Medical Decision Support System for Diagnosis of Cardiovascular Diseases using DWT and k-NN

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Abstract

Heart disease is a cardiovascular disorder that is most widespread cause of death in many countries all over the world. In this work, k-Nearest Neighbor machine learning tool was used to classify Electrocardiography (ECG) signals and satisfactory accuracy rate was achieved in classification of ECG signals. The model automatically classifies the ECG signals into 5 different kinds: normal, Premature Ventricular Complex (PVC), Atrial Premature Contraction (APC), Right Bundle Branch Block (RBBB) and Left Bundle Branch Block (RBBB). The best averaged performance over randomized percentage-split is also obtained by k-Nearest Neighbor (k-NN) classification model. Some conclusions concerning the impacts of features on the ECG signal classification were obtained through analysis of different parameters of kNN. The analysis suggests that kNN modeling is satisfactory performances in at least three points: high recognition rate, insensitivity to overtraining and computational time it takes for classification. The combined model with DWT and k-NN achieves the good. Obtained result shows that the suggested model have the potential to obtain a reliable classification of ECG

signals, and to support the clinicians for making an accurate diagnosis of cardiovascular disorders.

Keywords: Electrocardiogram (ECG); Discrete Wavelet Transform (DWT); k-Nearest Neighbor (k-NN); Heart Arrhythmia; Premature Ventricular Complex (PVC); Atrial Premature Contraction (APC); Right Bundle Branch Block (RBBB); Left Bundle Branch Block (RBBB).

1. INTRODUCTION

Heart diseases are a major cause of mortality in most of the countries around the world. In 2008, approximately 17 million people die each year due to this disease or 48 % of all deaths in 2008. It is estimated that this number will even grow. In 2030, it is estimated that 23.6 million people will die from cardiovascular diseases (WHO | Cardiovascular diseases (CVDs)). In Bosnia and Herzegovina, 35000 or 66% of all deaths were due to cardiovascular diseases (BiH). In Turkey, almost 31500 people (49 % of total mortality) died from cardiovascular diseases (Turkey). Because of this many researchers have conducted in this field in the world.

The Electrocardiography is noninvasive tool for detecting the electrical activity that originates in the heart. Expression cardiovascular arrhythmia is used to describe any irregular electrical activity originating from heart. Electrocardiogram (ECG) is one of the most significant apparatus for diagnosis of cardiovascular diseases. The ECG signal classification into different cardiovascular disease groups is a complex pattern recognition problem. These signals are highly nonlinear also. Therefore, different techniques such as signal processing techniques, machine learning methods, were used for this purpose.

The aim of this study is to introduce a method for detection of heart diseases in ECG recordings. We propose a method for differentiating normal heartbeats (N) from left bundle branch blocks (LBBB), right bundle branch blocks (RBBB), atrial premature contractions (APC) and premature ventricular contractions (PVC) heartbeats (Clifford, Azuaje, & McSharry, 2006). In this study, k-Nearest Neighbor (k-NN) classifiers combined with statistical features extracted from DWT is used to classify ECG signals. To contribute to the quantification of the routine ECG examination, a methodology has been developed for ECG signal classification which consists of three steps. In the first step, the ECG signals are decomposed into different frequency bands using discrete wavelet transform (DWT). In the second step, statistical features extracted from these subband decomposed ECG signals to get better accuracy for diagnosis of cardiovascular diseases. In the last step, an unknown ECG signal is classified as normal heartbeats (N) from left bundle branch blocks (LBBB), right bundle branch blocks (RBBB), atrial premature contractions (APC) and premature ventricular contractions (PVC) heartbeats using k-NN classifier.

The remainder of the paper is organized as follows. In the next section, information is given about the materials and datasets used in this research. This section also explains methods applied in each step of the ECG signal classification process. Also, three different k-NN methods are discussed and compared. Section 3 gives discussion on the results achieved in this study. Finally, the conclusions are summarized in Section 4.

2. MATERIALS AND METHODS

2.1. Database

The ECG signals for training and testing datasets are obtained from MIT-BIH arrhythmia database. Records were obtained by the Beth Israel Hospital Arrhythmia Laboratory between 1975 and 1979. This database is available online24. It contains two leads for upper and lower ECG signals for all 48 records from 47 different patients. Patients are 25 men aged 32 to 89 and 22 women aged 23 to 89. Two records (201 and 202) came from same patient. Each of these records is 30 minutes long with sampling frequency of 360 Hz. Each beat has been labeled by at least two cardiologists. There are more than 109,000 labeled ventricular beats from 15 distinct heartbeat types. There is an immense diversity in the amount of examples in each heartbeat category. The biggest category is “Normal beat” and the smallest is “Supraventricular premature beat” (with only two examples) (MIT-BIH Arrhythmia Database Directory).

