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ECG Arrhythmia Detection Using Choi-Williams Time-Frequency Distribution and Artificial Neural Network

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Abstract: Feature selection is one of the most important aspects of classification problem. Due to the nonlinear characteristic of the ECG signal, the time-frequency transformation is proposed for better feature extraction to classify different ECG arrhythmia beats. In our study Choi-Williams time-freqency distribution and short time Fourier transform are used to extract features from the ECG signals. Total sixteen features are extracted which are used as the input to the feed-forward backpropagation neural network using the conjugate gradient optimization algorithm. ECG signals of MIT-BIH arrhythmia dataset are used in this work. Six different classes of ECG beats, Normal (N) beat, Left Bundle Branch Block (L) beat, Right Bundle Branch Block(R) beat, premature ventricular contraction (V) beat, paced (PA) beat and fusion of paced and normal (f) beat are classified and the performance is compared.

Keyword: Time-Frequency Distribution, Backpropagation neural network, Pattern Classification, ECG Arrhythmia

I. INTRODUCTION

Electrocardiogram (ECG) is a very common noninvasive method to detect the health of the heart. Due to the infrequent appearance of some of the arrhythmias (which may lead to heart failure), it becomes necessary to capture them through monitoring the ECG waveform for a longer duration. Long-duration ECG has become an important diagnostic method for clinicians. As the manual examination of long-duration ECG is time-consuming and unreliable, development of computer aided diagnostic system with efficient classification algorithm is necessary. In the past several researchers have proposed different methods for classification of arrhythmias.

The performance of the classifier mostly depend the features of the class as it contains the information about that class. Some authors used morphological features [2],[4],[8],[9] where as temporal features [3],[5] , frequency based features [1],[6], statistical features[7] are used by others. Similarly, different methods such as backpropagation neural network [1-2], [8-10], support vector machine (SVM) [1], probabilistic neural network (PNN) [1] [4] are used by various authors.

In this work the time-frequency (T-F) transformation [11-14] is used for feature selection because of the nonlinear and nonstationary nature of ECG signals. Wigner-Ville T-F distribution is of interest of many researchers in the past, due to its good properties such as marginal property, time and frequency shift invariant property and sharp resolution. But the main drawback of the Wigner-Ville is the presence of the cross-terms (also known as interference terms).Methods have been proposed and a number of useful kernels have been developed to reduce the interference term. The common reduced interference distribution (RID) is known as Choi-Willians distribution which is used to get feature of different class and applied to the neural network for classification.

The rest of the paper is arranged as follows:

Section 2 describes the Choi-Willians distribution and short-time Fourier transform (STFT). In section 3 the results of the above two methods are analyzed. The last section is the concluding part.

II. METHODS

Classification of ECG signals is a pattern recognition problem consists of two steps: time-frequency transformation of the signal and then classification using neural network.

A) Short-term Fourier Transform

The short-time Fourier transform (STFT) [11]of a signal $x(t)$ is defined as

$$X(t,f) = \int_{-\infty}^{\infty} x(t_1)h^*(t_1 - t)e^{j2\pi f t_1}dt_1 \qquad (1)$$

Where the window function $h(t)$, centered at time t, is multiplied with the signal $x(t)$ before the Fourier transform. A fixed positive even window $h(t)$, of a certain shape, centered round zero, having power $\int_{-\infty}^{\infty}|h(t)|^2dt = 1$ is used. The spectrogram is

$$S_x(t,f) = |X(t,f)|^2 \qquad (2).$$

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B) Choi-Williams Distribution(CWD)

Wigner-Ville T-F distribution (WVD) suffers from cross terms, which is the appearance of intensity regions in place of zero values. A large area of research has been developed to reduce the cross-terms. Ambiguity functions and ambiguity kernels have shown to be an efficient way of reducing cross-terms.

