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ECG BEAT CLASSIFICATION USING CROSS-WAVELET AND LVQ

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ABSTRACT

This paper describes an automatic classification system based on combination of cross-wavelet and Learning Vector Quantization (LVQ) for the purpose of automatic heartbeat detection. The feature extractor is based on cross-wavelet approach, using the time frequency information. The ANN classifier uses a Learning Vector Quantization (LVQ) method which classifies the ECG beats into two categories: normal beats and abnormal beats. The ECG (electrocardiogram) signals in the MIT-BIH arrhythmia database are adopted as reference data. Total 98530 heart beats are used for testing the above classifier. The total classification accuracy (TCA) was about 91.66%.

Keywords: Cross-Wavelet Spectrum, Cross-Wavelet Coherence Spectrum , LVQ

I INTRODUCTION

The electrocardiogram (ECG) is the recording of the electrical property of the heartbeats, and has become one of the most important tools in the diagnosis of heart diseases. Due to the high death rate of heart diseases, early detection and precise discrimination of ECG arrhythmia is essential for the treatment of patients. This requisite contributes to intensive studies in recent years for high-precision computer-aided diagnosis (CAD) systems for ECG. An effective CAD system requires a powerful pattern classifier as well as a graceful feature extractor that is capable of extracting important, yet usually hidden, information from the raw data. Even more important is the mixing of suitable feature extractor and pattern classifier such that they can operate in coordination to make an effective and efficient CAD system. Statistical features [2], time-domain features [3, 4] and cross-correlation based frequency–domain features [5, 6] were used by different researchers for features extraction. In [7, 8], wavelet transform were used for features extraction, and the authors of [9] used Lyapunov exponents for the same purpose. For classification purpose different classifier [2 ,3, 5, 6] were used by the researchers. 21 features vector are extracted from cross-wavelet and cross-wavelet coherence spectrum. In this paper ,LVQ classifier is used for classify normal and abnormal beats.

A brief of the topics on which the different sections are concerned is given as follows. In section 2 information about ECG datasets used in our work is given. Section 3 gives an idea of cross-wavelet transform of two time domain signals. Section 4 deals with the idea of Learning Vector Quantization and how it works. Performance of the classifier scheme is shown in section 5. Section 6 describes the results obtained in this work and future research scope using EEG signal.

II THE ACQUISITION OF ECG SIGNALS

For the analysis of cardiovascular disorders, freely available benchmark ECG signals from the MIT/BIH arrhythmia database [1] have been utilized. This database enables researchers all over the world, to test the performance of their arrhythmia analysis algorithms against other competing algorithms, utilizing identical benchmark signals. The database contains 48 numbers of half-hour excerpts of two channel ambulatory ECG recording files, obtained from 47 different patients. Out of these 48 files, 23 recordings were randomly chosen and the remaining 25 files included less common but clinically significant and threatening arrhythmic heartbeat samples. The recordings were digitized with a sampling frequency of 360 Hz and acquired with 11-bit resolution over 10 mV ranges. Two or more cardiologists annotated each record of MIT/BIH arrhythmia database independently, with respect to both timing information and beat classification. The proposed algorithm has used the annotation to locate beats in ECG signals for the classification of heart beats. This work has not been directed towards beat detection because several highly accurate beat detection algorithms are already available in the literature. In the proposed algorithm, each ECG beat was extracted by selecting a window of -300 ms to 400 ms around the R-wave as found in the database annotation. Each such one dimensional signal vector comprises 252 samples. For beat extraction, first and last beat of each file is not considered in this work because 252 samples around the R-wave may not be present in first and last beat of each file [11].

A 6th order Butterworth band pass filter with pass band frequencies between 0.4 to 0.7 Hz is used to remove baseline wander from ECG signals. Fig.1 shows the ECG signal before and after removing the
base-line wander.

