the maximal negative peak (Pn), width of the QRS complex, time interval between the onset and the positive peak (Imax), and interval between the onset and the negative peak (Imin).

cardiogram descriptors which require multi-lead fusion. Vector-cardiography is a reconstruction of the time-course of the cardiac current dipole vector within the heart. The various leads can be considered as projections of this vector.

Other authors [58] have extracted a predefined number of evenly spaced samples directly from the QRS and the T-wave. Another approach was not to fix a priori the number of samples but the durations of the QRS complex and the T-wave. The wave amplitude may or may not be normalised.

These types of features seem to be well suited for detection of PVCs and other morphological variations. However, they are affected by the sampling frequency and by the reliability of fiducial points detection (waves onset and offset).

5.2. Features in Frequency Domain

Because of their particular characteristics, the detection of certain ventricular arrhythmias such as VF and VT and supraventricular arrhythmias such as AF can benefit from features derived in the frequency domain.

In particular, as ventricular fibrillation appears on the ECG as an irregular, undulating waveform (Figure 7), often preceded by ventricular tachycardia, a typical approach involves Dominant Frequency Analysis (DFA) [133] whose aim is to characterize the ECG periodicity using the most important frequency contained in a non-purely periodic rhythm.

A similar approach has been taken for supraventricular arrhythmia such as atrial fibrillation (AF) detection [135]. Another possible approach is Fourier Organisation Analysis (FOA) [129,134] which evaluates the harmonic distribution of the signal energy that remains unexplained by the periodicity mentioned above.

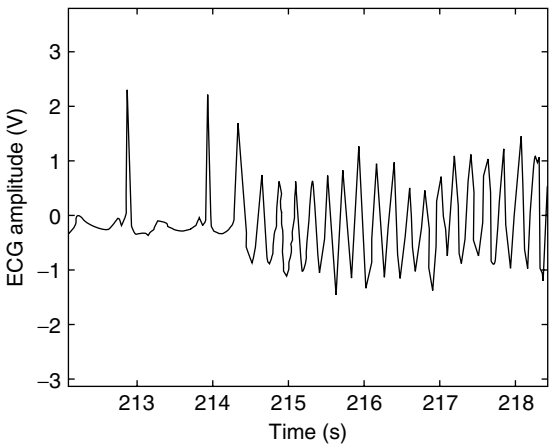

Figure 7. Example of an ECG record including a transition to ventricular tachycardia (subject cu01, holter ECG, from the "CU Ventricular Tachyarrhythmia" database, cudb available on physionet.org [136, 137]).

Another possibility is to use higher order spectra [71,138]. The Bispectrum is the Fourier Transform of the third order correlation of the signal which indicates cross correlation between frequency components in a two-dimensional (2-D) frequency plot. In the equation below, B(f1, f2) is the bispectrum, f1 and f2 are two generic frequencies, X(f) and X^*(f) are the Fourier transform of the signal of interest and its conjugate, respectively:

$$B(f1, f2) = E[X(f1)X(f2)X^*(f1 + f2)] \quad (3)$$

The Bispectrum gives information about the phase coupling between the frequency components at f1, f2, and f1 + f2. In general, higher order spectra (HOS) are spectral representations of moments and cumulants and can be defined for deterministic signals and random processes.

Features for arrhythmia detection in the frequency domain might include T wave alternans (TWA). TWA is a phenomenon characterizing the repetition of changes in shape and amplitude of the T wave, appearing with regularity [132]. It is associated to spatiotemporal heterogeneity of repolarisation. Higher levels of TWA indicate a greater risk of arrhythmias. Heart rate can affect TWA; even in a normal heart, very high heart rate (> 170 bpm) can induce TWA. Myocardial ischemia can increase TWA amplitude. TWA produces microvolt variations and cannot easily be detected by naked eye. Many methods have been proposed for TWA assessment; however, in commercial applications, TWA is widely assessed using a spectral approach [131]. ECG cycles are aligned to their QRS, and the amplitude of the T-wave in 128 predefined points (t) is registered for each cycle. The series of amplitudes for each t is Fourier transformed to give 128 spectra. All the spectra are then averaged. The power of this spectrum in the region around 0.5 cycles/beat can be used to decide if TWA is present.

5.3. Wavelet-Based Features

It is well known that Fourier analysis results in a poor representation of signals that are well localized in time, such as QRS. One simple approach to overcome this problem is to use a time-frequency approach, such as in Short Time Fourier Transform (STFT). The STFT of a signal x(t) is given below:

$$STFTx(t,f) = \int x(\tau)w(t-\tau)e^{-j2\pi f\tau}d\tau \tag{4}$$

where w(t) is an opportune window. However, difficulties still remain in selecting the optimal window. Moreover, a trade-off exists between the frequency and time-resolution.

Wavelet analysis could overcome these difficulties. This method has been applied in [73] to discriminate between VF and VT. In Continuous Wavelet Transform (CWT), a signal x(t) is expressed as a combination of dilated and translated versions of a mother wavelet ψ which is a small waveform satisfying certain properties. The coefficients of this combination are given by:

$$C_x(a,b) = \int_{-\infty}^{\infty} x(t)\psi^*\left(\frac{t-b}{a}\right)dt \tag{5}$$

In this way, it is possible to examine the energy pattern of a signal over time (b factor) and scale (a factor). Wavelet theory is extensively studied in [139]. The scale-time (scalograms) wavelet representations have been analysed [73] and it has been noticed that the energy distribution had different patterns for three groups (VT, VF, and VT partially overlapping VF). Therefore, features such as 'number of islands' (confined areas of energy distributed over time and scale) and average time-width were computed and passed to a Linear Discriminant Analysis.

Wavelet theory has been also used in detection of other types of arrhythmias [12,130]. In particular, the approach involved the Wavelet Matching Pursuit algorithm [140] uses a wavelet packet dictionary for describing ECG, where the ECG heart beat is iteratively approximated with orthogonal projections onto the waveforms of the dictionary. A small number (10) of waveforms was found to be sufficient for acceptable accuracy [130]. The wavelets allowed building the signatures of different types of heartbeat to be classified [130]. The features for each new heartbeat can be easily obtained in real time.

