Discrete Cosine Transform Features in Automated Classification of Cardiac Arrhythmia Beats

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Abstract Arrhythmia is an abnormal beat result from any disorder in the conduction of the cardiac electrical impulse. It is very essential to identify and detect arrhythmias correctly in its early phases. Manual diagnosis of arrhythmia beats is very difficult due to their unfamiliar mechanisms and composite nature. Current paper introduces, a machine learning-based methodology proposed for automated cardiac arrhythmia detection. The methodology follows ECG filtering and segmentation using general approach, followed by Discrete Cosine Transform (DCT) for feature extraction, Principal Component Analysis (PCA) for feature reduction and finally classification of arrhythmia beats using *k*-Nearest Neighbor (*k*-NN) classifier. In this study, the statistical significance of PCA features is verified using Analysis of Variance (ANOVA) test. Statistically significant features are classified using *k*-NN and tenfold cross validation. In this study, all the beats of entire *MIT-BIH (Massachusetts Institute of Technology—Boston's Beth Israel Hospital) arrhythmia database* are considered. The five classes recommended by ANSI/AAMI EC57:1998 standard: Non-ectopic (N), Supraventricular ectopic (S), Ventricular ectopic (V), Fusion (F) and Unknown (U) cardiac beats are recognized with an average class specific accuracy of 99.93, 98.41, 98.09, 96.93, 99.7 % respectively and overall average accuracy of 98.61 %. Added validation of the proposed method can result in suitable outcome for therapeutic applications.

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1 Introduction

Electrocardiogram (ECG) registers electrical activity against the time. Any disturbance in the heart's electrical system can cause irregular rhythm patterns, known as cardiac arrhythmia. Disturbance in the cardiac rhythm can be due to the cardiovascular disease (CVDs) or coronary artery disease [1]. Recently World Health Organization (WHO) reports CVDs which includes coronary heart disease, cerebrovascular disease and rheumatic heart disease are the leading noncommunicable diseases (NCD) among other NCD; cancer, diabetes and chronic respiratory diseases. Also, WHO estimates in 2014 mainly the CVDs alone contributing to 17 million deaths (48 % of NCD deaths) annually and 10 % of the global disease burden. This represents almost one-third of all the deaths globally, occurring mainly due to cardiac disorders in low-income countries and middle-income countries [2]. American Health Organization (AHA) estimates CVDs which is expected to grow to more than 23.6 million by 2030. As the magnitude of CVDs continues to accelerate globally the extreme need for increased awareness for stronger and more focused global and country responses is increasingly accepted for better life transformation [3].

Manual diagnosis of cardiac arrhythmias particularly for large dataset could be tedious, time consuming and may lead to misclassification of the normal and abnormal heartbeats. This difficulty can be overcome using computer-aided automated cardiac decision tool. The computer-aided or pattern recognition-based systems can improve the accuracy in cardiac health diagnosis by identifying subtle changes in amplitude and frequency components of the heartbeat [4].

Automated or computer-assisted systems for cardiac health monitoring has been earlier investigated by several researchers and are recently reviewed in [5]. Feature extraction is one of the important stage in the computer-aided diagnosis system. Since the time-domain features do not give good representation of the nonlinear and nonstationary data. Hence, there is a need for the transformation of data from one domain to another using which the hidden information can be extracted significantly [6]. Discrete cosine transform is one of the good feature extraction technique in the spatial frequency domain [7]. Further, the extracted features dimensionality can be reduced using principal component analysis (PCA) [8–18] and classification of arrhythmia beats using *k*-NN classifier.

Current paper summarizes recently conducted studies on cardiac arrhythmia beat classification using computer-aided methods. Martis, et al., extracted principal components of ECG to classify normal, right bundle branch block (RBBB), left bundle branch block (LBBB), atrial premature contraction (APC) and premature ventricular contraction (PVC) beats with an accuracy of 98.11 % and reported sensitivity (Se), specificity (Spe) and positive predictive value (PPV) during classification as 99.90, 99.10 and 99.61 % respectively, using 34,989 ECG beats from the *MIT-BIH arrhythmia database* [9]. Recently, reported that using DCT together with ICA for diagnosis of *MIT-BIH atrial fibrillation* and *MIT-BIH arrhythmia database* using *k*-NN classifier and achieved 99.45 % of Ac, 99.6 % of Se, 100 % of Spe, and 100 % of PPV, respectively [17].

Conversely, all these methods were tested on the fewer datasets and which use complex mathematical features imposing lots of computational complexity while computing these features. There is need to increase the classification accuracy using larger database. This paper introduces a simple cardiac arrhythmia detection methodology for complete *MIT-BIH arrhythmia database* [19] using DCT features. The paper is structured as follows: Sect. 2 presents material and methodology used in the study. In Sect. 3, results of ANOVA test, tenfold cross validation and classifier outputs are reported, outcomes are discussed in Sects. 4 and 5 concludes the paper.

