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A Comparative Study of Pseudo-Wigner-Ville Distribution(PWVD),WVD and STFT in ECG Signal Analysis

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ABSTRACT: In this paper, we have proposed pseudo Winger-Ville distribution(PWVD) to classify the ECG arrhythmias and compared the result with Wigner-Ville distribution(WVD) and short time Fourier transform(STFT). A three-layer Artificial neural network using conjugate gradient optimization techniques is used for classification. MIT-BIH arrhythmia database is used to classify six different arrhythmias. These are 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. The performance of the classifiers for different techniques is compared. Pseudo Wigner-Ville distribution performs better than the other two with maximum sensitivity, specificity, precision, and accuracy at 100% and minimum accuracy of 99.80%.

KEYWORDS: Artificial neural network, Time-Frequency Distribution, 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 a 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] whereas 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.

Time-frequency analysis is one of the most important areas of signal processing. The Fourier analysis decomposes the signal into individual frequency components and relative intensity of each component, but silent on the timing of occurrence of the frequencies. Hence time-frequency analysis of the signal is necessary. The simplest time-frequency method is short-time Fourier transform (STFT) also known as the spectrogram, in which Fourier transform is calculated to the pre-windowing signal x (u) around a particular time t and doing that for each time instant t. STFT though very easy, to implement, fails to provide high time and frequency resolution simultaneously. Long duration window gives a better frequency resolution but less time resolution, whereas shorter window gives a better time resolution only. When the spectral content of the signal changes rapidly, finding an appropriate short-duration window

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is difficult as there may not be any time interval for which the signal can be almost stationary. Due to this time-frequency problem, STFT is suitable for analysis of slow temporal varying signals but not rapidly varying one.

The classical work, of Gabor [17], Ville and Page [18] on time-varying spectra is not based on improving the spectrogram, but to develop a joint time and distribution function to describe the energy density of the signal simultaneously in time and frequency[10-14]. The ideal time-frequency distribution can tell[14] :

1. The fraction of energy in a certain frequency and time range.
2. The distribution of frequency at a particular time.
3. The local and global moments(such as the mean frequency and its local speed) of the distribution.
4. To construct a signal of desirable properties.

As no ideal time-frequency distribution exist, different distributions are used in different situations. Time-frequency distribution function can be used in almost every field where there are nonstationary signals.

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(WVD) was of interest to 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). The interference can be reduced by windowing operation of WVD. This windowing of WVD is known as pseudo-Wigner-Ville distribution(PWVD). Different distribution functions are used to get the 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 Wigner-Ville distribution its properties, interference in WVD, pseudo Wigner-Ville distribution (PCWD) 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 a neural network.

A) Short-term Fourier Transform

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

$$X(t,f) = \int_{-\infty}^{\infty} x(u)h^*(u-t)e^{j2\pi fu}du \tag{1}$$

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 around zero, having power $\int_{-\infty}^{\infty}|h(t)|^2dt = 1$ is used. The spectrogram is

$$S_x(t,f) = |X(t,f)|^2 \tag{2}$$

B) Winger-Ville Distribution(WVD)

The short - time Fourier transform is explicitly dependant on some short-time window h (t), thus limiting the evaluation of the Fourier transform to some specified neighborhood of the current time t. Because of the short-duration

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of the window h (t), the time resolution is better, whereas the frequency resolution is poor. Instead of fixed arbitrary h (t), Wigner tried to make it depend adaptively on the signal itself as:

$$W_x(t,f) = \int_{-\infty}^{\infty} x\left(t+\frac{\tau}{2}\right)x^*\left(t-\frac{\tau}{2}\right)e^{-j2\pi f\tau}d\tau \tag{3}$$

This is known as Winger-Ville distribution (WVD). An alternate expression of WVD is

$$W_x(t,f) = \int_{-\infty}^{\infty} X\left(f+\frac{\xi}{2}\right)X^*\left(f-\frac{\xi}{2}\right)e^{j2\pi t\xi}d\xi \tag{4}$$

Where x(t) is the analytic signal. A signal x(t) analytic if

$$X(f) = 0 \quad \text{for } f < 0\ , \quad \text{where } X(f) = \mathcal{F}\{x(t)\} \tag{5}$$

The above equation shows that the spectrum of the analytic signal is identical to the spectrum of real signal if the frequency is positive otherwise zero. The difference between Winger-Ville and Winger distribution is that in WVD the signal is analytic. The advantage of WVD in comparison to WD is that :

1. WD exhibits interference between negative and positive frequency components of the signal, whereas in WVD no such interference due to the absence of negative frequencies.
2. The instantaneous frequency of the signal x(t) can be recovered from WVD as its 1st order moment in frequency.
3. The practical algorithm for computation of the WD relay on oversampling of the original waveform to avoid aliasing in the frequency domain, whereas no such oversampling is required in case of WVD.