5.4. Parametric Modelling Approaches

Harmonic analysis can be improved if an autoregressive (AR) approach is used [106]. Essentially, the signal is modelled according to the Prony approach, and the energy contained in the modes (dubbed energy fractional factor, EFF) is analysed. It is expected that supraventricular tachycardia (SVT) shows lower EFF than VF/VT. Moreover, the predominant frequency (PF, the frequency carrying the maximum energy) is used to separate VT from VF. Simple linear discriminant analysis (LDA, see

section 9.3.1) can be performed to separate SVT from VT and VF in a two-stage classifier.

AR modelling was performed on ECG data from normal sinus rhythm and from various arrhythmias [13]. The AR coefficients were computed using the Burg's algorithm, and classified using a generalized linear model (GLM) based algorithm, evaluating the Euclidean distance between AR coefficients of different classes. Results showed that four AR coefficients were sufficient for modelling the ECG signals.

QRS has been expanded using Hermite polynomials as following [141]

$$x(t) = \sum c_n \frac{e^{-t^2/2\sigma^2}}{\sqrt{\sigma 2^n n! \sqrt{\pi}}} H_n(t/\sigma) \tag{6}$$

The coefficients of the expansion have been used as features for heartbeat recognition.

5.5. Multilead Features

In general, multi-leads ECG can be processed using certain feature transformation/selection in order to concentrate the information in a subset of features (see section 8). However, differences among leads can be used to detect some types of arrhythmias. In particular, P-wave dispersion is defined as the difference between the longest and the shortest P wave duration recorded by different surface ECG leads. Several studies showed that P wave dispersion has a predictive value for AF in patients without apparent heart disease, in hypertensive patients with coronary artery disease, and patients undergoing coronary artery bypass surgery [142, 143].

6. FEATURES FOR HEART RATE VARIABILITY ANALYSIS

Features for rhythm analysis are traditionally subdivided into time-domain, frequency-domain and nonlinear dynamics features. A comprehensive review is given in [15]. Table 2 lists selected papers using such features. Techniques for obtaining features in the time-frequency domain and wavelet domain have been described in sections 5.2 and 5.3; modelling approaches have been described in section 5.4.

6.1. Time Domain Features

Features in time domain are mainly statistics on the NN interval series (normal-to-normal beats; intervals between adjacent QRS complexes resulting from sinus depolarisation) [15]. They are summarised in table 3. For the purpose of comparison, the signal duration to compute the statistics has been standardised as 5 minutes (short-term recordings) and 24-hours (long-term recordings).

One of the first studies that examined the discriminative power of HRV features for CHF patients analysed the discriminative power of 9 commonly used long-term HRV measures, in conjunction with a Bayesian classifier, and identified the one that indicated the cardiac condition with higher sensitivity and specificity [26]. The results revealed that the standard deviation of all normal-to-normal beat intervals (SDNN) had

Table 2. Features and classifiers used for heart rate variability analysis

Reference	Disease	Features	Classifier
Yu *et al*. [22]	CHF	Time, frequency, non-linear	SVM
Hossen *et al*. [23]	CHF	Frequency	K-NN
Melillo *et al*. [24]	CHF	Time, frequency	CART
Pecchia *et al*. [25]	CHF	Time, frequency	CART
Asyali *et al*. [26]	CHF	Time, frequency	Bayesian
Isler *et al*. [27]	CHF	Wavelet	K-NN
Kampouraki *et al*. [68]	Coronary artery disease	Time, wavelet, modelling	SVM
Khandoker *et al*. [69, 70]	Obstructive sleep apnea	wavelet, respiration signal	SVM
Schuman *et al*. [3]	Coronary heart disease	Time, frequency	LDA
Malarvili *et al*. [4]	Seizure detection	Time-frequency features	K-NN

Table 3. Time-domain features typically used in HRV studies [10, 31]

Description	Acronym (unit)
Mean of all NN intervals	MEAN (ms)
Standard deviation of all NN intervals	SDNN (ms)
Standard deviation of the 5-min means	SDANN (ms)
Average of the 5-min standard deviations	ASDNN (ms)
Number of adjacent NN intervals differing by more than +50 ms	NN50-1
Number of adjacent NN interval differing by more than –50 ms	NN50-2
Sum of NN50-1 and NN50-2 as a percentage of all intervals	pNN50 (%)
Root mean square of successive differences	RMSSD (ms)
Standard deviation of differences between adjacent NN intervals	SDSD (ms)

the highest class discrimination power (measured using LDA on the MTI-BIH database).

6.2. Frequency Domain Features

Frequency domain distribution of RR intervals are typically measured using power in the low (PLF) (0.04–0.15 Hz) and high (PHF) (0.15–0.4 Hz) frequency bands [15]. In fact, they are believed to be closely related to the physiological activities of the autonomic nervous system. Additionally, the PHF and PLF are typically normalized to the total power, and the resulting parameters are denoted as NLF and NHF, respectively. Another measure of interest is the ratio of PHF and PLF [15]. For the computation of spectral components, guidelines [15] suggest to use autoregressive modelling with a number of parameters in the range of 8–20. An appropriate test, such as Akaike Information Criterion, should be applied to validate the fitting model.

Power spectral density (PSD) in different sub-bands has been also used [23]. It can be obtained by filtering the RR series with complementary low-pass and high-pass filters dividing the given frequency range into two bands. Successively, each filtered components is further filtered by two complementary filters as before. The process is repeated for a prefixed number of times. The power in each of the sub-bands obtained is measured.

6.3. Features Based on Non-Linear Dynamics

A common non-linear approach is the Poincare plot [27]. A technique adopted from nonlinear dynamics, it is a graph of each RR interval plotted against the previous or the next interval (see Figure 8). The plot provides summary information as well as detailed beat-to-beat information. Typically, an ellipse could be generated to fit the data points. The width (SD1) and length (SD2) of the ellipse can then be calculated, and it is possible to show that they are related to time-domain features, namely, (1) the standard deviation of differences between adjacent RR intervals (SDSD), and (2) the mean of the standard deviation of all RR intervals (SDRR).