Ambiguity function of $x(t)$ is defined as

$$A_x(\xi,\tau) = \int_{-\infty}^{\infty} x\left(t+\frac{\tau}{2}\right) x^*\left(t-\frac{\tau}{2}\right) e^{-j2\pi\xi t} dt \qquad (3)$$

is a degree of similarity between $x(t)$ and its translated versions in the time-frequency plane. Unlike the variables 't' and 'f' which are "absolute" time and frequency coordinates, the variables 'τ' and 'ξ' are relative coordinates (called delay and Doppler respectively). As the auto-term (signal components) always located at the center of the ambiguity function, independently of where they are located in the time-frequency plane, and the cross-terms always located away from the center, it is a natural approach to keep the terms located at the center and reduce the components away from the center.
The expression of Cohen's class in terms of ambiguity function is

$$C_x(t,f;\emptyset) = \iint_{-\infty}^{\infty} \emptyset(\xi,\tau) A_x(\xi,\tau) e^{-j2\pi(f\tau+\xi t)} d\xi d\tau \qquad (4)$$

$\emptyset(\xi,\tau)$ is the parameterization function or the kernel, acts as a weighting function that tries to keep the signal unchanged and reject the interference term. A number of kernels have been proposed to achieve this. For example,the WVD belongs this Cohen's class corresponds to a constant kernel function, that is $\emptyset(\xi,\tau) = 1$. This shows that no change is made between the different regions of the ambiguity plane. Studies show that removing the cross-terms of the Winger distribution violets some of the desired properties like the marginals. Choi and Wiliams in their method minimized the cross-terms, instead of removing them, in order to keep the desirable properties at a satisfactory level.

$$CW_x(t,f) = \sqrt{\frac{2}{\pi}} \iint_{-\infty}^{\infty} \frac{\sigma}{|\tau|} e^{\frac{2\sigma^2 (t_1-t)^2}{\tau^2}} x\left(t+\frac{\tau}{2}\right) x^*\left(t-\frac{\tau}{2}\right) e^{-j2\pi f\tau} dt d\tau \qquad (5)$$

Where the kernel function is

$$\phi(\xi,\tau) = e^{-\frac{(\pi\xi\tau)^2}{2\sigma^2}} \qquad (6)$$

C) Preprocessing and feature Extraction

ECG signal taken from the MIT-BIH arrhythmia database[155] is passed through a band-pass filter to remove different artifacts such as baseline wander, muscles noise and interference noise of 60Hz. The filtered signal is segmented into different beats after detecting the R-peak [10]. From each segment sixteen samples around the R-peak (seven before and eight after the R-peak) are considered for T-F transformation (STFT and CWD). The CWD for six different classes of ECG beats are shown in Fig 2(a)-7(a).1-D Wall slice from the T-F distribution is taken as the set of features. Fig 2(b) to 7(b) shows the graphs of the respective 1-D slice curve. These figures clearly show that the features value for each class are largely separated from the others.

D) Backpropagation Neural Network

A three layer neural network is used to feed-forward backpropagation conjugate gradient descent algorithm[16]. The hidden layer is fixed to 35 neurons and output layer to 06. The sigmoidal activation function of fixed parameter is taken. All the weights and biases are initialized to small random values. After initialization the input vectors and corresponding desired responses are presented to the network for training. The block diagram of feature extraction and classification is shown in Fig.1.

