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On Design of a Three- Class ECG Classifier

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Abstract

Objectives: Manual analysis of ECG, specifically the ambulatory type, is tedious and time consuming, hence automation is desired. In this paper the authors have focused on the design of a three class ECG classifier using feature extraction and artificial neural networks. Once feature extraction is done, ANNs can be trained to classify the patterns reasonably accurately. Arrhythmia is one such type of abnormality detect able by an ECG signal. The three classes of ECG signals are Normal, Fusion and Premature Ventricular Contraction (PVC). The task of an ANN based system is to correctly identify the three classes, most importantly the PVC type, this being a fatal cardiac condition. **Methods**: The ECG data is taken from MIT-BIH Arrhythmia database. Fifty-five different feature extraction schemes are examined, along with a compact set of statistical morphological features and a reasonably accurate and fast classifier is designed. These feature extraction techniques coupled with ten morphological features have not been collectively studied and compared in literature so far. **Findings:** Multilayer perceptron with momentum learning rule is found to be the best classifier topology, while the best performing feature extraction schemes are: bior2.2, coif1, db9, rbior1.1, sym2, DCT and PCA. **Application/Improvements**: The reported findings can be effectively used for automated ECG arrhythmia classification for rapid analysis by a cardiac specialist thus saving time and arriving at a quick and reliable diagnosis. A similar approach can be used for designing an ECG classifier for more number of arrhythmia conditions.

Keywords: Arrhythmia, Artificial Neural Networks, ECG Classifier Design, Wavelets

1. Introduction

The electrocardiogram analysis forms the basis of heart disease diagnosis and is preferred since it is non-invasive, reliable and less costly than other methods. Normally ECG related diagnoses are carried out by the medical practitioners manually. The major task in diagnosing the heart condition is analyzing each heart beat and co-relating the distortions found therein with various heart diseases. Since the abnormal heart beats can occur randomly it becomes very tedious and time-consuming to analyze say a 24 hour ECG signal, as it may contain hundreds of thousands of heart beats. Hence it is desired to automate the entire process of heart beat classification and preferably diagnose it accurately.

The major problem associated with ECG analysis is the number of beats available especially for ambulatory ECG and the inter-patient variation in the morphology of the QRS complexes. It becomes a time-consuming task for classifying/ separating the ECG beats and is also prone to errors induced by manual intervention. This paper describes the design of an automated ECG classifier. Three types of beats are considered here, the Normal, Premature Ventricular Contraction and Fusion of these two, termed as Fusion type beats. The ECG data was taken from MIT-BIH Arrhythmia database. Transform feature extraction and morphological feature extraction schemes are mostly preferred. Discrete Fourier Transform, Principal Component Analysis, and Discrete Wavelet Transform are the three transform schemes along with three other

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morphological feature extraction schemes are discussed and compared in this paper. The classifier achieved average classification accuracy exceeding 98.2%.

2. Transform Domain Features

Signals can be effectively represented in transform domains. There are several advantages of representing a signal in transform domains like Frequency domain representation removes insignificant or redundant information and reduces the dimension of the input vector, especially useful when using the signal with neural network structures, compression for efficient data storage, noise reduction.

Abundant usage of transforms like the Discrete Fourier Transform (using FFT), Discrete Cosine Transform, Principal Component Analysis and the Discrete Wavelet transform, in conjunction with the ECG can be found in the literature[1–7]. Only significant components in the transform domain can be retained without much loss of information, specifically the QRS morphology. The metrics used for feature selection were retention of 99% signal energy and Percent Root Mean Difference. These components then form the input vector to the ANN for training.

3. Selection of the Best ANN Topology

In this phase, an attempt was made to determine the best ANN model. Various models tested were: Multilayer Perceptron (MLP), Self-Organizing Feature Maps (SOFM), Radial Basis Function Network (RBF) and Support Vector Machine (SVM)[8–13]. Only Discrete Cosine Transform was used for feature extraction. A DCT on the 180 sample data yielded 180 coefficients, out of which thirty coefficients were used to form the feature vector. The thirty coefficients selected contribute to the 99.8% of the signal energy. Another metric, the Percent Root Mean Difference (PRD) was used to support the justification of the selection of thirty coefficients. The transformed data was then trained and tested with various ANN models. The ANN models tested are:

- Multilayered Perceptron (MLP).
- Self-Organizing Feature Maps (SOFM).
- Radial Basis Function Neural Networks (RBF).
- Support Vector Machine (SVM).

Table 1 summarizes the performance of the various ANN models. All the accuracy measures are computed as averages over five training-testing runs.

It can thus be concluded that the selected topology, the MLP, performs consistently good irrespective of data partitions. Therefore, MLP with single hidden layer, tan-sigmoidal activation functions for hidden and output layers and momentum weight update was finalized as the default network for the rest of the work.

It is very clear that the MLP outperforms the other ANN models thus making it a suitable candidate for the desired classifier.