7. FEATURES FOR HUMAN IDENTIFICATION

An emerging application of pattern recognition in ECG analysis concerns individual identification/authentication [36–56]. Identification is the process whereby an automatic system recognizes a valid user's identity. A user identification code is a non-confidential auditable representation of a user (e.g., a username). Authentication is the

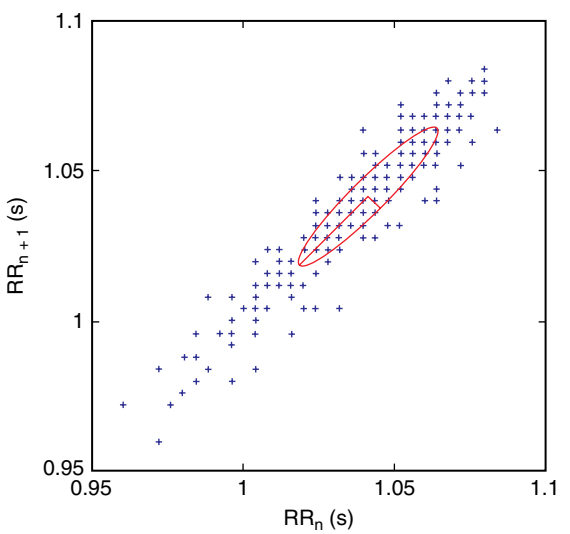

Figure 8. An example of a Poincare plot obtained from the first 5 minutes of the recording f1o01 from the Fantasia database [144]. The fitting ellipse and its axis are superimposed.

Table 4. Features used in human identification by ECG

Reference	Features	Classifier
Biel *et al*. [95]	Timing	PCA based
Israel *et al*. [97]	Timing	LDA
Wubbeler *et al*. [99]	Heart vector	Euclidean distance
Chan *et al*. [101]	Wavelet distance	Minimum distance
Irvine *et al*. [102]	PCA	Minimum distance
Wang *et al*. [104]	DCT, PCA, LDA	K-NN
Agrafioti *et al*. [105]	Autocorrelation, PCA, LDA	Euclidean distance
Chuang-Chien *et al*. [106]	Wavelet coefficients	Euclidean distance
Fang *et al*. [107]	Dissimilarity in phase space	Minimum distance
Irvine *et al*. [108]	Timing	Sequential statistics
Lee *et al*. [116]	Vectorcardiogram	SVM
Singh *et al*. [117]	Timing + amplitude	Euclidean distance
Safie *et al*. [118]	Timing	Euclidean distance

process of verifying the claimed identity of a user (e.g., the ECG). After the pioneering work by Biel *et al*. [35], a vast literature has accumulated on this subject. Human identification/authentication by ECG can contribute to several tasks including securing wireless body area sensor networks for telemedicine [37, 39, 48]. Table 4 summarizes the features used in such application. PCA is discussed in section 8, and classifiers in section 9.

The physiological basis for human identification using ECG stems from the inter-individual-differences among the electrical paths within the heart. Moreover, the timings of the P and QRS and T waves can be a discriminative feature. Many studies have attempted human identification using features derived from the shape of the ECG (such as height and duration of QRS, height of P-wave and T-wave, derivatives, etc.) [36], while other studies have used timing information (QT-interval, PR-interval, etc.) (see Figure 9) [39]. Wubbeler *et al*. [38] used the heart vector derived from the three main leads. Wang *et al*. [43] used an approach based on Discrete Cosine Transform (DCT).

Agrafioti *et al*. [44] tackled an important problem: human identification under cardiac irregularity conditions. They discarded premature ventricular contraction (PVC) and atrial premature contraction (APC) and used only heartbeats meeting specific criteria.

Other strategies include new types of transformations such as the Pulse Active Ratio through superposition of the ECG to a periodic triangular wave [145]. One study [55] attempted to use the vector-cardiogram which requires two leads; another study [42] used chaotic characterisation of the ECG. A few works recognised that performances of the ECG identification only are not enough and they tried to merge face, speech, and ECG recognition to achieve very high performances [56].

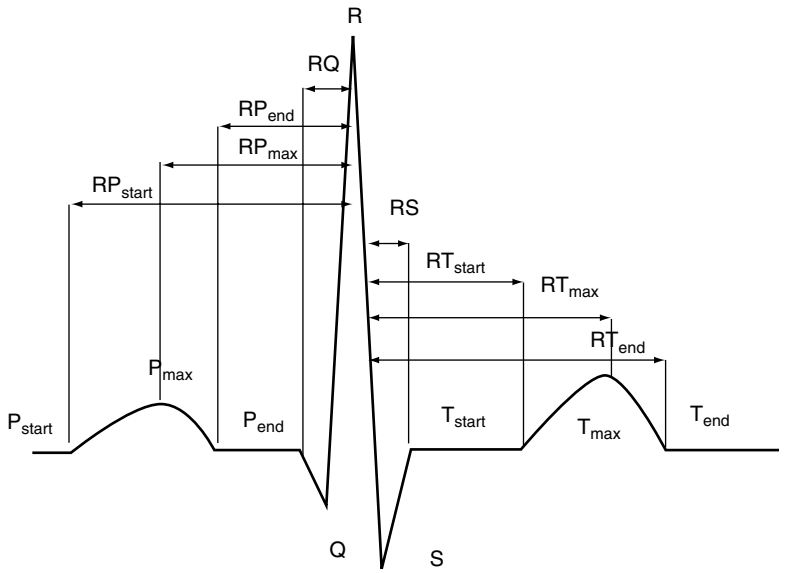

Figure 9. Typical timing information used in human identification by ECG analysis.

One main difference among these papers is the use of single lead or multilead ECG, an important issue for practical implementation of secure identification. Another issue is that the performance of the classification is very variable and a simple comparison is not possible because not all the studies used the same database. This is a delicate issue because differences in sampling interval can affect the performance. Moreover, not all studies validated the generalisation capabilities on a validation-set different from the data-set used for cross-validation (see section 3.3). However, this is still an area of intense research and there is still large variability of performance.

Another important difference among studies is the sampling frequency. Typically, high frequency (1000 Hz) is used in studies performed on private databases. High frequency seems to be suitable to detect subtle differences among subjects. Higher sampling frequency allows the use of high frequency components of ECG [33]. After 1000 Hz, the ECG filtered using a band-pass filter centred on the 40–300 Hz band.

8. FEATURE TRANSFORMATION/SELECTION

Many methods exist for feature transformation/selection. This section focuses on two commonly used approaches: principal components analysis (PCA) and independent component analysis (ICA). They are both linear techniques; the former is based on second order statistics, while the latter on higher order statistics.