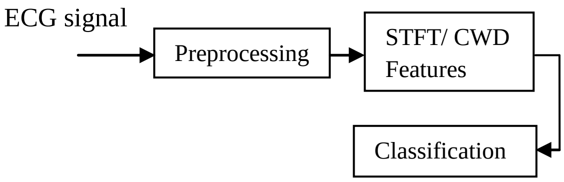

Fig. 1. Feature extraction & classification phase

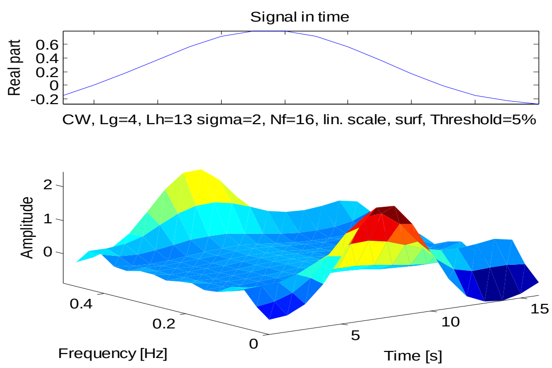

Fig. 2(a). CWD of N-Beat with signal in Time

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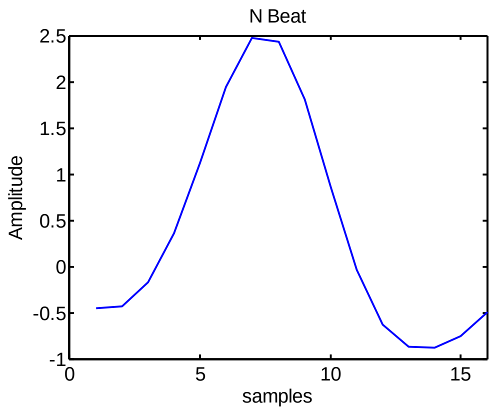