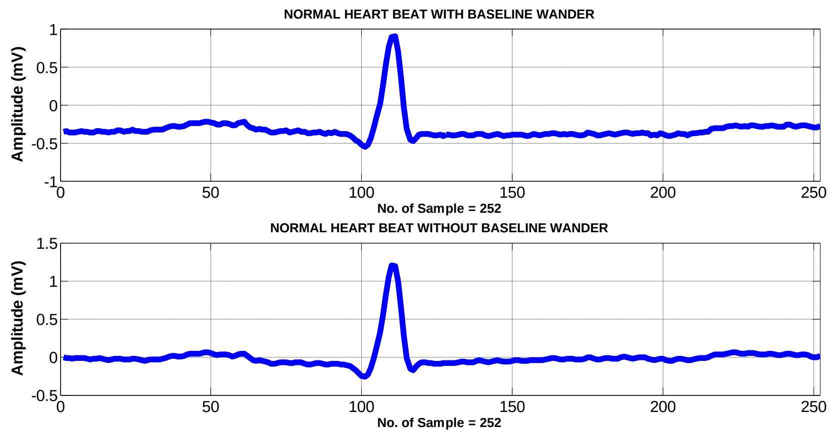


Fig.1 ECG signals with and without baseline wander

III OVERVIEWS OF WAVELET TRANSFORM

CWT is a common tool for analyzing localized intermittent oscillations in a time series; it is very often desirable to examine two time series together that may be expected to be linked in some way. In particular, to examine whether regions in time frequency space with large common power have a consistent phase relationship and therefore are suggestive of causality between the time series. Many ECG (time series) signal are not normally distributed and we suggest methods of applying the CWT to such time series. From two CWTs we construct the Cross Wavelet Transform (XWT) which will expose their common power and relative phase in time-frequency space. We will further define a measure of Wavelet Coherence (WTC) between two CWT, which can find significant coherence even though the common power is low, and show how confidence levels against red noise backgrounds are calculated**.**

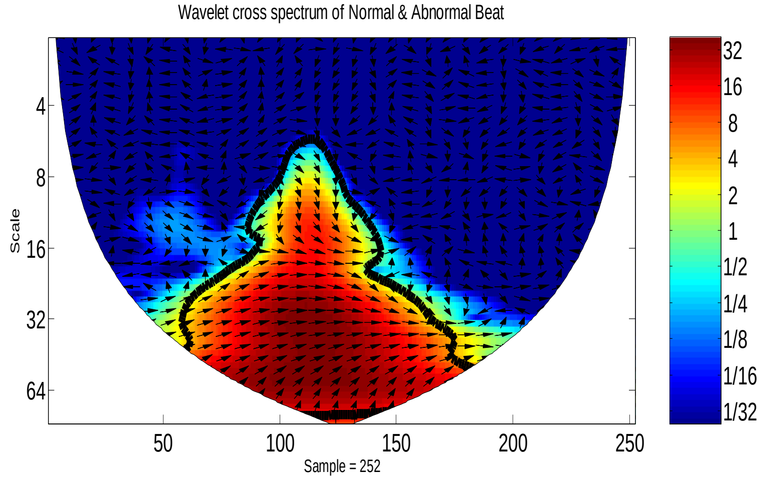
3.1. Cross-wavelet and wavelet coherence

The cross-wavelet transform of two time series x_n and y_n is defined as $W^{XY} = W^X W^{Y*}$, where * denote complex conjugate .$|W^{XY}|$ is the cross-wavelet power. The complex argument arg (W^{XY}) can be interpreted as the local relative phase between x_n and y_n in time frequency space. The theoretical distribution of the cross wavelet power of two time series with background power spectra P_k^X *and* P_k^Y is given in Torrence and Compo (1998) [10].

Another useful measure is how coherent the cross wavelet transform is in time frequency space. Following Torrence and Webster (1998) we define the wavelet coherence of two time series as

$$R_n^2(s) = \frac{|S(s^{-1} W_n^{XY}(s))|^2}{S(s^{-1} W_n^X(s)|^2) . S(s^{-1} |W_n^Y(s)|^2)} \qquad (1)$$

where S is a smoothing



operator.

Fig.2 Wavelet cross spectrum of Normal and Abnormal beat

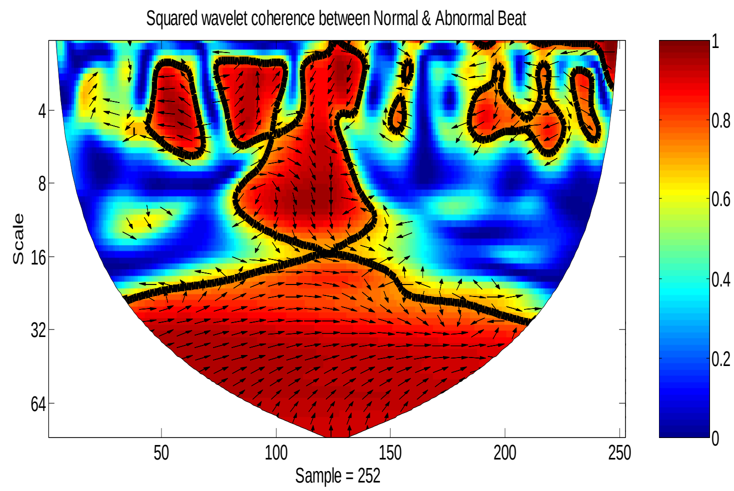


Fig.3 Squared wavelet coherence between Normal & Abnormal Beat Fig. 2 and Fig. 3 show the Wavelet cross-spectrum and squared cross-wavelet coherence. These are used for cross examination single normal with arrhythmia beat. These figures also show the distinguishing regions where two signal are locally similar in time & frequency space. It is evident from the gray-shed plots that there exist distinct variations in the spectral and coherence components. By inspecting the plots, it has been found that most prominent variation observed in the range of 4 to 64scales of the wavelet coefficients [11].

