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ORIGINAL CONTRIBUTION

Classification of ECG for Arrhythmia detection

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ABSTRACT

An electrocardiogram (ECG) measures the electric activity of the heart and has been widely used for detecting heart diseases due to its simplicity and non-invasive nature. By analyzing the electrical signal of each heartbeat, i.e., the combination of action impulse wave forms produced by different specialized cardiac tissues found in the heart, it is possible to detect some of its abnormalities. In the last decades, several works were developed to produce automatic ECG-based heartbeat classification methods. In this work, we survey the current state-of-the-art methods of ECG-based automated abnormalities heartbeat classification by presenting the ECG signal preprocessing, the heartbeat segmentation techniques, the feature description methods and the learning algorithms used. In addition, we describe some of the databases used for evaluation of methods indicated by a well-known standard developed by the Association for the Advancement of Medical Instrumentation (AAMI) and described in ANSI/AAMI EC57:1998/(R)2008 (ANSI/AAMI, 2008). Finally, we discuss limitations and drawbacks of the methods in the literature presenting concluding remarks and future challenges, and also we propose an evaluation process workflow to guide authors in future works

.**KEYWORDS:** ECG-based signal processing , Preprocessing, Feature extraction, Learning algorithms, Heartbeat segmentation.

1. INTRODUCTION

There are various types of arrhythmias and each type is associated with a pattern, and as such, it is possible to identify and classify its type. The arrhythmias can be classified into two major categories. The first category consists of arrhythmias formed by a single irregular heartbeat, herein called morphological arrhythmia. The other category consists of arrhythmias formed by a set of irregular heartbeats, herein called rhythmic arrhythmias. The classification of normal heartbeats and the ones composing the former group are on the focus of this survey. These heartbeats produce alterations in the morphology or wave frequency, and all of these alterations can be identified by the ECG examination .The process of identifying and classifying arrhythmias can be very troublesome for a human being because some times it is necessary to analyze each heartbeat of the ECG records acquired by a holter monitor for instance, during hours, or even days[1][2]. In addition, there is the possibility of human error during the ECG records analysis, due to fatigue. An alternative is to use computational techniques for automatic classification.A full automatic system for arrhythmia classification from signals acquired by a ECG device can be divided in four steps (1) ECG signal preprocessing; (2)heartbeat segmentation; (3) feature extraction; and (4) learning/classification. In each of the four steps, an action is taken and the final objective is the discrimination/identification of the type of heart beat. The first two steps of a such classification system (ECG signal preprocessing and heartbeat segmentation) have been widely explored in the literature . The techniques employed during the preprocessing step directly influence the final results, and therefore, should be carefully chosen. The results related to the heartbeat segmentation step, in the case of QRS detection, are very close to optimal. However, there is still room for exploration and improvements in the steps related to classification (feature extraction and learning algorithms). Even though the

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problem of ECG delineation is still open, it is not so useful for the methods in the literature surveyed here. This paper presents a survey of existing studies found in literature regarding the ECG based arrhythmia classification methods and discusses the main techniques used for the construction of these automatic systems as well as two main paradigms used for evaluation: inter patient and intra patient. In addition, the most popular databases and the problems related to the evaluation of current methods found in literature are also discussed [3][4]. From this discussion, a work flow is proposed to guide the evaluation process of future works. Note that this workflow for evaluation process constitutes an important contribution of this survey work. In the literature, we find a survey of knowledge based ECG interpretation reviewing methods proposed in the 20th century[5].