Principal components analysis (PCA) is similar to Fourier analysis in that the signal is described in terms of a predefined orthogonal basis. Instead of complex exponentials,

PCA uses a set of functions driven by the specific data at hand (it is therefore strictly related to the Karhunen-Loeve Transform, KLT). The resulting components are uncorrelated (orthogonal) to each other. PCA theory is extensively discussed in [146]. PCA can be used to perform inter-beat, intra-beat, or inter-lead analysis [148]. Considering a recording including *M* cardiac cycles, all heartbeats are aligned with respect to a fiducial point (typically QRS), and segments of equal duration (e.g., *N* samples) are extracted. Let x(*n*) be the ECG at time *n*, and $\mathbf{x}_i = [x(1) \ \ldots \ x(N)]^T$ the vector containing the values of the *i*-th segment; all the *M* segments can be organised in a data-matrix $\mathbf{X} = [\mathbf{x}_1 \ \ldots \ \mathbf{x}_M]$. Computing eigenvectors and eigenvalues of the correlation matrix $\mathbf{R} = \mathbf{X}\,\mathbf{X}^T / M$, an intra-beat correlation analysis is performed; this analysis is similar to the Karhunen-Loeve expansion, and the eigenvectors of **R** include the orthogonal basis functions for reconstruction of the heartbeats. Instead, using the matrix $\mathbf{R}_2 = \mathbf{X}^T\,\mathbf{X} / N$, inter-beat analysis can be performed. In this case, the eigenvectors of $\mathbf{R}_2$ are the weights of the single heartbeats in order to obtain the principal components. If multiple leads are available, then PCA-KLT can be used to concentrate the information into fewer leads. PC analysis has been applied to the study of ischemia-induced changes in ST segment, QT interval dispersion, beat-to-beat alternations in T-wave morphology, and atrial fibrillation [131,148],

Independent Component Analysis (ICA) is a similar but more general form of PCA in which the components are independent rather than uncorrelated. For ICA, higher order statistics has to be used. The basic idea of ICA is that the matrix data **X** can be obtained from independent and unknown sources **S** via an unknown mixing matrix M with $\mathbf{X} = \mathbf{MS}$. The most popular algorithms for ICA computation are based on non-gaussianity of the sources, that can be measured via kurtosis or neg-entropy, both being zero for Gaussian variables. Extensive treatment of ICA is presented in [147].

9. BEAT AND ARRHYTHMIA CLASSIFIERS

The present review is focussed on the most commonly used classifiers, including ANN and SVM. In addition to a brief description of these classifiers presented in this section, we refer the readers to [108–111] for more details. Moreover, we briefly describe a few other approaches to classification for completeness.

9.1. Neural Networks

ANN have been used alone or in combination with other classifiers for ECG classification [12, 33, 34, 59, 60, 74, 149], as summarized in Table 5.

The *i*-th neuron in a net ($i = 1,\ldots, N$) is an object able to compute the dot product between a feature vector, $\mathbf{x} = [x_1,\ldots,x_P]^T$, and a set of weights, $\mathbf{w}_i = [w_{i1},\ldots,w_{iP}]^T$, and to apply a function φ(.)for the result $y_i = \varphi(\mathbf{w}_i^T\mathbf{x})$. If φ(.) is a non-linear function, then the neuron is a non-linear object (Figure 10a).

A single neuron (also called perceptron) can be used to draw a hyperplane (orthogonal to the weight vector) in the feature space, therefore solving linear problems involving two-classes. In order to solve linear problems for three or more classes, Single-Layer-Perceptron (SLP) is adopted by increasing the number of output neurons (parallel SLP, Figure 10b).

Table 5. Studies using Neural Networks for ECG analysis

Reference	Features	Application
Shyu *et al*. [12]	Wavelet	PVC detection
Minami *et al*. [59]	Fourier descriptors	VT detection
Clayton *et al*. [60]	Fourier descriptors	VF
Tashiro *et al*. [33]	Fourier descriptors	Individual identification
Mai *et al*. [34]	QRS descriptors	Individual identification
Song *et al*. [74]	First Derivative+RR intervals	PVC, APC, VF, LBBB, RBBB
Ozbay *et al*. [149]	Unsupervised fuzzy clustering	AF, LBBB, RBBB, APC

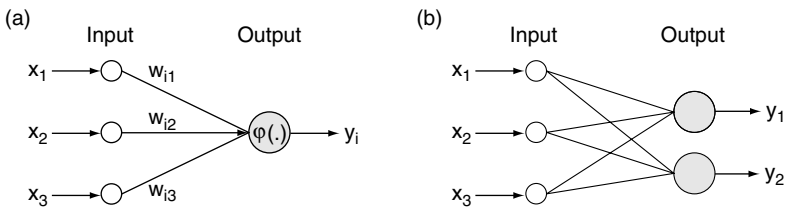

Figure 10. **(a)** The structure of a single neuron. x_i are the features, y_i is the output, w_{ij} are the weights, φ(.) can be a linear or non-linear function. (b) Single-layer-perceptron.

However, non-linear problems cannot be solved using SLP, and Multi-Layer-Perceptron (MLP) must be used (Figure 11). An MLP typically includes one or more intermediate hidden layers of neurons. This architecture can handle non-linear problems because their separating boundaries are combinations of hyperplanes.

The weights of the net, which determine the boundaries among classes, must be optimised in view of the characteristics of the data at hand. In particular, like other learning machines, an MLP must 'learn' its weights from training data via a learning algorithm called backpropagation [108–111].

The advantages of neural network are simplicity and short computation time, that are very important when operating in real time [59, 60]. One limitation of neural network is that the backpropagation algorithm is not guaranteed to find the globally optimal solution, but may be stuck in a local optimum. Moreover, neural network could suffer from difficulties in generalisation to data not used for training [108–111]. When generalisation is an important issue, SVM could be a better choice.

9.2. Support Vector Machines

SVM are one of the most widely used classifiers. They have good generalisation capabilities and, with opportune transformation, can deal also with nonlinear problems [111]. Table 6 summarizes published studies applying SVM for ECG analysis.

An SVM draws a hyperplane between different classes in the features space. The hyperplane is drawn in such a way that provides the maximal margin (i.e., the distance

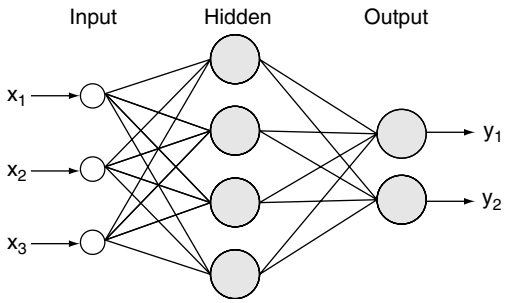

Figure 11. A typical MLP architecture (with two layers).