2.2. Discrete wavelet transform

The DWT is a signal-processing technique having a lot of applications in science and engineering. The wavelet transform (WT) permits the non-stationary signals discrimination with diverse frequency characteristics [14]. It disintegrates a signal into wavelets (group of simple functions. These wavelets result from a single function ψ, called the mother wavelet, by dilations and translations as (Daubechies, Mallat, & Willsky, 1992; Vetterli & Herley, 1992).

$$\psi_{a,b}(t)=\frac{1}{\sqrt{|a|}}\psi\left(\frac{t-b}{a}\right) \quad (1)$$

where a is positive number. Typically, a is 1 for the mother wavelet and growing a > 1 dilates the wavelet, getting bigger on the interval over which it takes non-zero values.

24 http://physionet.ph.biu.ac.il/physiobank/database/html/mitdbdir/mitdbdir.htm

The discrete wavelet transform (DWT) is used to disintegrate a signal. It uses filters to extract out of the ordinary frequency resolution components within the signal. The DWT has compact support in time and frequency domain (Mallat, 1999; Marchant, 2003; Semmlow, 2004; Sornmo & Laguna, 2006). It examines the signal at different frequency bands, with different resolutions. It separates the signal into two parts: a coarse approximation and detail information. DWT uses two function sets called scaling functions and wavelet functions. These two sets are allied to low-pass and high-pass filters, respectively. Every phase of this scheme has two digital filters and scale changes by power of 2. In the process of reducing the sampling rate, outputs of first high-pass and low-pass filters give the detail, D1 and the approximation, A1, respectively. The first approximation, A1 is later decomposed and this process is continued. Approximation and detail records are rebuilded from the Daubechies 4 (DB4) wavelet filter. More detailed explanation is given in (Mallat, 1999; Marchant, 2003; Semmlow, 2004; Sornmo & Laguna, 2006; Adeli, Zhou, & Dadmehr, 2003; Akay, 1997; Subasi, ECG signal classification using wavelet feature extraction and a mixture of expert model, 2007; Subasi, Automatic recognition of alertness level from EEG by using neural network and wavelet coefficents, 2005). The extracted wavelet coefficients give a firm illustration showing the energy distribution of the ECG signal in time and frequency.

2.3. k-Nearest Neighbor (k-NN)

k-Nearest Neighbor (k-NN) is proper mechanism for solving biomedical engineering problems and, particularly, in evaluating biomedical signals, because of their wide range of applications and usage and their potential to learn difficult and nonlinear relations. It is very simple machine learning tool. The k-NN algorithm is object classification tool based on nearest training samples in the feature. The algorithm does not depend on any kind of statistical distribution of training examples. A number of distance measures are capable of being used in k-NN algorithm. Still, the most popular distance is Euclidean. An object classification is done by a mass election of its neighbors. Object is assigned to the class being most frequent one its k nearest neighbors. k is usually selected to be small. When k is selected to be 1, the object is just prescribed to the class of its nearest neighbor. Due to this, the algorithm is called as the k-Nearest Neighbor (Jekova, Bortolan, & Christov, 2008). In Our study, we used three different techniques implementing k-NN algorithm. All these three methods are implemented in Weka (Weka 3 - Data Mining with Open Source Machine Learning Software in Java). These three different techniques are called as: IBk, KStar and LWL. Detailed description of these three different k-NN techniques is given in (Aha, Kibler, & Albert, 1991; Cleary & Trigg, 1995; Frank, Hall, & McShary, 2003).

3. RESULTS AND DISCUSSION

In this study five different heartbeat classes were analyzed. These are: N (normal heart beat), RBBB (Right Bundle Branch Block), LBBB (Left Bundle Branch Block), APC (Atrial Premature Contraction) and PVC (Premature Ventricular Complex).

The classification abilities for three different implementations of k-NN method applied on the morphological ECG descriptors are estimated set obtained by processing all heartbeats from MIT-BIH arrhythmia database. Two statistical indices; sensitivity (Sej) and specificity (Spj); were computed for every heartbeat class j (N, PVC, APC, LBBB and RBBB). They are calculated as (Jekova, Bortolan, & Christov, 2008):

$$Sp_j = \frac{TN_j}{TN_j + FP_j} \qquad Se_j = \frac{TP_j}{TP_j + FN_j} \tag{2}$$

where TPj (true positives) represents the amount of correctly classified heartbeats of jth class (e.g. RBBB classified as RBBB); TNj (true negatives) represents the amount of heartbeats not being part of the jth class and not classified in the jth class (e.g. PVC, APC, LBBB and RBBB not classified as N); FPj (false positives) is the amount of incorrectly classified heartbeats in the class j (e.g. PVC,APC, LBBB and RBBB classified as N); FNj (false negatives) is the amount of heartbeats of class j, classified in a different class (e.g. RBBB not classified as RBBB) (Jekova, Bortolan, & Christov, 2008). 66 % percentage split gave the best results in this research and results are given in Table 1 and their graphical representation is illustrated in Fig. 1.

