Expert Systems with Applications 39 (2012) 2047–2058

Contents lists available at SciVerse ScienceDirect

Expert Systems with Applications

journal homepage: www.elsevier.com/locate/eswa

ECG arrhythmia recognition via a neuro-SVM–KNN hybrid classifier with virtual QRS image-based geometrical features

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ARTICLE INFO

Keywords:
Feature extraction
Curve length method
Support vector machine
K-nearest neighbors
Multi layer perceptron
Fusion (hybrid) classification
Arrhythmia classification
Supervised learning machine

ABSTRACT

In this study, a new supervised noise-artifact-robust heart arrhythmia fusion classification solution, is introduced. Proposed method consists of structurally diverse classifiers with a new QRS complex geometrical feature extraction technique.

Toward this objective, first, the events of the electrocardiogram (ECG) signal are detected and delineated using a robust wavelet-based algorithm. Then, each QRS region and also its corresponding discrete wavelet transform (DWT) are supposed as virtual images and each of them is divided into eight polar sectors. Next, the curve length of each excerpted segment is calculated and is used as the element of the feature space. Discrimination power of proposed classifier in isolation of different Gold standard beats was assessed with accuracy 98.20%. Also, proposed learning machine was applied to 7 arrhythmias belonging to 15 different records and accuracy 98.06% was achieved. Comparisons with peer-reviewed studies prove a marginal progress in computerized heart arrhythmia recognition technologies.

1. Introduction

Heart is a special myogenic muscle which its constitutive cells (myocytes) possess two important characteristics namely as nervous (electrical) excitability and mechanical tension with force feedback. The heart's rhythm of contraction is controlled by the sino-atrial node (SA node) called the heart pacemaker. This node is the part of the heart's intrinsic conduction system, made up of specialized myocardial (nodal) cells. Each beat of the heart is set in motion by an electrical signal from the SA node located in the heart's right atrium. The automatic nature of the heartbeat is referred to as automaticity which is due to the spontaneous electrical activity of the SA node. The superposition of all myocytes electrical activity on the skin surface causes a detectable potential difference which its detection and registration together is called electrocardiography (Sachse, 2004). However the heart's electrical system controls all the events occurring when heart pumps blood. So if according to any happening, the electro-mechanical function of a region of myocytes encounters a failure, the corresponding abnormal effects will appear in the electrocardiogram (ECG) which is an important part of the preliminary evaluation of a patient suspected to have a heart-related problem. Based on a comprehensive literature survey among many documented works, it is seen that several features and extraction (selection) methods have been created and implemented by authors. For example, original ECG signal (Ozbay, Ceylan, & Karlik, 2006), preprocessed ECG signal via appropriately defined and implemented transformations such as discrete wavelet transform (DWT), continuous wavelet transform (CWT) (Lin, Du, & Chen, 2008), Hilbert transform (HT) (Benitez, Gaydecki, Zaidi, & Fitzpatrick, 2001), fast Fourier transform(FFT) (Christov et al., 2006; Lin, 2008), short time Fourier transform (STFT) (Tsipouras & Fotiadis, 2004), power spectral density (PSD) (Kar & Okandan, 2007; Stridh, Sörnmo, Meurling, & Olsson, 2004), higher order

Abbreviations: KNN, K-nearest neighbors; SVM, support vector machine; ECG, electrocardiogram; DWT, discrete wavelet transforms; SNR, signal to noise ratio; ANN, artificial neural network; MEN, maximum epochs number; NHLN, number of hidden layer neurons; RBF, radial basis function; MLP-BP, multi-layer perceptron back propagation; FP, false positive; FN, false negative; TP, true positive; P+, positive predictivity (%); Se, sensitivity (%); CPUT, CPU time; MITDB, MIT-BIH Arrhythmia Database; SMF, smoothing function; FIR, finite-duration impulse response; LBBB, left bundle branch block; RBBB, right bundle branch block; PVC, premature ventricular contraction; APB, atrial premature beat; VE, ventricular escape beat; CHECK#0, procedure of evaluating obtained results using MIT-BIH annotation files; CHECK#1, procedure of evaluating obtained results consulting with a control cardiologist; CHECK#2, procedure of evaluating obtained results consulting with a control cardiologist and also at least with 3 residents.