2. ECG SIGNAL

The heart is a muscle that contracts in a rhythmical manner, pumping blood throughout the body. This contraction has its beginning at the atrial sine node that acts as a natural pacemaker, and propagates through the rest of the muscle. This electrical signal propagation follows a pattern[6] . As a result of this activity, electrical currents are generated on the surface of the body, provoking variations in the electrical potential of the skin surface. These signals can be captured or measured with the aid of electrodes and appropriate equipment. The difference of electrical potential between the points marked by the electrodes on the skin, usually is enhanced with the aid of an instrumentation (operational) amplifier with optic isolation. Then, the signal is submitted to a high-pass filter; and as a second stage, submitted to an sing low-pass filter[7]. Finally, it appears in an analogical to digital converter. The graphical registration of this acquisition process is called electrocardiogram (ECG)[8]. Even so, the ability to recognize the normal cardiac rhythm and/or arrhythmias did not become routine in medical check-ups until 1960. Within the in-the-person category, there are equipments designed to be used inside human body, such as surgically implanted ones, sub dermal applications or even ingested in the form of pills. These devices are used when less invasive approach are not applicable. Contrasting with the in-the-person category, there is off-the-person category. Devices on this category are designed to measure ECG without skin contact or with minimal skin contact[9][10]. This category is aligned with future trends of medical application where pervasive computer systems are a reality. Examples of such equipments are the ones based on capacitive devices which measure the electric field changes induced by the body allowing ECG measurement at distance of 1 cm or more even with clothing between the body and the sensor .The majority of devices used for ECG measurements are in the on-the-person category. Devices on this category normally require the use of some electrodes attached to the skin surface[11].

3. PREPROCESSING

Among all proposals for reducing noise in ECG signals, the simplest and most widely used is the implementation of recursive digital filters of the finite impulse response (FIR) ,which was made computationally possible with the advance in microcontrollers and microprocessors. These methods work well for the attenuation of the known frequency bands, such as the noise coming from the electrical network (50 Hz or 60 Hz), since they allow quick and easy application of the reject-band-filter[12]. The problem with this approach is that the frequency of the noise is not always known, which can be solved by applying filters for various frequency bands to the signal. However, the indiscriminate use of filters, i.e., high-pass and low-pass ones, distorts the morphology of the signal, and many times, makes it unusable for diagnosing cardiac diseases. Architectures with adaptive filters were also employed for noise removal from the ECG signals significantly improved[13][14]. This strategy proportioned better detection of the QRS complex, when com-pared with the same method using linearly adaptive filters. In the last decade, many methods based on wavelet trans-forms have been employed to remove noise, since they preserve ECG signal properties avoiding loss of its important physiological details and are simple from a computational point of view. The modification of the wavelet transform called the multi adaptive bionic wavelet transform and it was applied to reduce noise and baseline variation of the ECG signal. This method presented superior results when compared to the ones based on the traditional wavelet transform. Other methods have also presented interesting results on noise attenuation. have proposed the use of nonlinear Bayesian filters for ECG signal noise reduction, presenting promising results[15]. A new algorithm based on the Extended Kalman Filter , which incorporates the parameters of the ECG dynamic model for ECG noise reduction and signal compression, yielded a significant contribution because the method showed the greatest effectiveness to date. Methods focusing on the heartbeat segmentation from the ECG signal (i.e., detection of the QRS complex, other waves or fiducial points aiming at heartbeat delimitation) tend to require a pre-processing that is different from the methods focusing on the automatic classification of arrhythmias.

4. SEGMENTATION

Heartbeat segmentation methods (i.e., detection of the R peak or the QRS complex) have been studied for more than three decades and the generations of these algorithms and newly developing methods reflect the evolution of the processing power of computers. With the facility of using faster processing computers, authors stopped worrying about computational cost and started concentrating on the heartbeat segmentation accuracy. Two measures are usually considered for evaluating the accuracy of heartbeat segmentation: sensitivity and positive predictivity, which are defined as:

Sensitivity SEG = TP/(TP+FN), (1)

and

Positive predictivity SEG =TP/(TP+FP), (2)

where TP (True Positive), FP (False Positive) and FN (False Neg-ative) indicate the number of heartbeats correctly segmented, number of segmentations that do not correspond to the heartbeats, and number of segmentations that were not performed, respectively. For a fair comparison of the methods focusing on the heartbeat segmentation, a standard database needs to be used. The most utilized, and recommended by ANSI/AAMI for the validation of medical equipment , is the MIT-BIH database for arrhythmia analysis in this case, used for heartbeat segmentation, although other databases are also used, such as that of AHA many of the methods presented in the literature do not use a standardized database, or use only part of it, which makes it difficult to fairly compare methods[16]. An approach widely used for segmentation, due to its simplicity and promising results, is based on digital filters for the attenuation of the noise and removal of the fluctuating baseline, nonlinear translations that enhance the R peak and adaptive detection threshold were proposed by Pan and Tompkins . More sophisticated methods have also been used, such as methods based on neural networks , genetic algorithms , wavelet transform , filter banks.

5. FEATURE EXTRACTION

The feature extraction stage is the key to the success in the heartbeat classification of the arrhythmia using the ECG signal. Any information extracted from the heartbeat used to discriminate its type maybe considered as a feature. The features can be extracted in various forms directly from the ECG signal's morphology in the time domain and/or in the frequency domain or from the cardiac rhythm. Even though some works regard feature extraction and feature selection as two inter changeable terms, these two process are in fact different[17]. While feature extraction is defined as the stage that involves the description of a heartbeat, feature selection consists in choosing a subset with the most representative features with the objective to improve the classification stage. The RR interval is the time between the R peak of a heartbeat with respect to another heartbeat, which could be its predecessor or successor. With exception of patients that utilize a pacemaker, the variations perceived in the width of the RR interval are correlated with the variations in the morphology of the curve, frequently provoked by arrhythmias .Thus, the features in the RR interval have a great capacity to discriminate the types of heart beats and some authors have based their methods only on using the RR interval features. Variations of this feature are used to reduce noise interference and are very common, e.g., the average of the RR interval in a patient for a certain time interval . Only normalized RR-intervals are used in that work and the results are comparable to the state-of-the-art methods even under the inter patient paradigm[18]. Other features extracted from the heart beat intervals are also found in literature, such as other distances between the fiducial points of a heartbeat (here called ECG-intervals or ECG segments), among these intervals ,the QRS interval, or the duration of the QRS complex, is the most utilized. Some types of arrhythmias provoke variations in the QRS interval, making it a good discriminating feature. It is worth mentioning that there exist other algorithms available to determine these fiducial points, considering a healthy human being with no cardiac abnormalities[19]. Features extracted from the domain of time/frequency together with the features of the RR interval appear as part of the methods that produced the highest accuracies in literature to date. The simplest way to extract features in the time domain is to utilize the points of the segmented ECG curve, i.e., the heartbeat, as features . However, the use of samples of the curve as features is a technique that is not very efficient, since besides producing a vector of the features with high dimensions (depending on the amount of samples used to represent the heartbeat), it suffers from several problems related to the scale or displacement of the signal with respect to the central point (peak R). Aiming at reducing the dimension of the feature various techniques have been applied directly on the samples that represent the heartbeat (in the neighborhood of the R peak) as principal component analysis (PCA) , or independent component analysis (ICA) , in which new coefficients are extracted to represent the heartbeat. A comparative study between the use of PCA and ICA to reduce the noise and artifacts of the ECG signal and showed that PCA is a better technique to reduce noise, while ICA is better one to extract features. The ICA technique enables statistically separate individual sources from a mixing signal. The ECG is a mix of several action potentials and each action potential could be strongly related to an arrhythmia class[20] .The rationale behind ICA for ECG heartbeat classification is to separate the action potentials sources as well as the noise sources. The PCA technique separates the sources according to the energy contribution to the signal. Moreover, it has been shown that the combination of these two techniques, i.e., PCA for noise reduction and ICA for feature extraction, can offer greater advantages when compared to using only one of them. Another technique based on PCA, the Kernel Principal Component Analisys (KPCA). In that work, a comparison between PCA and KPCA was performed and it was concluded that KPCA is superior to the PCA technique for classifying heartbeats from the ECG signal.

6. CONCLUSION

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