Properties of WVD

1. Energy Conservation:

$$E_x = \iint_{-\infty}^{\infty} W_x(t,f)dtdf \tag{6}$$

Where E_x is the energy of the signal x(t).

2. Marginality:

$$\left.\begin{aligned}\int_{-\infty}^{\infty} W_x(t,f)\,dt &= |X(f)|^2\\ \int_{-\infty}^{\infty} W_x(t,f)\,df &= |x(t)|^2\end{aligned}\right\} \tag{7}$$

Marginality shows that by integrating T-F energy density along one variable, the energy density corresponding to other variable is obtained.

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3. Real-valued:

$$W_x(t,f) \in \mathcal{R}, \quad \forall \ t,f \tag{8}$$

4. Translation Covariance:

$$\left.\begin{aligned} y(t) = x(t-t_0) &\Longrightarrow W_y(t,f) = W_x(t-t_0,f) \\ y(t) = x(t)e^{j2\pi f_0 t} &\Longrightarrow W_y(t,f) = W_x(t,f-f_0) \end{aligned}\right\} \tag{9}$$

5. Dilation Covariance:

$$y(t) = \sqrt{k}x(kt); \quad k > 0 \Longrightarrow W_y(t,f) = W_x\left(kt,\frac{f}{k}\right) \tag{10}$$

6. Compatibility with Filtering:

If h(t) is the impulse response of the LTI(linear time invariant) filter and x(t) the input to the filter then WVD of the output y(t) of the filter is the time convolution between the WVD of h(t) and the WVD of x(t).

$$y(t) = \int_{-\infty}^{\infty} h(t-s)x(s)ds \Longrightarrow W_y(t,f) = \int_{-\infty}^{\infty} W_h(t-s,f)\, W_x(s,f)ds \tag{11}$$

7. Compatibility with Modulations:

This is the duality of property (6).

$$y(t) = m(t)x(t) \quad \Longrightarrow \quad W_y(t,f) = \int_{-\infty}^{\infty} W_m(t,f-\xi)\, W_x(t,\xi)d\xi \tag{12}$$

8. Wide-sense Support Conservation:

$$\left.\begin{aligned} x(t) = 0, \ |t| > T \ &\Longrightarrow \ W_x(t,f) = 0, \ |t| > T \\ X(f) = 0, \ |f| > B \ &\Longrightarrow \ W_x(t,f) = 0, \ |f| > B \end{aligned}\right\} \tag{13}$$

9. Instantaneous Frequency:

The instantaneous frequency of the signal x(t) can be recovered from the WVD as its first order moment in frequency.

$$f_x(t) = \frac{\int_{-\infty}^{\infty} f W_x(t,f)df}{\int_{-\infty}^{\infty} W_x(t,f)df} \tag{14}$$

10. Group Delay:

This is the duality of the property (9). Group delay of x(t) can be obtained as the first order moment in time of its WVD.

$$t_x(f) = \frac{\int_{-\infty}^{\infty} t W_x(t,f)dt}{\int_{-\infty}^{\infty} W_x(t,f)dt} \tag{15}$$

C) Psedo-Winger-Ville Distribution(PWVD)

Consider a signal z(t) = x(t) + y(t). The WVD is

$$W_z(t,f) = W_x(t,f) + W_y(t,f) + 2\mathcal{R}W_{x,y}(t,f) \tag{16}$$

Where $W_x(t,f)$, and $W_y(t,f)$ is called auto-terms. $W_{x,y}(t,f)$ is the cross-term, which is always located in the midway between the auto-terms. The cross-terms oscillate proportionally to the distance between the auto-terms, and the direction of oscillation is orthogonal to the line connecting the auto-terms. However, due to this cross-terms, the good

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properties of WVD, such as marginality, instantaneous frequency, and group delay are satisfied. In other words, the absence of cross-terms does not satisfy the above-mentioned properties. Hence there must be a trade-off between cross-terms and good properties.