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0957-4174/$ - see front matter © 2011 Elsevier Ltd. All rights reserved.
doi:10.1016/j.eswa.2011.08.025

spectral methods (Khadra, Al-Fahoum, & Binajjaj, 2005; Yu & Chen, 2009), statistical moments (de Chazal, O'Dwyer, & Reilly, 2004), nonlinear transformations such as Liapunov exponents and fractals (Nopone, Kortelainen, & Seppanen, 2009; Owis, Abou-Zied, Youssef, & Kadah, 2002; Povinelli, Johnson, Lindgren, Roberts, & Ye, 2006) have been used as appropriate sources for feature extraction. In order to extract feature(s) from a selected source, various methodologies and techniques have been introduced. To meet this end, the first step is segmentation and excerption of specific parts of the preprocessed trend (for example, in the area of the heart arrhythmia classification, ventricular depolarization regions are the most used segments). Afterwards, appropriate and efficient features can be calculated from excerpted segments via a useful method. Up to now, various techniques have been proposed for the computation of feature(s). For example mean, standard deviation, maximum value to minimum value ratio, maximum-minimum slopes, summation of point to point difference, area, duration of events, correlation coefficient with a pre-defined waveform template, statistical moments of the auto (cross) correlation functions with a reference waveform (Minhas & Arif, 2008), bi-spectrum (Yu & Chen, 2009), differential entropy (Liu, Sun, Liu, & Zhang, 2009), mutual information (Peng, Long, & Ding, 2005), nonlinear integral transforms and some other more complicated structures (Abe & Kudo, 2006; Christov & Bortolan, 2004; Chudacek1 et al., 2009; Exarchos et al., 2007; Lin, Du, & Chen, 2009; Liu et al., 2009; Nopone et al., 2009; Owis et al., 2002; Peng et al., 2005; Polat, Kara, Güven, & Günes, 2009; Povinelli et al., 2006; Rohani Sarvestani, Boostani, & Roopaei, 2009; Wang, Zhu, Thakor, & Xu, 2001) may be used as an instrument for calculation of features.