2 Materials and Methdology

Figure 1 represents the proposed system for automated classification of five classes of cardiac arrhythmia Non-ectopic (N), Supraventricular ectopic (S), Ventricular ectopic (V), Fusion (F) and Unknown (U) beats. The working of each block is explained in the following subsections.

2.1 Database Used

In the current work, *MIT-BIH arrhythmia database* [19, 20] which is sampled at 360 Hz is considered. The database consists of 48 extracts, each of half-an-hour duration of Holter monitoring. In this experiment, we have used the complete database for analysis as recommended by ANSI/AAMI EC57:1998 standard [21]. In which, we have identified 90,575 Non-ectopic (N) beats, 2972 Supraventricular ectopic (S) beats, 7707 Ventricular ectopic (V) beats, 1784 Fusion (F) beats and 7055 Unknown (U) beats. Beats at the starting/end of the database, not having enough samples are ignored.

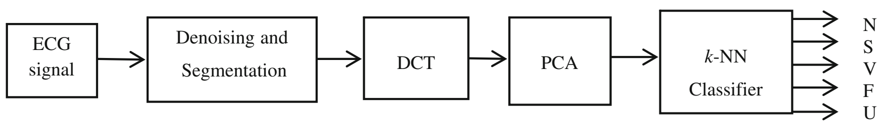

Fig. 1 System approach for the proposed system

2.2 Denoising and Segmentation

ECG signal taken from the *MIT-BIH arrhythmia database*, prominent episodes tested by the medical experts are selected based on the rhythm annotations provided in the database. However, the cardiac signals from the database can contain noise such as baseline wander, muscle artifacts, power-line interference, etc. Thus, the ECG signal is denoised using Discrete Wavelet Transform (DWT)-based subband decomposition and reconstruction method [22]. Later, the signal is subjected to Pan-Tompkin's algorithm for detection of the R-peak and segmentation [23], which involves derivatives, absolute, moving average integrator and squaring operations. Once the QRS complex is detected, the entire window starting from 99 samples to the left of R-peak till 100 samples to the right of R-peak as a segment of 200 samples is chosen as a beat of ECG for subsequent analysis.

2.3 Discrete Cosine Transform (DCT)

DCT of a particular heartbeat consists of 200 samples is computed as,

$$D(v) = \beta(v) \sum_{n=0}^{N-1} x(n) \cos\left[\frac{\pi(2n+1)v}{2N}\right], \textit{ for } v = 0, 1, 2, \ldots, N-1. \tag{1}$$

where $\beta(v)$ is defined by, $\beta(v) = \begin{cases} \frac{1}{\sqrt{N}}, & v = 0 \\ \sqrt{\frac{2}{N}}, & v \neq 0 \end{cases}$

$D(v = 0)$ is average value of the samples of heartbeat, also known as the DC coefficient. Like other transforms, DCT also provides energy compaction. The cosine basis of DCT is orthogonal to each other. The 200 samples of ECG signal are subjected to DCT; there will be 200 DCT coefficients. The first one-third coefficients consist of most of the variability present in the signal [24]. After DCT transformation the first 67 coefficients are considered and rest are discarded. These chosen DCT coefficients are subjected to dimensionality reduction using PCA.

2.4 Principal Component Analysis (PCA)

PCA is a linear dimensionality reduction technique which is used in this study to reduce the dimensionality of DCT coefficients. It is a standard tool in modern data analysis, which uses orthogonal transformation to convert a set of observations into a set of linearly uncorrelated variables. In case the observations were correlated, PCA reduces the dimensionality of the dataset by finding orthogonal representations, which have a lower dimensionality. These new variables are found through establishing unit patterns. In performing PCA, the first twelve principal components (PCs) are used which have more variability of data [25].

2.5 Analysis of Variance Test (ANOVA)

ANOVA evaluates mean, standard deviation and statistical difference of two or more data classes. It returns the *p*-value, which indicates the certainty that the null hypothesis holds. The Null hypothesis puts forward the assumption that the class means are equal. The *p*-value is low when the class means are different and high when they are similar. A p-value < 0.05 is considered to be clinically significant [26].

2.6 **k-***Fold Cross Validation*

Cross-validation is a technique, to assess how statistical analysis results will generalize to an independent data set. In current study, tenfold cross validation performed on *k*-NN classifier. The algorithm starts by partitioning the PCA processed and further labelled feature sets into ten equally sized disjoint subsets known as folds. During the partitioning, the algorithm ensures that each class is uniformly distributed over all folds. In a sequence of tests, each fold was used as test set, while the remaining ninefolds are used as training set [27].