4. Statistical Morphological Features of QRS complex

In addition to the transform domain features, the QRS complex contains important morphological features. These features are specific and distinct for each type of QRS morphology. Literature suggests a large number of

Table 1. Summary of performance of various ANN models

ANN Model	Best configuration	FUSION Accuracy (%)	NORMAL Accuracy (%)	PVC I Accuracy (%)	Average Accuracy (%)	Time/exemplar/1000 epochs (seconds)
MLP	Single hidden layer, 10 Hidden Layer neurons, Momentum learning	97.8	98.9	98.4	**98.3666667**	**23.808**
SOFM	8 x 8 Map size	96	99.7	99.1	98.2666667	276.906
RBF	50 clusters, kernel adatron	97.9	99.3	95.1	97.4333333	469.953
SVM	-	97	99.5	98	98.1666667	550

possible features, but again the number of features has to be limited to restrain the dimensionality of the input vector. Hence an optimal morphological feature set is desired. On computing and graphical representation, nine features were found to be supportive for good classification in addition to the R-R interval[14]. These features are:

- The R-peak amplitude.
- Mean Power Spectral Density.
- The Q-S distance.
- Signal Energy.
- QRS area.
- Singular Value Decomposition.
- Area under auto-correlation curve.
- Q-R slope.
- R-S slope.
- R-R interval.

5. Evaluation of the Best Feature Extraction Scheme

Various transforms are available for creating the dimensionally reduced feature vector. DFT (FFT), Principal Component Analysis, DCT, Daubechies Wavelets (db1 through db10, Biorthogonal Splines Wavelets (bior1.1, bior1.3, bior1.5, bior2.2, bior2.4, bior2.6, bior2.8, bior3.1, bior3.5, bior3.7, bior3.9, bior4.4, bior5.5, bior6.8), Reverse Biorthogonal wavelets (rbio1.1, rbio1.3, rbio1.5, rbio2.2, rbio2.4, rbio2.6, rbio2.8, rbio3.1, rbio3.5, rbio3.7, rbio3.9, rbio4.4, rbio5.5,rbio6.8), Coif let Wavelets (coif1 through coif5), Symlet Wavelets (sym2 through sym8) for feature extraction (pre-processing of data) for three classes Fusion, Normal and PVC I. In all 55 transforms were employed to create the partial feature vectors for further training. As discussed earlier the only 30 coefficients (excluding first coefficient that corresponds to DC and is negligible since the data is mean adjusted), for DCT are considered. For PCA only 14 principal components are considered, for FFT only 20 coefficients (real part) are considered. The selection of coefficients is based on the signal energy retained up to 99.5% and PRD value of 0.5. For wavelet transforms, a three level decomposition is used and only the low frequency components are considered. In addition to the transforms ten statistical features (R-peak amplitude, Mean Power Spectral Density (MPSD), Q-S distance, Energy of the Signal, QRS area, Singular Decomposition Value (SVD), Area under auto-correlation curve, Q-R slope, R-S Slope, R-R interval) were computed. Finally, the transformed data and the statistical features were concatenated to generate the final feature vector. Classes are "one-hot encoded" for supervised training. We used 600 exemplars per heartbeat class for the experiment. 600 exemplars from the data set were used for training, 600 for cross-validation and the remaining was used for test. The search for the best topology was made by varying the hidden layer neurons between 5 through 60 and training the network five times.

6. Results

Table 2 summarizes the performance of all the schemes. For the sake of narrowing down the search for the best scheme, the performances are evaluated in terms of percentage average accuracy, percentage PVC I accuracy and low data pre-processing time are selected from each transform category. The best performing schemes are: **bior2.2, coif1, db9, rbior1.1, sym2, DCT and PCA**. However, in case of FFT, the data pre-processing time is far too high as seen in Figure 1.

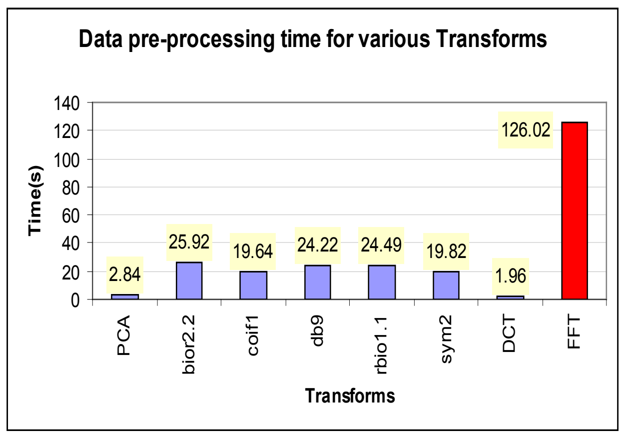

Figure 1. Pre-processing time consumed by best performing schemes.