Table 6. Studies using SVM for ECG analysis

Reference	Features	Application
Osowski *et al*. [61]	HOS, Hermite expansion	Arrhythmia detection
Kampouraki *et al*. [62]	HRV time domain features	HRV classification
Mohebbi *et al*. [63]	RR time and frequency features	AF detection
Melgani *et al*. [64]	Morphology + timing	Arrhythmia detection
Mehta *et al*. [65]	Entropy	QRS detection
Kostka *et al*. [66]	Wavelet	AF detection
Mehta *et al*. [72]	ECG slope	P T detection

between the closest data points, called support vectors) between classes (see Figure 12). For linearly separable problems, the hyperplane providing the maximal margin to the training data is considered the optimal hyperplane, since it is expected to guarantee optimal generalisation. The optimal hyperplane is calculated from a quadratic programming problem to ensure a globally optimal solution. This approach can be extended to nonlinear problems by transforming the original data to a higher-dimensional feature space in which the training data become linearly separable. However, this transformation does not have to be explicitly calculated if special classes of transformations ("kernel functions") are considered, e.g., radial basis functions.

9.3. Other Approaches

9.3.1. Linear Approaches

One of the simplest approaches to classification of an instance x is to measure the distance from a template, and the unknown vector is assigned to the class of the closest template ("minimum distance classifier"). The Mahalanobis distance is commonly used, which takes into account different variances along different axes.

Another common approach is LDA. It was originally used as a mean for dimensionality reduction. It is based on the within-class scatter matrix $\mathbf{S}_w$ and the between-class scatter matrix $\mathbf{S}_b$. Data are projected onto a subspace with a lower number of features. The directions of the projections are chosen to have the maximum

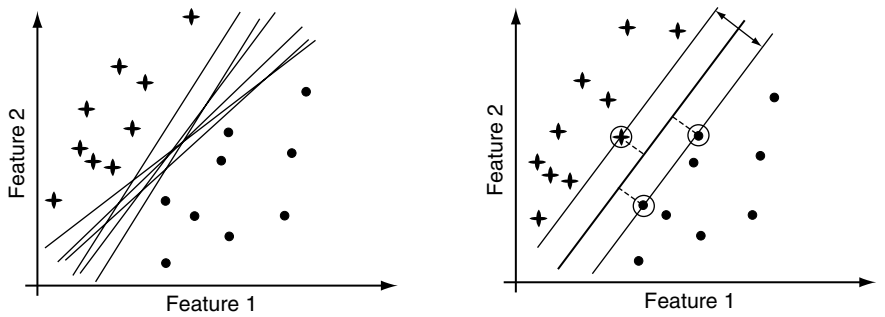

Figure 12. Support vector machines. With two features, individuals are represented on a plane. (a) Possible lines separating the two classes; a perceptron is guaranteed to converge to one of these solutions. (b) The line drawn using support vectors (circled).

separability among classes. This implies the maximization of a cost-function based on eigenvectors of $\mathbf{S}_w^{-1}\mathbf{S}_b$.

9.3.2. Hidden Markov Models

A Hidden Markov Model (HMM) is a stochastic finite-state machine where transitions between states (q_i) occur casually according to a matrix of state-transition probabilities $a_{ij} = \Pr(q_j(t + 1)|q_i(t))$. The current state of the machine is not directly observable (hidden). Instead, for each state, there is a probabilistic function $b_i = \Pr(o(t)|q_i(t))$ giving the probability to observe a specific output $o(t)$.

Given a sequence of N observations, $o(t_1)\ldots o(t_N)$, the main task is to estimate the most probable sequence of states that generate the outputs. This is a complex problem that can be solved using the Viterbi algorithm [150].

HMM can be used to model the hidden heart 'state'. Each waveform is the observable associated to the electrical activation (unobservable) within the heart. HMMs have been used mainly for heartbeat segmentation and arrhythmia detection [88, 89, 90, 92, 93].

9.3.3. Kalman Filter

Kalman Filtering (KF) is an approach for estimating hidden states of a system (discretised in the time domain) through a set of noisy measurements observed over time. The conventional KF assumes a known linear dynamical model. Typically, the equations of the model are non-linear: $x_{k+1} = f(x_k, w_k, k)$, $y_k = g(x_k, v_k, k)$, where x_k is the state of the system at time k, w_k is the process noise, y_k is the observation at time k, v_k is the observation noise, and $f(.)$ and $g(.)$ are non-linear functions. After linearization of the equations, the Extended KF (EKF) is obtained.

The EKF operates in a recursive manner. At time k, it first evaluates the *a priori* estimates of the state, $x^-_k = f(x^+_k{-}1, w, k)$, using all the observations, $y_1\ldots y_{k-1}$; then it evaluates the *a posteriori* estimate of x^+_k using y_k. At the time k + 1, the *a posteriori* estimate will be used to compute the *a priori* estimate x^-_k, and so on.

Recently, EKF has been used in ECG processing using the nonlinear model for ECG proposed by McSharry et al. [151]. EKF has also been used for detection of PVC [82]. To this aim, each ECG wave was modelled as a Gaussian, and the EKF was used to track the location of the Gaussians. As PVC induces a modification of Gaussian location (included in the model parameters), a procedure for PVC detection is realized.

10. ECG DATABASES AND VALIDATION

In the past decades, the Physionet [137] databases have become a standard for both classifier design (training) and validation (testing) in the field of ECG analysis. These databases include the AHA, MIT, and ESC databases that required many years of effort made by large teams of researchers and clinicians from many institutions. They include a collection of ECGs associated to several pathologies. Other standard ECG databases are available, such as Common Standard for Electrocardiography (CSE) (a list of other databases is available on http://www.physionet.org).

Physionet databases provide many advantages. They have a number of annotations made by one or more cardiologists. These annotations identify the type of heartbeat (see Table 7 for some examples). Moreover, the user does not need to develop a number of basic routines because they are already implemented in the WFDB software package. Of course, the existence of a large publicly available database has allowed, as regards the recent literature, easy comparisons between different methodologies.