Pseudo-WVD (PWVD) makes the trade-off between cross-terms and good properties by windowing WVD. PWVD of x(t) is defined as

$$PW_x(t,f) = \int_{-\infty}^{\infty} h(\tau)x\left(t+\frac{\tau}{2}\right)x^*\left(t-\frac{\tau}{2}\right)e^{-j2\pi f\tau}d\tau \qquad (17)$$

Where h(t) is the window function. This windowing operation is equivalent to frequency smoothing of WVD.

$$PW_x(t,f) = \int_{-\infty}^{\infty} H(f-\xi)\, W_x(t,\xi)d\xi \qquad (18)$$

Where H(f) is the Fourier transform of h(t). This windowing operation, though attenuated the interference term of WVD, the frequency width of the auto-terms is increased as shown in the Fig.1. This is in addition to losing some important properties as described before.

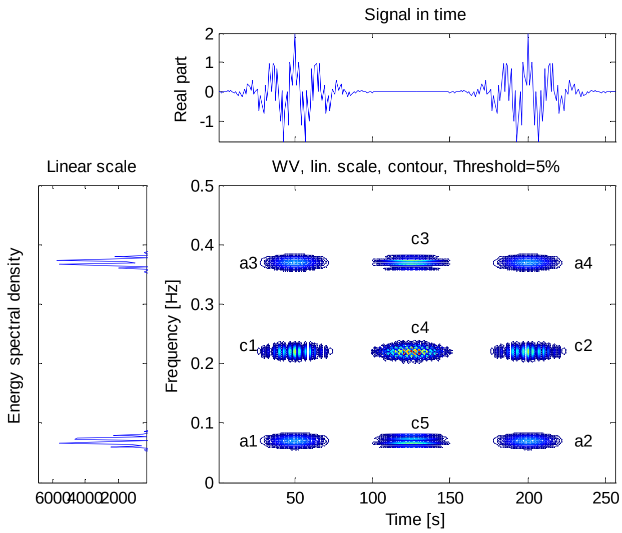

Figure 1.(a) Signal in time consists of four Gaussian windowed sinusoidal components located at time t=50 and 200, frequencies at 0.07 and 0.37. a1,a2,a3 and a4 are the auto-terms(WVD of the four signal components)and c1,c2,c3,c4 and c5 are the four cross-terms (interference due to WVD). Left side curve is the spectral density.

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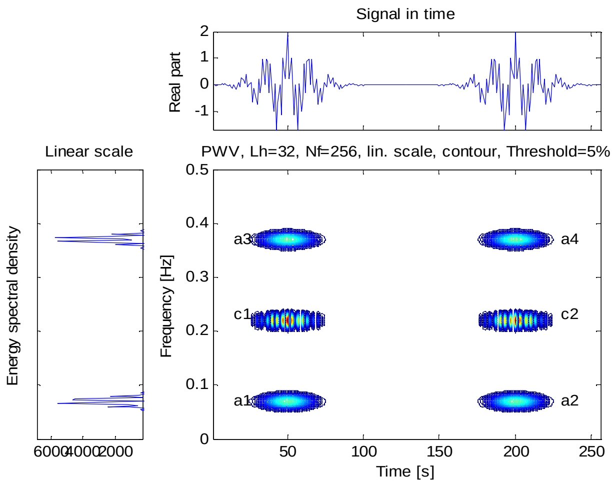

Figure 1. (b) Cross-terms c3, c4 and c5 due to WVD in Fig.1(a) are attenuated by the frequency smoothing operation of pseudo Winger-Ville distribution.

D) Preprocessing and Feature Extraction

ECG signal taken from the MIT-BIH arrhythmia database[15] 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 (PWVD, WVD, and STFT). The PWVD for six different classes of ECG beats are shown in Fig 3-Fig.8. 1-D Wall slice from the different T-F distribution for six different class of arrhythmia beats is taken as the set of features. Fig 9-11 shows the graphs of the respective 1-D slice curve. These figures clearly show that the feature value for each class are largely separated from the others for different T-F distribution.