Fig.2(b).1-D wall slice from CWD of N Beat

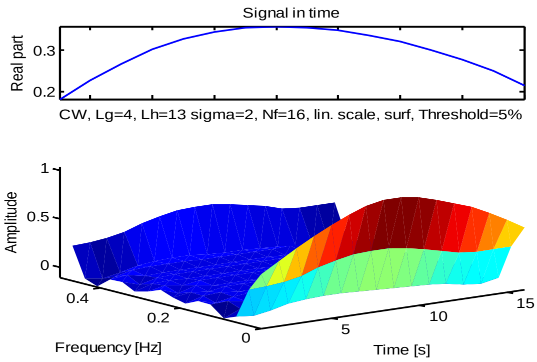

Fig. 3(a). CWD of L-Beat with signal in Time

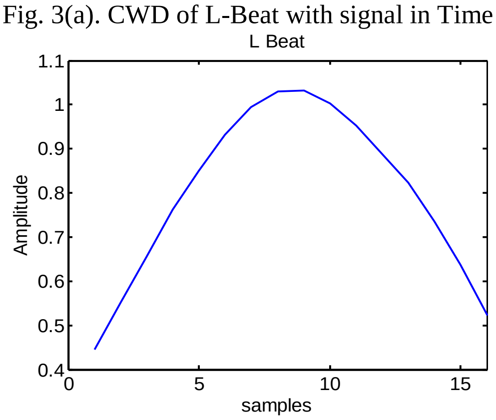

Fig. 3(b). 1-D wall slice from CWD of L Beat

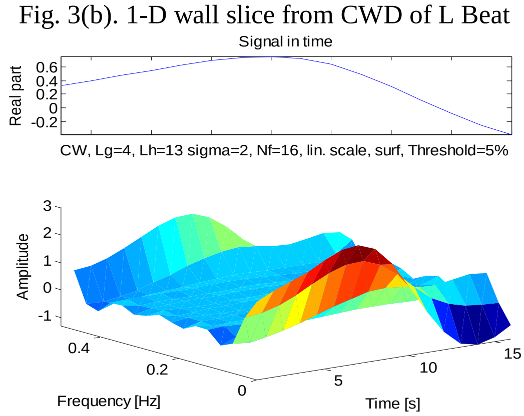

Fig. 4(a). CWD of R-Beat with signal in Time

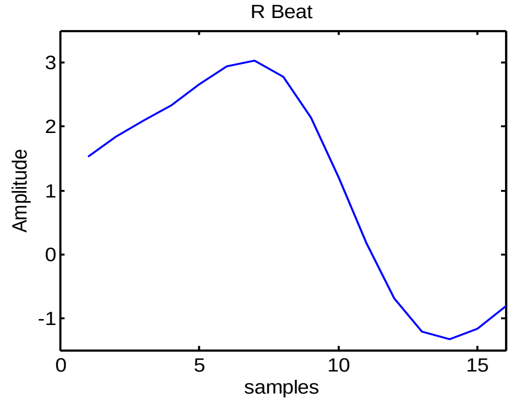

Fig 4(b). 1-D wall slice from CWD of R Beat

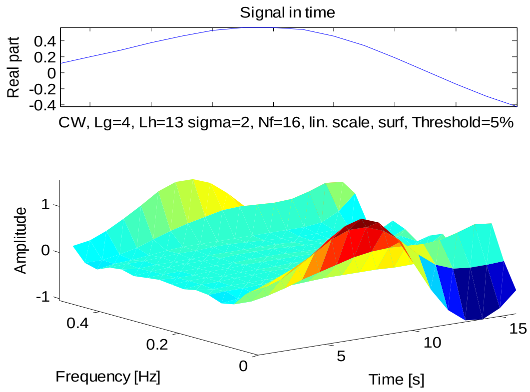

Fig. 5(a). CWD of V-Beat with signal in Time

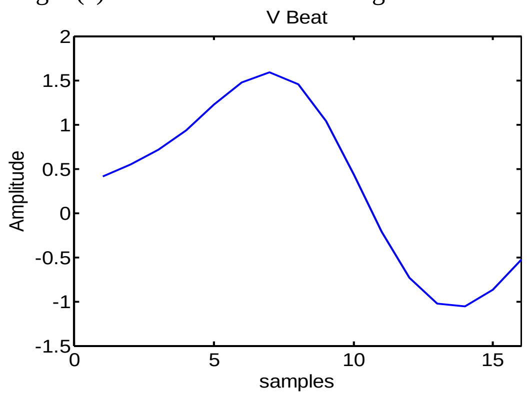

Fig. 5(b). 1-D wall slice from CWD of V Beat

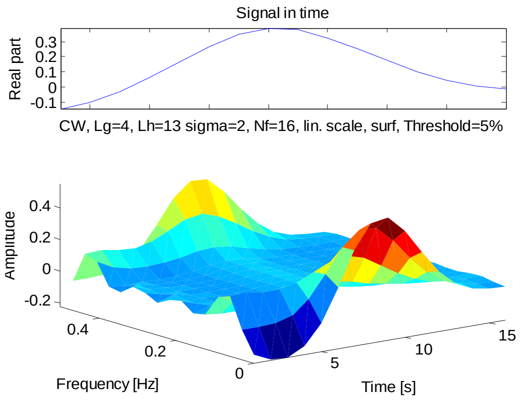

Fig. 6(a). CWD of PA-Beat with signal in Time

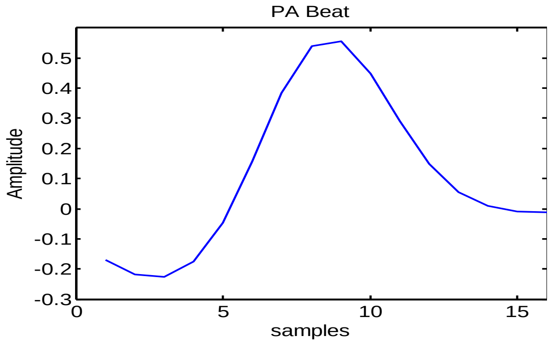

Fig. 6(b). 1-D wall slice from CWD of PA Beat

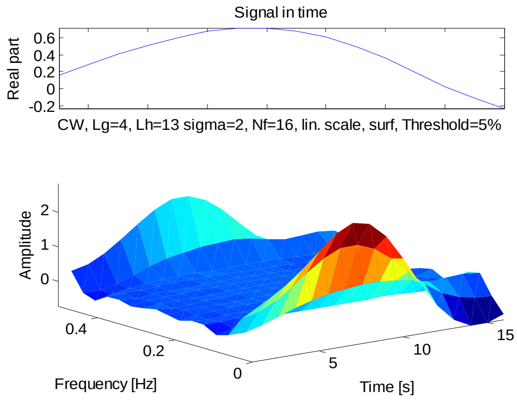

Fig. 7(a). CWD of f-Beat with signal in Time

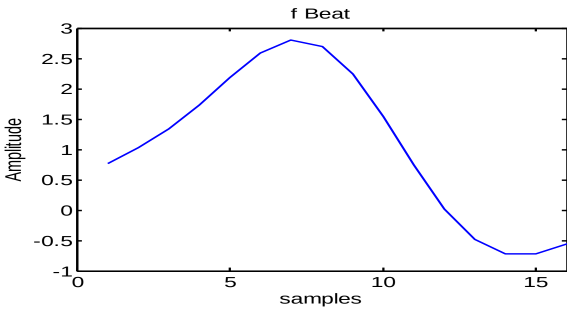

Fig 7(b). 1-D wall slice from CWD of f- Beat

III. RESULTS AND DISCUSSION

A three layer neural network is used for classification in this work. Total 1500 beats from six different classes (1074 beats from N class,132 beats from L class, 111 beats from R class, 66 beats from V class,99 beats from PA class and 18 beats from f class) are classified using STFT & CWD based features. STFT & CWD are computed for each beat using MATLAB R2010a with a time-frequency toolbox. Each feature vector consists of 16 features which are the input to the neural network for training. The training data contains 90 different patterns taking 15 from each class for balanced training. After training the test data of high class imbalance ratio are used to evaluate the performance of the system. The performance of the system is evaluated from the assessment matrix. The terms used in evaluating the system are defined as

TP: true positive, TN: true negative
FP: false positive, FN: false negative
Pc = TP + FN & Nc = FP + TN

$$\text{sensitivity} = \frac{\text{TP}}{\text{TP} + \text{FN}} \tag{7}$$

$$\text{specificity} = \frac{\text{TN}}{\text{TN} + \text{FP}} \tag{8}$$

$$\text{accuracy} = \frac{\text{TP} + \text{TN}}{\text{P}_\text{c} + \text{N}_\text{c}} \tag{9}$$

Precision is the percentage of positive predictions done correctly.

$$\text{Precision} = \frac{\text{TP}}{\text{TP} + \text{FP}} \tag{10}$$