Table 7. Heartbeat classes and beat annotations used in the MIT-BIH arrhythmia database

Acronym	Annotation	Description
NORMAL	N	Normal beat
LBBB	L	Left bundle branch block beat
RBBB	R	Right bundle branch block beat
BBB	B	Bundle branch block beat (unspecified)
APC	A	Atrial premature beat
ABERR	A	Aberrated atrial premature beat
NPC	J	Nodal (junctional) premature beat
SVPB	S	Supraventricular premature or ectopic beat (atrial or nodal)
PVC	V	Premature ventricular contraction
RONT	R	R-on-T premature ventricular contraction
FUSION	F	Fusion of ventricular and normal beat
AESC	E	Atrial escape beat
NESC	J	Nodal (junctional) escape beat
SVESC	N	Supraventricular escape beat (atrial or nodal) [1]
VESC	E	Ventricular escape beat
PACE	P	Paced beat
PFUS	F	Fusion of paced and normal beat
UNKNOWN	Q	Unclassifiable beat
LEARN	?	Beat not classified during learning

Considering the large variability of ECG waveforms among individuals, two main strategies can be identified concerning the training set organisation in performing a new study [95–97]. The first strategy involves building a large global learning set (GLS) database using signals collected from many subjects. This approach is typically suitable for commercial applications because it avoids the need for time-consuming and human expert annotations associated with manual editing of patient-specific ECG records. A second strategy is building a local learning set (LLS) which enables implementing patient-specific learning strategies. In arrhythmia monitors for intensive care units, for example, only the normal or predominant beats could be annotated/identified by the cardiologist, while the irregular beats (such as PVC) are classified automatically on the basis of the difference with respect to the annotated beats.

One important issue in the evaluation of algorithms for heartbeat classification is the validation scheme. As suggested in [152], the classical validation scheme [61, 77, 141] is based on a 'class-oriented' or 'heartbeat-oriented' approach where the data-set is subdivided into training set and test set with both sets containing heartbeats from the same subjects, leading to optimistic measure of performance because of limited inter-individual variability. A more realistic evaluation scheme could be the 'subject-oriented' approach [58, 153] where the subjects included in the training set are excluded from the test set.

Table 8. Performances of various algorithms tested on public databases. The best results for each paper are reported

Study	Algorithm	Class	Database	TPR (%)
Al-Fahoum and Howitt [159]	ANN	5 heartbeats	MIT/BIH arrhyth	97.50
Chen [106]	LDA	VT, VF, SVT	MIT/BIH	95.56
Christov *et al*. [95]	k-NN	5 heartbeats	MIT/BIH arrhyth	99.00
De Chazal *et al*. [58]	LDA	VEB	MIT/BIH arrhyth	77.70
Jekova *et al*. [96]	kNN	5 heartbeats	MIT/BIH arrhyth	99.91
Kampouraki *et al*. [62]	SVM	2 classes	Fantasia	100.00
Khandoker *et al*. [69, 70]	SVM	OSAS	Apnea	100.00
Kostka *et al*. [66]	SVM	AF	MIT/BIH	(Se) 87.00
Krasteva *et al*. [97]	k-NN	VEB	MIT/BIH arrhyth	98.40
Mai *et al*. [34]	ANN	Subj recog	MIT/NSR	99.69
Melgani *et al*. [64]	SVM	6 classes	MIT/BIH arrhyth	92.70
Mohebbi *et al*. [63]	SVM	AF	MIT/BIH arrhyth	99.07
Osowski and Linh [157]	ANN	7 heartbeats	MIT/BIH arrhyth	96.06
Osowski *et al*. [61]	SVM	13 heartbeats	MIT/BIH arrhyth	(ER) 4.03
Owis *et al*. [105]	k-NN	VT-VF-VC	MIT/BIH	(Se) 98.00
Ozbay *et al*. [149]	ANN	10 classes	MIT/BIH arrhyth	99.00
Shyu *et al*. [12]	ANN	PVC	MIT/BIH	99.79
Song *et al*. [74]	ANN	7 classes	MIT/BIH arrhyth	97.49
Ye *et al*. [152]	SVM	5 heartbeats	MIT/BIH arrhyth	99.70
Zadeh *et al*. [158]	SVM	PVC	MIT/BIH arrhyth	97.14

11. ALGORITHM PERFORMANCE EVALUATION AND COMPARISON

In this section, a comparison among the performances of the previously described approaches is presented. It must be noted that such a comprehensive comparison is difficult because of many reasons: (a) many studies did not use public databases; (b) in analysing arrhythmias, not all studies classified the heartbeats into the classes suggested by AAMI guidelines [107], and some studies used a one-versus-others classification (e.g., PVC vs. other types of heartbeats); (c) some studies excluded a few patients or recordings in the analysis (according to AAMI recommendations [107]) while others did not; (d) not all studies used the same leads, and the number of leads could be dependent on the application; (e) classification was often based on mixed techniques (e.g., not 'pure' or original SVM); and (d) not all studies reported the same performance metrics (while the most commonly used was True Positive Rate (TPR), Sensitivity (Se), Positive Predictivity (P+) and Error Rate (ER) were also used).

11.1. Arrhythmia Detection

As noted above, organisation of dataset used for the training is important. Jakova *et al*. [96] compared several classifiers (LDA, ANN, kNN, fuzzy logic) using two learning strategies: a global training set from all patients in the databases and a local (patient-specific) training set including 30% of heartbeat from a specific recording. They reported a large variability in the performance with the heartbeat type (N, PVC, LBBB, PB, RBBB) and the training set used. Very high performances were achieved using local training set.

The choice of single classifier or multiple classifiers can affect the performance. Combining the trained networks helps to integrate the knowledge acquired by the individual classifiers and can improve the accuracy of the final classification. For arrythmia identification, Osowski *et al*. [61,157] proposed the use of multiple classifiers, relying on different feature sets, combined by the weighted voting principle. The SVM classifier and two different preprocessing techniques of the ECG waveform were applied. One feature set was derived by Hermite basis functions expansion while the second feature set by the cumulants of the second, third, and fourth orders. Each classifier influenced the final decision according to its performance on the training data. They tested their algorithm on the MIT-BIH arrythmia database and found that combination of the two classifiers demonstrated better performances than each of the single classifiers.