E) Backpropagation Neural Network

A three layer feed-forward backpropagation neural network with conjugate gradient descent algorithm[16] for error function optimization is used in this work. The hidden layer is fixed to 35 neurons[9] and output layer to 06. The sigmoidal activation function of the 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.2

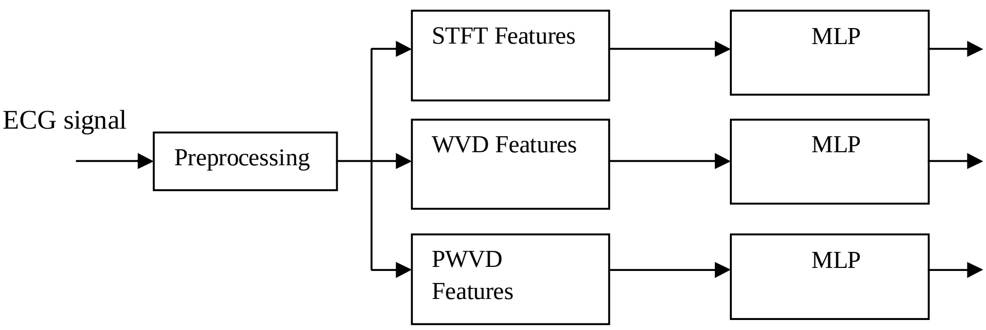

Figure 2.Feature extraction & classification

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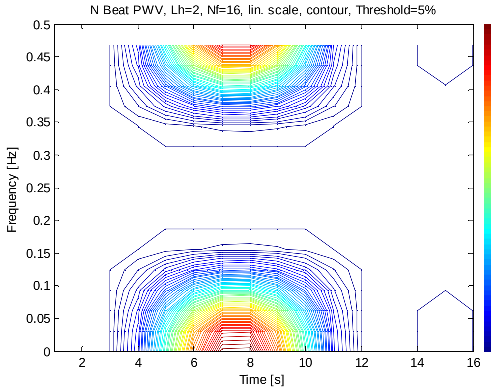

Figure 3. PWVD of N Beat

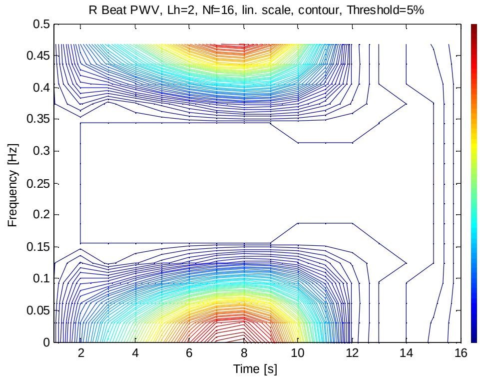

Figure 5. PWVD of R Beat

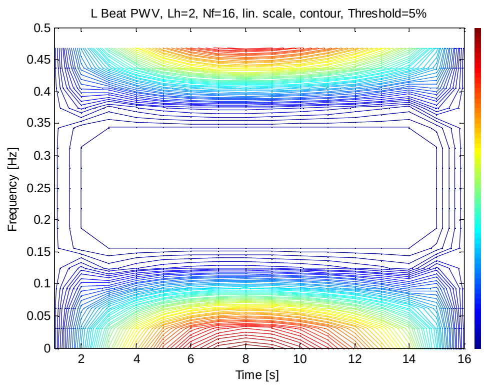

Figure 4. PWVD of L Beat

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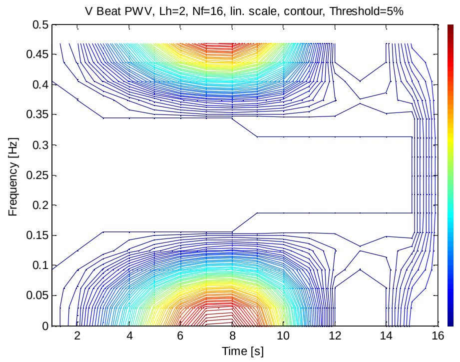