After applying cross-wavelet transform we have taken 21 features. These features are sufficient for the classification of normal and arrhythmia beat.

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IV LEARNING VECTOR QUANTIZATION

Learning Vector Quantization (LVQ) has been introduced by T. Kohonen [12] as a simple, universal and efficient classification algorithm and has since found many applications and extensions [13].The presented work employs Learning Vector Quantization (LVQ) algorithms for the purpose of classification of ECG beats. LVQ is a supervised version of vector quantization that can be used when we have labelled input data. This learning technique uses the class information to reposition the Voronoi vectors slightly, so as to improve the quality of the classifier decision regions. It is a two stage process – a SOM followed by LVQ. LVQ is a local classification algorithm, where the classification boundaries are approximated locally. The difference is that instead of using all the points in the training dataset, LVQ uses only a set of appropriately chosen prototype vectors. This way the classification method is much more efficient, because the number of vectors that should be stored and compared with is significantly reduced. In addition, a carefully chosen prototype set can greatly increase classification accuracy on noisy problems. There are several different LVQ algorithms that deal with the updates of the prototypes in different ways.

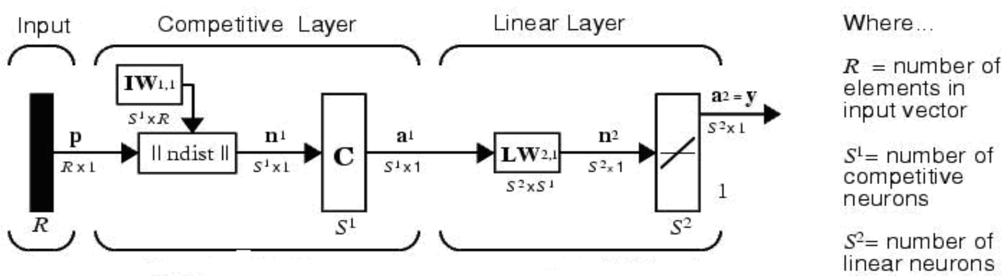

Fig. 4 Architecture of LVQ classifier

In our proposed approach, the optimized learning rate LVQ1 and LVQ2.1 algorithms have been used for training and fine-tuning purposes respectively [14,15].

LVQ network has a first competitive layer and a second linear layer. The linear layer transforms the competitive layer's classes into target classifications defined by the user. Both the competitive and linear layers have one neuron per (sub or target) class. Thus, the competitive layer can learn up to S^1 subclasses. These, in turn, are combined by the linear layer to form S^2 target classes. (S^1 is always larger than S^2.) In Fig.4 P is input vector with R elements and IW1,1 is the weights matrix of neurons in competitive layer . Each row in this matrix is the weights of one neuron. **||ndist||** block computes the distance of input vector P from weight vectors of each neuron. Thus if the number of competitive layer neurons were S1, then IW1,1 is S1 by R matrix. In this case the **||ndist||** output, that determined by n1 in figure, is an s1 element vector that each element is the distance of input to one neuron. The C block is a competitive function that its output (a1) is a vector with one element equal 1 and others equal 0. The element that equals 1, determines the input subclass. In linear layer, the target class is determined. The neurons number in linear layer is equal to target class's number. The LW2,1 block with elements equal to 1 or 0, is the neurons weight matrix in linear layer. This layer determines the subclasses of each target class. In LVQ1, for a given M-dimensional input vector p, an M-dimensional code word wk is found such that

$$k = argmin\{\|p - w_i\|\} \qquad (2)$$

The code word is then updated as follows:

$$w_k(t+1) = w_k(t) + \alpha(t)s(t)[p - w_k(t)] \quad (3)$$

Where s(t)=+1 if p and w_k are in same class and s(t)=-1, otherwise; $\alpha(t)$ is the time varying learning rate. The other code words in the code book remain unchanged. LVQ2.1 applied after first applying LVQ1. It can improve the result of the first learning. In LVQ2.1 algorithm, two vectors of layer 1 that are closest to the input vector can be updated, provided that one belongs to the correct class and one belongs to a wrong class, and further provided that the input falls into a "window" near the midplane of the two vectors. The window is defined by

$$\min\left(\frac{d_i}{d_j}, \frac{d_j}{d_i}\right) > s \ \ where \ \ s \equiv \frac{1-w}{1+w}$$

where di and dj are the Euclidean distances of p from wi andw_j. Here each M-dimensional p and wk vectors can be denoted as: p = {p1, p2, ..., pm, ..., pM} and wk = {wk1, wk2, ..., wkm, ..., wkM}.