2.7 **k-***Nearest Neighbour Classifier (***k-***NN)*

k-Nearest Neighbour Classifier [27] is a supervised classifier which makes use of the *k*-Nearest Neighbour principle. In this classification algorithm, the training patterns with class identifiers are used to obtain the class separation to the test patterns. This process is repeated until the algorithm converges. A value of two is used for *k* and Euclidean distance metric is used in this research for neighbouring search.

3 Results

The proposed methodology is implemented using MATLAB simulation tool. ECG signals are subjected to DWT-based denoising and followed by R-peak detection using Pan-Tompkin's [23] algorithm. Once the peak is detected, ECG is segmented such that one complete cycle of 200 samples is chosen as a beat. Each ECG beat is subjected to DCT transformation for better representations and then PCA on DCT features to provide the dimensionality reduction. Features from first twelve PCs chosen are subjected to statistical test using *one*-way ANOVA. When the variation between classes was seen to be relatively high compared to the variation within the class, the test was considered to be statistically significant (low value of p). The results of ANOVA test are provided in Table 1. All the features are statistically significant with $p \leq 0.0001$, which indicates first twelve PCs have more discrimination of data, as shown in Fig. 2. These features are class labelled and subjected to tenfold cross validation which consists of partitioning the features, followed by training the labeled feature set and testing without labels. Cross validated features are fed to the k-NN classifier. Figure 3 signifies five arrhythmia classes N, S, V, F and U with average of tenfold class specific accuracy of 99.93, 98.41, 98.09, 96.93 and 99.7 % respectively and five class average accuracy of 98.61 %.

4 Discussion

Current paper discusses cardiac arrhythmia beat identification using principal component (PCs) of DCT features of ECG beats. Table 2, provides summary of studies conducted on automated classification of ECG beats using *MIT-BIH arrhythmia database*. In [8] morphological DWT and time interval features were used and obtained 98.3 and 97.4 % of class accuracy for detection of ventricular escape and supraventricular escape beats respectively. In [10] classify the AAMI (Association for Advancement of Medical Instrumentation) recommended beats using DWT features and ICA as dimensionality reduction method, and recorded a classification accuracy of 99.28 %. Authors reported sensitivity, specificity and PPV during classification as 97.97, 99.83 and 99.21 % respectively. AAMI recommended ECG classes are classified in [11] with an accuracy of 99.52 % using PCs of DCT coefficients of ECG. Here, authors reported sensitivity, specificity and PPV during classification as 98.69, 99.91 and 99.58 % respectively. In [10, 11] all the beats from the entire *MIT-BIH arrhythmia database* [19] are used. In [12] using PCs of higher order bispectrum authors reported an accuracy of 93.5 % for five classes of beats. In [13] classify the principal components of cumulants and report 94.52 % of accuracy in classifying five types of beats. The current work, presents performance of DCT features with PCA for dimensionality reduction and k-NN in classification stage for arrhythmia beat recognition problem where the classes were recommended by AAMI and the entire *MIT-BIH arrhythmia database* considered. The results are reported in Sect. 3 which signifies that for larger dataset of 110,093 cardiac beats using combination of discrete cosine transformed features along with principal component analysis gives good performance measure with respect to average class specific accuracy for Non-ectopic beats (N), Supraventricular ectopic beats (S), Ventricular ectopic beats (V), Fusion beats (F) and Unclassifiable beats (U) using tenfold cross validation and k-NN as classifier. In this paper the class specific accuracy performance measure is a state-of-the-art study compared with other similar studies reported in literature.

Table 1 ANOVA results (mean ± standard deviation), *F*-value and *p*-value for PCA on DCT

PCs	N	S	V	F	Q	*F*-value	*p*-value
PC1	−0.15 ± 1.48	0.39 ± 0.56	0.13 ± 0.71	0.53 ± 0.52	0.15 ± 0.69	2892.63	≤0.0001
PC2	0.01 ± 0.98	0.52 ± 0.36	0.55 ± 0.41	0.52 ± 0.31	0.56 ± 0.40	1513.35	≤0.0001
PC3	−0.06 ± 0.73	−0.15 ± 0.36	−0.11 ± 0.49	−0.14 ± 0.36	−0.11 ± 0.49	597.44	≤0.0001
PC4	0.04 ± 0.63	0.06 ± 0.42	0.05 ± 0.46	0.06 ± 0.42	0.05 ± 0.46	328.35	≤0.0001
PC5	−0.02 ± 0.48	0.07 ± 0.41	0.04 ± 0.40	0.09 ± 0.42	0.04 ± 0.41	192.28	≤0.0001
PC6	−0.01 ± 0.38	0.04 ± 0.26	0.02 ± 0.30	0.04 ± 0.25	0.02 ± 0.30	196.13	≤0.0001
PC7	0 ± 0.29	0.03 ± 0.22	0.02 ± 0.24	0.03 ± 0.22	0.03 ± 0.24	133.13	≤0.0001
PC8	0 ± 0.25	0.03 ± 0.19	0.02 ± 0.20	0.05 ± 0.19	0.03 ± 0.20	125.86	≤0.0001
PC9	0 ± 0.22	−0.01 ± 0.19	−0.01 ± 0.21	−0.01 ± 0.19	−0.01 ± 0.21	93.66	≤0.0001
PC10	0 ± 0.19	0 ± 0.19	0 ± 0.19	0.01 ± 0.19	0 ± 0.19	82.90	≤0.0001
PC11	0 ± 0.16	−0.01 ± 0.15	0 ± 0.15	−0.01 ± 0.15	−0.01 ± 0.15	69.70	≤0.0001
PC12	0 ± 0.15	0.02 ± 0.15	0.01 ± 0.15	0.01 ± 0.15	0.01 ± 0.16	64.74	≤0.0001