Figure 6. PWVD of V Beat

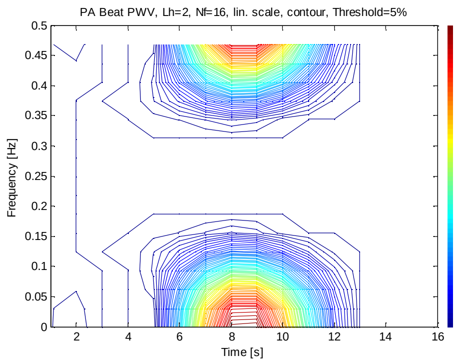

Figure 7. PWVD of PA Beat

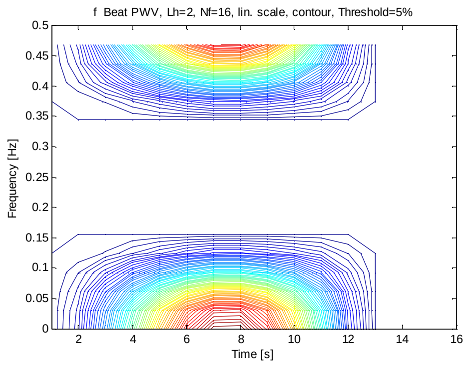

Figure 8. PWVD of f Beat

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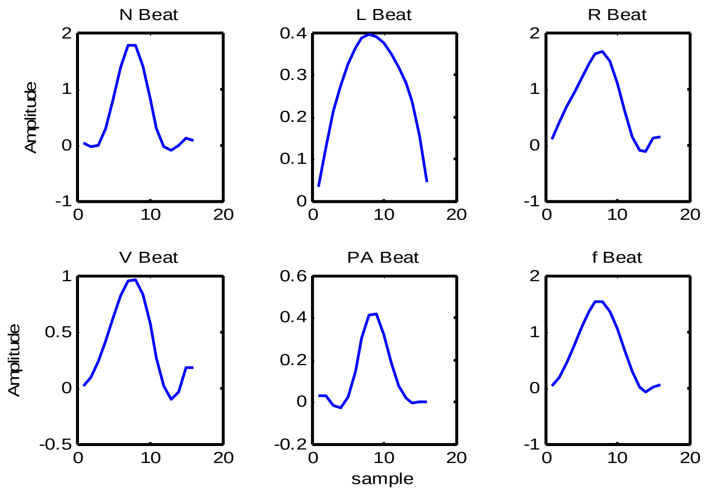

Figure 9. 1D slice of PWVD for different class of arrhythmia beats

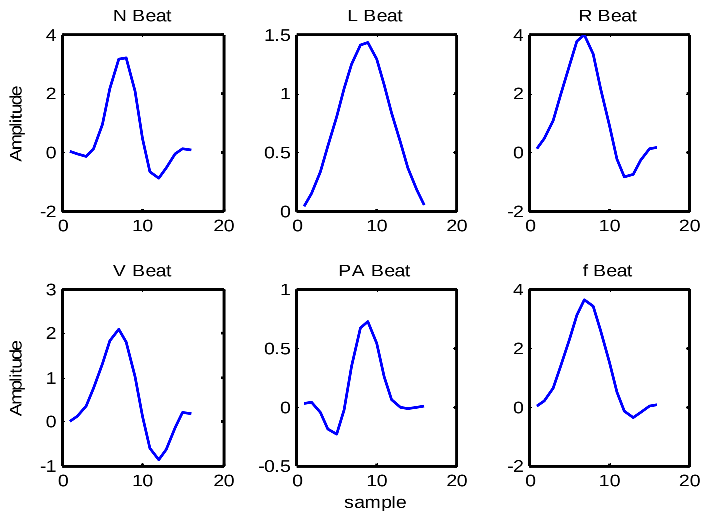

Figure 10. 1D slice of WVD for different class of arrhythmia beats

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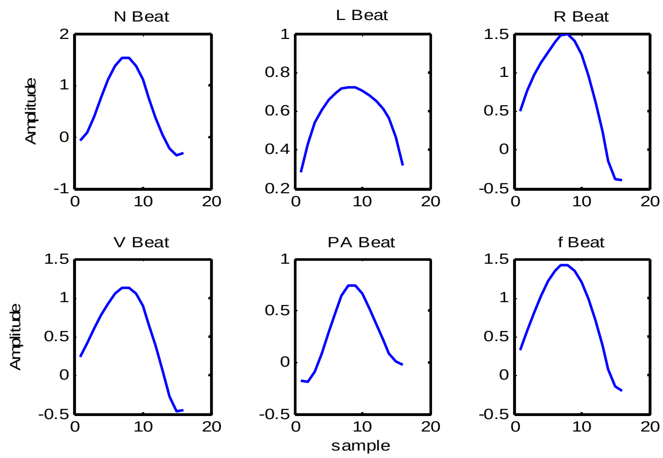