Table I
Confusion Matrix of Choi-Williams T-F Distribution based Neural Network (CWDNN) and Short Time Frequency Transform based Neural Network (STFTNN)

	CWDNN						STFTNN					
	N	L	R	V	PA	f	N	L	R	V	PA	f
N	1066	5	0	0	0	3	1052	22	0	0	0	0
L	0	132	0	0	0	0	0	132	0	0	0	0
R	0	0	111	0	0	0	0	0	111	0	0	0
V	0	0	1	65	0	0	0	0	2	64	0	0
PA	0	0	0	0	96	3	0	0	0	0	93	6
f	0	0	0	0	1	17	0	0	0	1	2	15

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Table II
Assessment Metrics of Choi-Williams T-F Distribution based Neural Network (CWDNN) and Short Time Frequency Transform based Neural Network (STFTNN)

	CWDNN					STFTNN			
	Sensitivity	Specificity	Precision	Accuracy		Sensitivity	Specificity	Precision	Accuracy
N	0.9926	1.0000	1.0000	0.9947		0.9795	1.0000	1.0000	0.9853
L	1.0000	0.9963	0.9635	0.9967		1.0000	0.9839	0.8571	0.9853
R	1.0000	0.9993	0.9911	0.9993		1.0000	0.9986	0.9823	0.9987
V	0.9851	1.0000	1.0000	0.9993		0.9697	0.9993	0.9846	0.9980
PA	0.9697	0.9993	0.9897	0.9973		0.9394	0.9986	0.9789	0.9947
f	0.9444	0.9960	0.7391	0.9953		0.8333	0.9960	0.7143	0.9940

Table 1 shows the confusion matrix for both Choi-Williams T-F Distribution based Neural Network (CWDNN) and Short Time Frequency Transform based Neural Network (STFTNN) where the main diagonal is the true positive value. The true positive, in case of CWDNN is either same or more than that of STFTNN for all the classes. From the assessment metrics it is observed that though both the methods give good classification result, CWDNN has edge over STFTNN. Also the number of features used only sixteen. The highest and lowest accuracy in case of CWDNN is 99.93%,99.47%,whereas in case of STFTNN it is 99.87% and 99.40% respectively. The maximum sensitivity, specificity and precision are 100%, whereas the minimum sensitivity, specificity and precision is 99.44% ,99.60% and 73.91% in case of CWDNN and 83.33%, 99.60% and 71.43 respectively for STFTNN.

IV. CONCLUSION

Though number features used in this classification are only sixteen, the performance of the classifier is encouraging. As in both the methods (CWD and STFT) the classification accuracy is more than 99% , the other T-F distribution functions may be used for feature extraction in classification problems

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