Owis *et al*. [105] compared PCA and ICA approach for ECG feature extraction by apply both techniques on the Fourier transform of the signal. The samples analysed included five different ECG signal types: normal, ventricular couplet (VC), ventricular tachycardia (VT), ventricular bigeminy (VB), and ventricular fibrillation (VF). The analyzed intervals were windowed using either a rectangular or a Hamming window. The methods demonstrated a detection rate of 98% sensitivity and 100% specificity using nearest neighbour classification of features from ICA and a rectangular window.

Melgani *et al*. [64] used SVM for classifying the arrhythmia MIT-BIH dataset in 6 classes. They used SVM with 300 morphologic features and 3 temporal features, and compared the performances with a k-NN classifier.

Atrial fibrillation detection via SVM approach has been attempted also by Kostka *et al*. [66]. They used discrete fast wavelet transform coefficients parameters including energy and entropy measures and ICA. Literature review of papers connected to AF detection problem showed positive influence of ventricular activation cancellation by removing QRST complex from original signal for further analysis.

Mohebbi *et al*. [63] proposed an algorithm for AF detection based on SVM. The features were combinations of both linear (standard HRV in time and frequency domains) and nonlinear (SD1/SD2 derived from the Poincare plot, Approximate entropy, and Liapunov exponent). The dimensionality of the feature set was reduced using PCA and LDA.

11.2. Heart Rate Variability Analysis

For HRV analysis, Kampouraki *et al*. [62] used the Fantasia Database from Physionet (see Section 10) for classifying young and elderly people's HRV while watching a Disney film, through conventional HRV features (section 6). Kampouraki *et al*. [62] used SVM for RR series classification and found that SVM performed better than ANN. They used conventional statistical HRV features, autocorrelation, Shannon entropy, autoregressive coefficients and discrete wavelet transform. SVM correctly classified 100% of the heartbeats at signal-to-noise-ratio (SNR) of 3dB, while the performance degraded to 78% for lower SNR.

Khandoker *et al*. [69,70] used HRV analysis for recognising patients with OSAS with wavelet-based features. They compared LDA, KNN and SVM, and confirmed the superiority of SVM compared to others. SVM showed a performance of 100% sensitivity with a small number of features.

11.3. Human Identification

As discussed in section 7, features for subject recognition should be based on timing and morphological differences among subjects. One major issue is the stability of these features [41]. Mai *et al*. [34] proposed a method for subject recognition based on the QRS complex morphology, which showed a great stability with changes in heart rate, while P and T waves vary with the heart rate. They took 324 QRS signals from 18 subjects in the MIT-Normal Sinus database, classified them by means of a Multilayer Perceptron, and obtained 99.69 % of correct recognition.

In the area of subject recognition, there is a lack of standardised database; therefore, a large number of studies used their own private ECG signals. For example, Israel *et al*. [36] obtained subject recognition rate as high as 100% using one-lead ECG from a private database of 29 individuals, with their own fiducial points detector. However, it is difficult to compare their results with results from other studies in the absence of standardisation.

12. DISCUSSION

In this review, many algorithms for ECG analysis based on pattern recognition have been reviewed. In particular, this review was focussed on the description of commonly used features for arrhythmia detection, HRV analysis and human identification; moreover, the most popular learning machines discussed here were ANN and SVM.

The objective of this review was not to provide a meta-analysis of the classification algorithms or a direct comparison of the performances, which is difficult because of the diversity of the databases used and the validation approaches. Instead, we aimed to provide a survey of the most important and popular methodologies used in pattern recognition analysis of the ECG.

Despite the limited scope of this review, a few key points could be outlined in order to summarise the literature and to gain insights into probable future research directions.

Given the huge literature available on ECG processing in various areas, in our opinion, it was necessary to restrict the scope to a limited number of application areas. The three chosen applications areas are all related to healthcare engineering, and all have significant scientific and commercial relevance. Automatic arrhythmia detection is a central task in commercial computer aided diagnosis (CAD) systems. HRV analysis has revealed a potential for monitoring CHF patients and other pathologies. Human identification has recently gained an increasing attention because of potential in telemedicine and other commercial applications. These three areas present some similarities in algorithms and features, and they are potentially related to one another with pattern recognition being the common underlying framework. Features for heart rhythm analysis can be useful also in arrhythmia detection. Temporal and morphological features (timing and shape of the waves) for human identification have been derived partially from the body of knowledge available in arrhythmia detection and HRV analysis. Biometric application might include pre-processing stages for identification of pathological conditions before recognition can be performed.

This review provides an overview of the most popular ECG feature sets and highlights similarities and differences among features and classification techniques suitable for various applications, in terms of the common framework of pattern recognition. A large number of features for ECG analysis have been proposed in the literature (temporal relations among waves, morphological descriptors, state-space features, linear transformation, spectral representation, wavelet analysis, etc.). However, 'pure' approaches (based on only single types of features) are in general incapable of dealing with the complexity of the ECG signal. Therefore, mixed algorithms are widely adopted.

Available knowledge on patho-physiological conditions suggests the use of specific features for a specific applications. For instance, detection of PVC is greatly simplified using the timing of the QRS because it occurs prematurely. As reduced HRV is a predictor of mortality after myocardial infarction, it is a suitable feature for clinical monitoring of infarcted subjects. Heartbeats associated to abnormal electrical conduction can be detected on the basis of shape descriptors. Ventricular tachycardia can be detected on the basis of spectral characteristics. Timing of the waveforms seems to be associated to the unique paths within the heart and could be suitable for human identification.

The majority of studies have used these 'knowledge based' features instead of 'brute force' approaches (i.e., applications of the conventional transformation/selection procedures to the raw ECG). However, a few studies suggest that aggregation of features of different types can improve the overall performance.

Different applications may require different features. However, the lesson learned from the literature is that there are 'overlapping' types of features, in the sense that the knowledge available on a specific application could be used as a starting point in other applications. For example, features such as the temporal information used in arrhythmia detection might be useful in human identification, because the timing of the main waves is associated to unique electrical paths in each individual.

The key point in each application is the extraction/transformation/selection of suitable features. Notwithstanding the long history, arrhythmia detection and HRV analysis are still areas of intense research, mainly because optimal features can only be dictated by the specific pathology to be studied, and general purpose features may not exist. Patient adaptive approaches, particularly for arrhythmia detection, are capable of improving performance with respect to non-patient specific algorithms; however, the disadvantage is the training phase for each patient that must be supervised by an expert.