Figure 11. 1D slice of STFT for different class of arrhythmia beats

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 PWVD, WVD, and STFT based features. T-F distribution is computed for each beat using MATLAB R2010a using 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

$P_c = TP + FN$ & $N_c = FP + TN$

$$\text{sensitivity} = \frac{TP}{TP + FN} \quad (19)$$

$$\text{specificity} = \frac{TN}{TN + FP} \quad (20)$$

$$\text{accuracy} = \frac{TP + TN}{P_c + N_c} \quad (21)$$

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Precision is the percentage of positive predictions done correctly.

$$\text{Precision} = \frac{TP}{TP + FP} \quad (22)$$

Table I

Confusion and Assessment matrices of Pseudo-Winger-Ville T-F Distribution based Neural Network (PWVDNN), Winger-Ville T-F Distribution based Neural Network (WVDNN) and Short Time Frequency Transform based Neural Network (STFTNN)

	PWVDNN									
	N	L	R	V	PA	f	Sensitivity	Specificity	Precision	Accuracy
N	1074	0	0	0	0	0	1.0000	1.0000	1.0000	1.0000
L	0	132	0	0	0	0	1.0000	1.0000	1.0000	1.0000
R	0	0	111	0	0	0	1.0000	0.9993	0.9911	0.9993
V	0	0	1	65	0	0	0.9848	1.0000	1 .0000	0.9993
PA	0	0	0	0	99	0	1.0000	0.9979	0.9706	0.9980
f	0	0	0	0	3	15	0.8333	1.0000	1.0000	0.9980
	WVDNN									
N	1067	2	0	5	0	0	0.9935	1.0000	1.0000	0.9953
L	0	132	0	0	0	0	1.0000	0.9985	0.9851	0.99987
R	0	0	111	0	0	0	1.0000	1.0000	1.0000	1.0000
V	0	0	0	66	0	0	1.0000	0.9965	0.9296	0.9967
PA	0	0	0	0	90	9	0.9091	0.9964	0.9474	0.9907
f	0	0	0	0	5	13	0.7222	0.9939	0.5909	0.9907
	STFTNN									
N	1047	27	0	0	0	0	0.9749	1.0000	1.0000	0.9820
L	0	132	0	0	0	0	1.0000	0.9803	0.8302	0.9820
R	0	0	110	0	1	0	0.9910	0.9978	0.9735	0.9973
V	0	0	2	61	3	0	0.9242	0.9993	0.9839	0.9960
PA	0	0	1	0	92	6	0.9293	0.9964	0.9485	0.9920
f	0	0	0	1	1	16	0.8889	0.9960	0.7273	0.9947

Table 1 shows the Confusion and Assessment matrices for the whole dataset using pseudo Winger-Ville T-F Distribution based Neural Network (PWVDNN), Winger-Ville T-F Distribution based Neural Network (WVDNN) and Short Time Frequency Transform based Neural Network (STFTNN) where the main diagonal is the true positive value which is 100%, for four different classes in case of PWVDNN classifier, for three different classes in case of WVDNN and only one class in case STFTNN. The PWDNN classifier shows that sensitivity for N,L,R, & PA class, specificity & precision for N,L,V, & f and accuracy for N and L class is 100%, whereas sensitivity for L, R, & V class, specificity and precision for N & R class, and accuracy for R class is 100% in case of WVDNN. In case of STFTNN 100% sensitivity, specificity and precision are achieved for L, R,& R class respectively. From the assessment metrics, it is observed that the performance of WVDNN is better than STFTNN.This may be due to the time-frequency resolution problem of STFT which has been taken care in WVD. PWVDNN shows better performance in comparison to the other

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two techniques. This may be due to attenuation of interference, appear in WVD, using a frequency smoothing operation in PWVD. Again the number of features used only sixteen. The lowest accuracy in case of PWVDNN is 99.80%, whereas in case of STFTNN it is 98.20%. The maximum number of beats misclassified from any class is twenty-seven from N class in case of STFTNN, whereas this number is five and three in case of WVDNN and PWVDNN respectively.