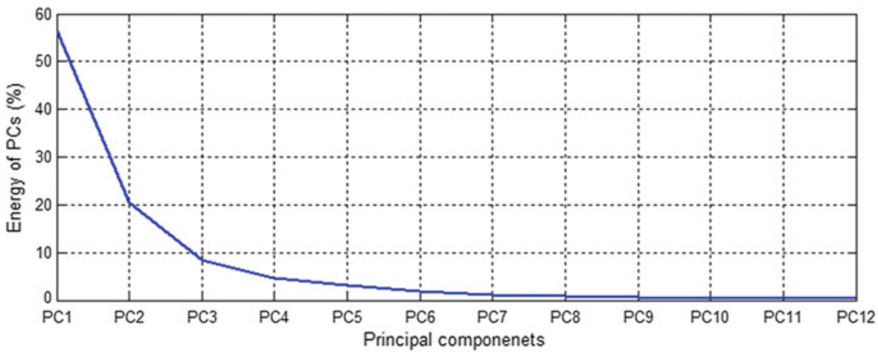

Fig. 2 Eigen value profile of principal component (PCs) in the discrete cosine domain

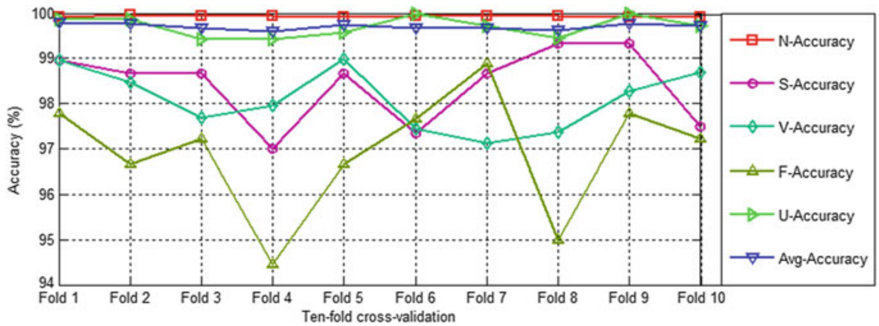

Fig. 3 Plot of class accuracy (%) versus different folds of tenfold cross-validation for *k*-NN classifier

Table 2 Summary of the studies on the automated identification of ECG beats obtained using MIT–BIH database

Literature	Features	Classifier	Classes	Accuracy (%)
Ince et al. [8]	PCA on DWT	Multidimensional PSO	5	95.58
Martis et al. [10]	ICA on DWT	PNN	5	99.28
Martis et al. [11]	PCA on DCT	PNN	5	99.52
Martis et al. [12]	PCA on Bispectrum	SVM with RBF kernel	5	93.48
Martis et al. [13]	PCA on Cumulant	NN	5	94.52
Current study	PCA on DCT	*k*-NN	5	99.7

PSO Particle swarm optimization, *PNN* Probabilistic neural network, *SVM* Support vector machine, *RBF* Radial basis function, *NN* Neural network, *ICA* Independent component analysis

5 Conclusion

The present work concludes using DCT transform domain features ECG arrhythmia beats can be detected with highclassification accuracy. Also applying PCA on DCT coefficients can reduce the dimensionality of the feature sets and classification using k-NN works well for large dataset of 110,093 ECG beats, yielding of average accuracy for five classes 98.61 %. Proposed work is unique in classifying class specific accuracy of five classes of arrhythmia beats.

Currently, there is peak increase in the cardiovascular diseases all over the globe. ECG is the primary physiological signal to detect cardiac abnormalities. Hence, using this simple and low-cost computer-aided automated tool the cardiac abnormalities can be precisely detected for different classes of cardiac arrhythmias. The developed methodology has massive applications in practical arrhythmia monitoring and rural mass screening for diagnosis of cardiac health.

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