In this work LVQ classifier is used to classify normal and abnormal beats of ECG signal. Usually the classification results obtained with LVQ2.1 algorithm are more robust than with LVQ1 algorithm. The usual practice is to employ the LVQ2.1 algorithm after the LVQ1 algorithm has been implemented.

V PERFORMANCE EVALUATIONS

The training dataset contains 815 normal beats and 815 arrhythmia beats**.** Total 98530 heart beats are tested from 43 files. Less than 2% of total heart beats

are used for train the classifier. Heart beat in file #100_19 is taken as reference normal heart beat. The total accuracy of the classifier for each record is determined using the following formula:

$$\text{TCA} = \frac{\text{the number of correctly classified beats}}{\text{the number of total beats}}$$

$$= \sum \frac{TP_c}{T_r}$$

Where TP_c(true positive) denote the total number of heart beats that are correctly classified (normal as well as arrhythmia), and $T_r$represent the total number of heart beats present in each record.

The classifier was tested by taking 7, 14, 18 and 21 features, and corresponding results are shown in table.1

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The total accuracy obtained with 14 features vector is 91.66%. Using the same features vector, classified normal beat accuracy and classified arrhythmia beat accuracy are found to be 94.72% and 84.05% respectively. Classification result as shown in table.2

Table.1 Maximum classified normal and

Arrhythmia beat based on different feature sets

Feature set	Total classification Accuracy (TCA)%	% of Classified Normal Beat	% of Classified Arrhythmia Beat
	89.399	91.9	83.68
14	**91.65**	**94.72**	**84.05**
18	88.29	88.44	87.89
21	96.66	90.24	87.23

Table. 2: Classified normal and abnormal beats using
14 feature vectors

File	Total Beats	Accuracy(%)	Normal Beats	Classified normal	Abnormal Beats	Classified Abnormal
a100	2270	98.55	2236	2236	34	1
a101	1863	99.62	1858	1855	5	1
a102	2185	98.95	99	93	2086	2069
a103	2082	99.90	2080	2080	2	0
a104	2209	78.45	163	163	2046	1570
a105	2570	93.77	2524	2406	46	4
a106	2026	90.28	1506	1505	520	324
a107	2135	99.77	0	0	2135	2130
a108	1761	10.56	1738	172	23	14
a109	2530	99.76	0	0	2530	2524
a112	2537	94.25	2535	2390	2	1
a113	1793	99.67	1787	1787	6	0
a114	1877	94.73	1818	1730	59	48
a115	1943	100.00	1943	1943	0	0
a116	2410	99.09	2300	2290	110	98
a117	1533	95.17	1532	1459	1	0
a118	2276	99.56	0	0	2276	2266
a119	1985	100.00	1541	1541	444	444
a121	1861	66.42	1859	1235	2	1
a122	2474	99.96	2474	2473	0	0
a123	1515	100.00	1512	1512	3	3
a124	1617	63.51	0	0	1617	1027
a200	2597	96.42	1742	1731	855	773
a201	1961	96.94	1623	1621	338	280
a202	2134	97.84	2059	2058	75	30
a203	2978	63.57	2527	1694	451	199

a205	2654	98.94	2569	2569	85	57
a207	1858	94.73	0	0	1858	1760
a208	2951	90.34	1585	1567	1366	1099
a209	3003	87.21	2619	2618	384	1
a210	2638	95.30	2421	2412	217	102
a213	2897	98.55	2639	2638	258	217
a215	3361	95.03	3193	3136	168	58
a217	2206	92.57	244	243	1962	1799
a219	2152	99.07	2080	2077	72	55
a220	2046	95.41	1952	1952	94	0
a221	2425	99.34	2029	2029	396	380
a222	2481	76.10	2060	1886	421	2
a223	2603	89.86	2027	2009	576	330
a228	2051	98.78	1686	1679	365	347
a230	2254	99.91	2253	2251	1	1
a233	3077	95.22	2229	2110	848	820
a234	2751	98.18	2698	2698	53	3
Total Beat	98530		73740	69848	24790	20838

Accuracy: 91.65%
Classified Normal beats: 94.722%
Classified Abnormal beats: 84.05%

VI CONCLUSION

In this paper, the LVQ neural network and the cross-wavelet Transform have been used to distinguish normal and arrhythmia beats. The performance of the proposed scheme has been tested using benchmark signals available in MIT/BIH arrhythmia database, where a small sized training file and large-sized testing file was used to demonstrate the generalization capability of the system, when presented with unknown inputs. An overall classification accuracy of 91.66% was achieved over the 43 files of the database. Future work can be done by classifying all the beats in the manner recommended by Association for the Advancement of Medical Instrumentation (AAMI) of the dataset instead of binary classification.

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