IV. CONCLUSION

In this work PWVD, WVD and STFT are used to extract the features of different arrhythmia beats and then used for classification. These three T-F distributions are discussed along with their merits and demerits. As Though number features used in this classification are only sixteen, the performance of the classifiers is encouraging. Among all these methods clearly, PWVDNN perform better than other two. The highest accuracy is 100%, and lowest is 99.80%. The neural network used is optimized for ECG arrhythmia classification, and the conjugate gradient algorithm is used for error surface optimization instead of traditional steepest descent one. The other T-F distribution functions may be used for feature extraction in classification problems as the ECG signal is nonstationary.

REFERENCES

[1] Roshan Joy Martis, U.R.Acharya and Lim Choo Min, ECG beat classification using PCA,LDA,ICA and Discree Wavelet Transform, Biomedical Signal Processing and Control,Vol.8, 2013,pp.437-448.
[2] Y. Ozbay and G. Tezel, A new method for classification of ECG arrhythmias using neural network with adaptive active function, Digital Signal Processing, Vol. 20,2010,pp.1040-1049.
[3] S. Shadmand and B. Mashoufi, A new personalized ECG signal classification algorithm using Block-based Neural Network and Particle Swarm Optimization, Signal Processing and Control,Vol.25,2016,pp.12-23.
[4] J.S.Wang, W.C.Chiang, Y.L.Hsu and Y.C.Yang, ECG arrhythmia classification using a probabilistic neural network with a feature reduction method, Neurocomputing, Vol. 116,2013,pp.38-45.
[5] Sun-Nien Yu and Kuan-To Chou, Integration of independent component analysis and neural networks for ECG beat classification, Expert Systems with Applications,Vol. 34,2008, pp. 2841-2846.
[6] M.K.Das and S.Ari, ECG Arrhythmia Recognition using Artificial Neural Network with S-transform based Effective Features, Annual IEEE India conference(INDICON),Mumbai,Dec.2013,p.1-6.
[7] S.Karimifard and A.Ahmadian,Arobust method for diagnosis of morphological arrhythmias based on Hermitian model of higher-order statistics , Biomedical Enginering online 2011.
[8] Sanjit K. Dash and G.Sasibhusana Rao, Robust Multiclass ECG Arrhythmia Detection Using Balanced Trained Neural Network, IEEE International Conference on Electrical, Electronics & Optimization Techniques(ICEEOT-2016),3rd -5th March 2016, Chennai, Tamilnadu,India.
[9] Sanjit K.Dash and G.Sasibhusan Rao, "Optimized Neural Network for Improved Electrocardiogram Beat classification", 6th IEEE International Advanced Computing conference (IACC-2016),27th-28th Feb 2016, Bhimavaram, AP, India.
[10] Sanjit K.Dash and G.Sasibhusan Rao, "Arrhythmia Detection Using Wigner-Ville Distribution Based Neural Network", Procedia Computer Science,Vol. 85, 2016,pp. 806 – 811. www.sciencedirect.com .
[11] M.Hariharan,R.Sindhu and S.Yaacob, Normal and hypoacoustic infant crysignal classification using time-frequency analysis and general regression neural network, computer methods and programs in biomedicine,2011,www.intl.elsevierhealth.com/journals/cmpb.
[12] Lin Yun,Xu Xiaochum,Li Bin and Pang Jinfeng, Time-Frequency Analysis Based on the S-Transform, International Journal of Signal Processing,Image Processing and Pattern Recognition,Vol.6,No.5,2013,pp.245-254.
[13] P. Wahlberg and M. Hansson. Kernels and multiple windows for estimation of the Wigner-Ville spectrum of gaussian locally stationary processes. IEEE Transaction on Signal Processing, Vol.55,No.1,pp.73-84, January 2007.
[14] Leon Cohen, Time-Frequency Distribution- A Review, proceedings of the IEEE,Vol.77,No.7, July 1989,pp.941-981.
[15] MIT-BIH Arrhythmia Database-Physionet. https://www.physionet.org/..../database/.
[16] Sanjit K.Dash and G.Sasibhusan Rao, First and Second order Training Algorithms for Artificial Neural Network to Detect the Cardiac State, International Journal of Latest Trend in Engineering and Technology(IJLTET),Vol.7,Issue.2, July.2016.
[17] D.Gabor,Theory of communication,J.IEE (London), Vol.93,pp.429-457,1946.
[18] C.H.Page,Instantaneous power spectra, J. Appl.Phys.,Vol.23,pp.103-106,1952.