7. Discussions

Feature extraction for ANN based pattern classification of ECG signal can be done by using transforms such as FFT, DCT, PCA and DWT. Ten statistical morphological features like R-peak amplitude, Mean Power Spectral Density

Table 2. Performance of various feature extraction schemes

Sr. No.	Feature Extraction Scheme	# of HLN	AVG ACCURACY (%)	# of HLN	PVCI ACCURACY (%)	DATA PRE-PROCESSING TIME(s)
1	bior1.1	35	98.36666667	31	98	24.48604222
2	bior1.3	26	98.13333333	27	97.7	25.21850682
3	bior1.5	42	98.23333333	42	97.6	25.88835453
4	**bior2.2**	**50**	**98.53333333**	**17**	**97.8**	25.91511212
5	bior2.4	26	98.16666667	34	97.8	26.29315653
6	bior2.6	27	98.1	18	97.5	26.9502596
7	bior2.8	34	98.33333333	19	97.7	27.64683668
8	bior3.1	19	98.43333333	22	97.6	27.45190213
9	bior3.3	47	98.13333333	22	97.5	28.06218807
10	bior3.5	33	98.4	33	97.7	28.6771179
11	bior3.7	33	98.46666667	24	97.9	29.36470278
12	bior3.9	29	98.1	38	97.6	29.97012916
13	bior4.4	38	98.13333333	38	97.8	30.27596412
14	bior5.5	17	98.06666667	17	97.5	30.84614916
15	bior6.8	27	98.16666667	5	97.5	31.86008306
16	**coif1**	**33**	**98.26666667**	**11**	**97.8**	19.63888064
17	coif2	9	98.1	22	97.4	20.3571222
18	coif3	27	98.16666667	27	97.6	21.17331979
19	coif4	42	98.06666667	42	97.5	22.07603089
20	coif5	23	98.06666667	22	97.5	23.1011623
21	db1	28	98.36666667	15	98	18.83059411
22	db2	41	98.26666667	41	97.9	19.37694204
23	db3	24	98.33333333	32	98	19.8945866
24	db4	27	98.33333333	21	98	20.32141571
25	db5	18	98.26666667	19	97.9	20.92922285
26	db6	20	98.33333333	6	97.8	21.39219147
27	db7	11	98.23333333	15	97.8	21.88092537
28	db8	45	98.16666667	39	97.7	22.35431207
29	**db9**	**23**	**98.46666667**	**23**	**97.9**	24.21786763
30	db10	50	97.61111111	50	96.33	23.74037929
31	**rbio1.1**	**10**	**98.4**	**21**	**98**	24.48604222
32	rbio1.3	36	98.2	28	97.7	26.5201284
33	rbio1.5	20	98.06666667	32	97.5	27.23356879
34	rbio2.2	41	98.23333333	41	97.9	25.91511212
35	rbio2.4	19	98.13333333	19	97.5	27.50555587
36	rbio2.6	7	98.06666667	37	97.8	28.42842177
37	rbio2.8	6	98.2	6	97.6	28.828688
38	rbio3.1	44	98.23333333	44	97.9	28.64269872
39	rbio3.3	5	98.13333333	46	97.6	29.21951784
40	rbio3.5	52	98.06666667	52	97.4	30.21323492

41	rbio3.7	8	98.1	25	97.5	30.69864019
42	rbio3.9	6	97.93333333	12	97.3	31.17549633
43	rbio4.4	22	98.1	26	97.8	31.02255706
44	rbio5.5	8	98.06666667	8	97.7	31.6179981
45	rbio6.8	7	98.1	38	97.6	32.61682169
46	**sym2**	**31**	**98.33333333**	**31**	**97.8**	19.82002657
47	sym3	30	98.26666667	24	98	20.25987577
48	sym4	25	98.2	26	97.9	20.60113534
49	sym5	28	98.23333333	28	97.6	21.33076774
50	sym6	26	98.06666667	13	97.6	21.97217412
51	sym7	27	98.2	27	97.6	22.60090319
52	sym8	18	98.13333333	16	97.6	23.21384366
53	**DCT**	**55**	**98.5**	**42**	**98.4**	1.960774344
54	**FFT**	**21**	**98.7**	**21**	**98.1**	126.0217164
55	**PCA**	**24**	**98.23333333**	**21**	**97.4**	2.836394849

Note: # of HLN means the number of hidden layer neurons

(MPSD), Q-S distance, Energy of the Signal, QRS area, Singular Decomposition Value (SVD), Area under auto-correlation curve, Q-R slope, R-S slope, R-R interval also form an important feature set for use with ANN based ECG classification. This set of statistical features is compact and results in a reduced dimension feature vector.

8. Conclusion

The ANN model consisting of single layer MLP with momentum learning was found to perform best with respect to average accuracy, PVCI accuracy and training time.

It was confirmed that a minimum 200 heartbeats/class are sufficient to train the classifier. This experimentation is important since it highlights the power of the ANN model to learn from a comparatively small amount of data. This is a welcome result which entails a possibility of patient adaptable (customizable) diagnostic system.

Upon experimenting with 55 different combinations of feature vector formation for three class problem, it was found that the best performing schemes in terms of percentage average accuracy, percentage PVC I accuracy and low data pre-processing time are: bior2.2, coif1, db9, rbior1.1, sym2, DCT and PCA with the combinations of ten statistical morphological features each. PCA is a good candidate for feature extraction since it offers good accuracy as well as compact feature set.

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