After generation of the feature source, segmentation, feature selection and extraction (calculation), the resulted feature vectors should be divided into two groups "train" and "test" to tune an appropriate classifier such as a neural network, support vector machine or ANFIS (Abe & Kudo, 2006; Christov & Bortolan, 2004; Christov & Bortolan, 2005; Chudacek1 et al., 2009; Exarchos et al., 2007; Lin, Du, et al., 2009; Liu, Sun, et al., 2009; Minhas & Arif, 2008; Peng et al., 2005; Polat et al., 2009; Tsipouras, Voglis, & Fotiadis, 2007). As previous researches show, occurrence of arrhythmia(s) affects RR-tachogram and Heart Rate Variability (HRV) in such a way that these quantities can be used as good features to classify several rhythms. Using RR-tachogram or HRV analysis in feature extraction and via simple if-then or other parametric or nonparametric classification rules (de Chazal & Reilly, 2006; Nilsson, Funk, Olsson, von Scheele, & Xiong, 2006; Tsipouras, Fotiadis, & Sideris, 2005), artificial neural networks, fuzzy or ANFIS networks (Acharya, Sankaranarayanan, Nayak, Xiang, & Tamura, 2008; Kannathal, Lim, Rajendra Acharya, & Sadasivan, 2006; Tsipouras & Fotiadis, 2004; Yu & Chou, 2008; Yu & Chou, 2009), support vector machines (Mohammadzadeh Asl, Kamaledin Setarehdan, & Mohebbi, 2008) and probabilistic frameworks such as Bayesian hypotheses tests (Yu & Chou, 2007), the arrhythmia classification would be fulfilled with acceptable accuracies. Heretofore, the main concentration of the arrhythmia classification schemes has been on morphology assessment and/or geometrical parameters of the ECG events. Traditionally, in the studies based on the morphology and the wave geometry, first, during a preprocessing stage, some corrections such as baseline wander removal, noise-artifact rejection and a suitable scaling are applied. Then, using an appropriate mapping for instance, filter banks, discrete or continuous wavelet transform in different spatial resolutions and etc., more information is derived from the original signal for further processing and analyses. In some researches, original and/or preprocessed signal are used as appropriate features and using artificial neural network or fuzzy classifiers (Ceylan, Uzbay, & Karlik, 2009; de Chazal, O'Dwyer, & Reilly, 2004; Ebrahimzadeh & Khazaee, 2009; Inan, Giovangrandi, & Kovacs, 2006; Lin et al., 2008; Osowski, Markiewicz, & Tran Hoai, 2008; Ozbay et al., 2006; Polat, Sahan, & Gune, 2006; Wen, Lin, Chang, & Huang, 2009), parametric and probabilistic classifiers (Bartolo et al., 2001; Polat & Gunes, 2007; Wiggins, Saad, Litt, & Vachtsevanos, 2008), the discrimination goals are followed. Although, in such classification approaches, acceptable results may be achieved, however, due to the implementation of the original samples as components of the feature vector, computational cost and burden especially in high sampling frequencies will be very high and the algorithm may take a long time to be trained for a given database. In some other researches, geometrical parameters of QRS complexes such as maximum value to minimum value ratio, area under the segment, maximum slope, summation (absolute value) of point to point difference, ST-segment, PR and QT intervals, statistical parameters such as correlation coefficient of a assumed segment with a template waveform, first and second moments of original or preprocessed signal and etc. are used as effective features (Christov & Bortolan, 2004; Christov & Bortolan, 2005; Chudacek1 et al., 2009; Exarchos et al., 2007; Minhas & Arif, 2008; Tsipouras et al., 2007; Yeh, Wang, & Chiou, 2009). The main definition origin of these features is based on practical observations and a priori heuristic knowledge whilst conducted researches have shown that by using these features, convincing results may be reached. On the other hand, some of studies in the literature focus on the ways of choosing and calculating efficient features to create skillfully an efficient classification strategy (Abe & Kudo, 2006; Liu et al., 2009; Peng et al., 2005; Polat et al., 2009). In the area of nonlinear systems theory, some ECG arrhythmia classification methods on the basis of fractal theory (Lin, Du, et al., 2009; Wang et al., 2001), state-space, trajectory space, phase space, Liapunov exponents (Nopone et al., 2009; Povinelli et al., 2006; Rohani Sarvestani et al., 2009) and nonlinear models (Owis et al., 2002) have been innovated by researchers. Amongst other classification schemes, structures based on higher order statistics in which to analyze features, a two or more dimensional frequency space is constructed can be mentioned (Khadra et al., 2005; Yu & Chen, 2009). According to the concept that upon appearance of changes in the morphology of ECG signal caused by arrhythmia, corresponding changes are seen in the frequency domain, therefore, some arrhythmia classifiers have been designed based on the appropriate features obtained from signal fast Fourier transform (FFT), short-time Fourier transform (STFT), auto regressive (AR) models and power spectral density (PSD), Christov et al., 2006; Lin, 2008; Chen, 2000; Kar & Okandan, 2007; Stridh et al., 2004; Jekova, Bortolan, & Christov, 2008. Finally, using some polynomials such as Hermite function which has specific characteristics, effective features have been extracted to classify some arrhythmias (Jiang & Kong, 2007; Lagerholm, Peterson, Braccini, Edenbrandt, & Sörnmo, 2000). The general block diagram of the proposed heart arrhythmia recognition-classification algorithm including two stages train and test is shown in Fig. 1. According to this figure, first, the events of the ECG signal are detected and delineated using a robust wavelet-based algorithm (Ghaffari, Homaeinezhad, Akraminia, Atarod, & Daevaeiha, 2009; Ghaffari, Homaeinezhad, Khazraee, & Daevaeiha, 2010). Then, each QRS region and also its corresponding DWT are supposed as virtual images and each of them is divided into eight polar sectors. Next, the curve length of each excerpted segment is calculated and is used as the element of the feature space and to increase the robustness of the proposed classification algorithm versus noise, artifacts and arrhythmic outliers, a fusion structure consisting of six different classifiers namely as SVM, KNN and four MLP-BP neural networks with different topologies were designed. The new proposed algorithm was applied to all 48 records of the MIT-BIH Arrhythmia Database (MIT-DB) and as the result, the average value of Acc = 98.20% was obtained as the accuracy. Also, the proposed hybrid classifier was