As CHF becomes a more and more important disease in most of the world, accurate systems for CHF diagnosis assume relevance in this field. It appears that pattern recognition applied to HRV analysis is a promising technique for automatic diagnosis of CHF patients.

The use of single lead or multi-leads is an issue depending on the application. In general, as the QRS complex can be easily identified and detected on one single lead, HRV applications will not require the use of multi-lead devices. Similarly, PVC detection is possible with single-lead recordings. However, some applications in arrhythmia detection (e.g., analysis of p-wave dispersion, TWA, etc.) that are mainly based on ECG shape descriptors could benefit from simultaneous processing of multiple leads available. Practical issues in human identification limit the ECG acquisition to only one lead, perhaps with non-conventional electrodes (such as metal plates for hands).

Commercial clinical systems for ECG analysis can be roughly divided into real-time (monitoring devices) and off-line systems (Holter analysis). While off-line systems present typically a device for ECG recording and separate software for advanced processing, real-time systems have very stringent requirements that processing speed should be as high as possible. Low-cost digital signal processors (DSP) and field programmable gate array (FPGA) have been proposed for QRS detection, feature selection and heartbeat classification based on neural networks and support vector machines [155,156]. However, a comprehensive study of this issue is outside the scope of the present review.

Human ECG identification has gained a considerable attention from scientific community in the last decade. Identification/authentication of users is an important task in a large number of applications. For example, patient identification by ECG and/or other biometrics could be of help in telemedicine applications involving networks of body sensors. Since the pioneer work by Biel *et al.* [35], a number of approaches have been attempted based on temporal or amplitude features, wavelet coefficients and cross correlation, together with various classifiers such as minimum distance, K-NN, SVM, etc. The majority of human identification studies up to now used minimum Euclidean distance.

Human identification by ECG is a promising technique that could become a complementary method to the conventional identification systems using e.g., fingerprints and iris. Large public ECG databases, such as Physionet, are important to the progress in this area. However, so far, many studies used their own databases,

making it very difficult or impossible to compare the performances of different algorithms.

Some issues concerning ECG for human identification require further investigation. In particular, enrolment and management of subjects with implanted devices, or with infrequent arrhythmias, have not been extensively studied. Such subjects require a more complex device capable of detecting and managing abnormal or artificial beats for reliable recognition.

Moreover, it is known that QT duration may vary with age, and may be modified by heart rate. When this parameter is employed to be a feature for human identification, it should be corrected for heart rate [104]. Other studies suggest that QRS wave is a more reliable feature, not varying with age, and independent of the heart rate [41]. However, in using these temporal features, the first step of the algorithm is to detect wave boundaries, which is currently an area of research and several methodologies have been proposed. One of the main issues is that, as discussed in sections 10 and 11, currently, the comparison among studies on human identification is a difficult task. Future studies should stimulate the establishment of databases of large number of subjects, with specific characteristics (e.g., sampling frequency) optimised for this application.

It is known that inclusion of *a priori* knowledge can improve the performance of a classification system. The inclusion of 'imprecise' and 'fuzzy' medical knowledge has been attempted in various studies (see [154] for a review) but they are outside the scope of this review.

Another important issue not addressed in this review is the ECG waves delineation procedure [43,120,126]. Accurate location of the several ECG waves and in particular, the onset and offset of P and T, can improve those algorithms based on temporal information.

CONCLUSIONS

This paper reviewed pattern recognition applications in ECG analysis. In particular, we covered features for arrhythmia recognition, HRV analysis and human identification via ECG, with a focus on ANN and SVM.

In spite of the limited scope of our review, it can be argued that ECG analysis continues to be an area of intense research. Pattern recognition methodologies have been widely applied in this field in the past decades. Although considerable efforts have been and are currently made in the definition of optimal features suited for various applications, the emerging application of human identification has not yet achieved an established status, and it is expected that future efforts of the scientific community will be directed to this field.

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CONFLICT OF INTEREST

The authors certify that there is no conflict of interest with any financial organization regarding the materials presented in the manuscript.

LIST OF ABBREVIATIONS

AAMI	Association for the Advancement of Medical Instrumentation
AF	Atrial Fibrillation
ANN	Artificial Neural Networks
ANS	Autonomic Nervous System
APC	Atrial Premature Contraction
AR	AutoRegressive
CAD	Computer Aided Diagnosis
CHD	Coronary Heart Disease
CHF	Congestive Heart Failure
CWT	Continuous Wavelet Transform
DCM	Dilated CardioMyopathy
DCT	Discrete Cosine Transform
DFA	Dominant Frequency Analysis
DSP	Digital Signal Processing
DT	Decision Tree
ECG	Electrocardiogram
EKF	Extended Kalman Filter
EFF	Energy Fractional Factor
ER	Error Rate
ESC	European Society of Cardiology
FFT	Fast Fourier Transform
FN	False Negative
FNN	Fuzzy Neural Network
FOA	Fourier Organisation Analysis
FP	False Positive
FPGA	Field Programmable Gate Array
FPR	False-Positive Rate
GLM	Generalized Linear Model
GLS	Global Learning Set
HHT	Hilbert Huang Transform
HMM	Hidden Markov Models
HOS	Higher order spectra
HRV	Heart Rate Variability
ICA	Indeipendent Component Analysis
ICU	Intensive Care Units
KF	Kalman Filtering
k-NN	K Nearest Neighbours
LDA	Linear Discriminant Analysis
LLS	Local Learning Set
LVQ	Learning Vector Quantization

MI	Myocardial Infarction
NASPE	North American Society Pacing Elecrophysiology
NSR	Normal Sinus Rhythm
OSAS	Obstructive Sleep Apnoea Syndrome
P+	Positive Predictivity
PCA	Principal Component Analysis
PF	Predominant Frequency
PHF	Power In The High Frequeancy
PLF	Power In The Low Frequeancy
PNS	Parasympathetic Nervous System
PVC	Premature Ventricular Contraction
SDNN	Standard Deviation of all Normal-to-Normal beat intervals
SE	Sensitivity
SNR	Signal to Noise Ratio
SNS	Sympathetic Nervous System
SVEB	Supra Ventricular Ectopic Beats
SVM	Support Vector Machines
SVT	SupraVentricular Tachycardia
TN	True Negative
TP	True Positive
TPR	True Positive Rate
VEB	Ventricular Ectopic Beats
VF	Ventricular Fibrillation
VT	Ventricular Tachycardia

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