Table 1. ECG Signal Classification Results for k-NN Classifiers.

	IBk		KStar		LVL	
	Se	Sp	Se	Sp	Se	Sp
N	0.897	0.897	0.891	0.897	0.891	0.908
APC	0.909	0.995	0.848	0.991	0.879	0.99
PVC	0.639	0.958	0.656	0.953	0.754	0.967
RBBB	0.907	0.991	0.893	0.993	0.92	0.993
LBBB	0.951	0.975	0.971	0.978	0.931	0.969

Accuracy obtained for these three different k-NN methods are also compared. For IBk accuracy obtained is 88.24 %, for KStar accuracy is 87.91 % and for LVL, accuracy obtained is 88.73 %. As we can see from Figure 2, accuracies obtained LVL k-NN gave the best result. Beside these results, time required for classification is small compared to other two methods, what is showing that LVL kNN is the most appropriate k-NN method for ECG signal classification.

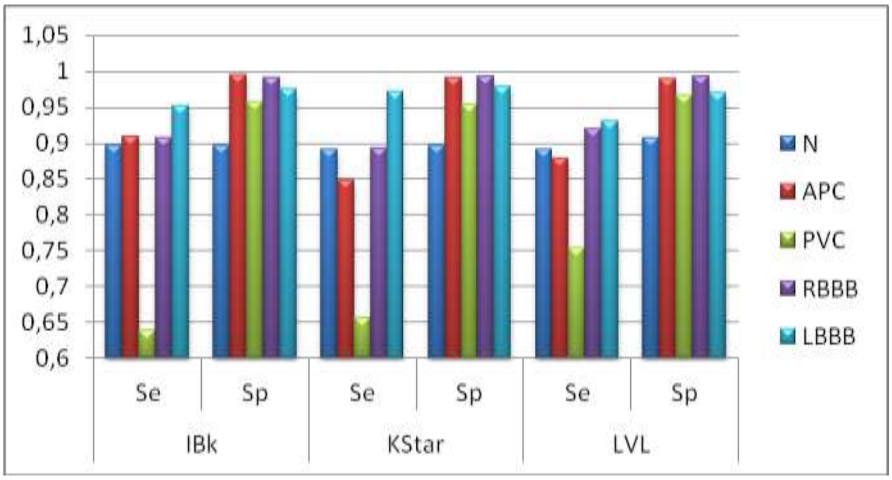

Figure 1 Graphical representation of evaluation performance of k-NN classifiers

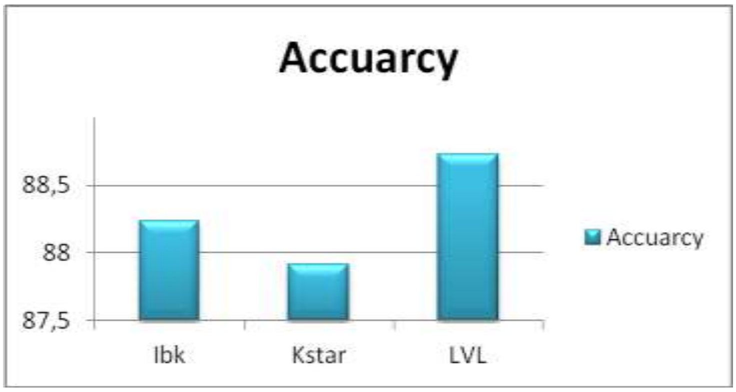

Figure 2 Graphical representation of accuracies achieved by using k-NN classifiers

4. CONCLUSION

In this study, we developed an efficient combination of classifier and signal processing technique, which proved by the different experiments is applicable for the classification of the ECG signals. This was accomplished using combination of DWT and kNN methods. These three kNN methods are IBk, KStar, and LVL. Because the experiments proved, the combination represented as LVL k-NN and DWT subbands can achieve a better performance than other two k-NN classifier methods over the five ECG signal patterns: normal (N), Premature Ventricular Complex (PVC), Atrial Premature Contraction (APC), Right Bundle Branch Block (RBBB) and Left Bundle Branch Block (RBBB). The proposed LVL k-NN classifier together with DWT subbands meets the requirements for five ECG signal patterns characterization and is able of classifying the ECG signals accuracy rate. In addition, the suggested LVL k-NN classifier shows guarantee as a clinically valuable method of providing numerical inputs to the next step of the interpretation phase of an ECG examination. This proves that the LVL k-NN classifier can be important for capturing and expression of knowledge helpful to a clinician. These results provide encouragement to develop and evaluate a LVL k-NN method for quantifying the level of contribution of a cardiovascular disorder.

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