35th Annual International Conference of the IEEE EMBS
Osaka, Japan, 3 - 7 July, 2013

Accurate Arrhythmia Classification using Auto-Associative Neural Network

[1]Sandipan Chakroborty

Abstract— **Currently about one in eighteen of the American population suffer from cardiac Arrhythmias that lead to Coronary Heart Diseases and this rate is steadily increasing. An early monitoring and diagnosis of Arrhythmia based on Electrocardiogram signals can help in reducing mortality. This paper primarily focuses on the application of Auto Associative Neural Network as a new classification approach, which does not require feature extraction task. The weights of a trained Neural Network are stored as class representative models that results in high compression gain with respect to the size of training data. The evaluation of the proposed technique is tested on segmented ECG beats of four different classes of Arrhythmia excluding normal pattern. These beats have been extracted from the MIT/BIH Arrhythmia database and compared against the state-of-the art template matching technique such as Dynamic Time Warping. The proposed technique yields an average accuracy of more than 97% and a relative compression gain of above 90%.**

I. Introduction

The classification of Electrocardiogram (ECG) signal is very important to diagnose and treat patients with cardiac abnormalities like Arrhythmia [1]. Such Arrhythmias can especially be life threatening for a patient recovering from post Myocardial Infarction. The automatic detection of Arrhythmia is very indispensable for preventing the risk of heart attack or sudden death for cardiac patients, who are in the high-risk category.

An ECG waveform is a graphical representation of the electrical activity of the heart. The waveform in itself is composed of the fusion of various activities of the heart such as Atrial De-polarization, Ventricular Repolarization, etc. Most of the important information in the ECG signal is concentrated in the P wave, QRS complex and the T wave. While making a diagnosis or investigation, a cardiologist often looks at the following features before making a decision: the relative positions of the waves, their magnitudes, shapes, and other derived interval features such as PR interval, PR segment, and width of QRS, QT interval and ST segment [2].

In general, most of the Arrhythmias [2] tend to exhibit a come-and-go kind of nature over the period of time. Therefore, it is required to have long-term analysis of ECG signal. Current signal processing algorithms are capable of analyzing the signal, recognizing the patterns and interpreting the anomalies associated with it.

A. Prior Work

Over the years, automatic classifications of cardiac Arrhythmias were reported in several literatures [3-23]. It is the trend to choose rule-based and non-trainable approaches over classical machine learning-based methods because of lower computational and storage (not always) complexity and ease of implementation. Often, rule based engines are implemented using *if-then-else* logic, assuming that there is sufficient medical-domain knowledge in the rules to cover all the Arrhythmias. The important interval features such as RR time interval, QRS width, PR interval, QT interval derived from each beat (one cardiac cycle) of ECG, are used to form the rule engine. Rule-based engine could be used reliably to detect Arrhythmias like Bradycardia and Tachycardia, which are dependent on the heart-rate. On the other hand, machine learning algorithms can distinguish two similarly looking waveforms representing two different kinds of Arrhythmias. For such discrimination, various features [4-11] corresponding to different wave morphologies are exploited to train the machine learning algorithms [12-14]. Machine learning algorithms give better accuracy than rule-based approaches, but at the expense of higher computational complexity. Hence, there is a need for further investigation of an Arrhythmia classifier, which can involve lower complexity while still retaining reasonably high classification accuracy.

This paper presents an Arrhythmia classification technique using an Auto Associative Neural Network (AANN) [15]. AANN was successfully used in diverse pattern classification problems such as face, speaker and language recognition [15]. In addition, it has also found to be successful in dimensionality reduction problems. The uniqueness of this Neural Network (NN) is that the input data to the network is also fed into the output stage. This ensures that the data can map onto itself by the non-linear mapping functions (or activation functions) present in the several nodes at various hidden stages. Note that, this classification paradigm does not involve any feature extraction module as such and can accept direct inputs of normalized data. Our experiments were conducted on MIT-BIH [16] data on four different Arrhythmia classes along with normal ECG.

The organization of this article is as follows. In the Section II, we present the proposed framework. The detailed experimental setup is discussed in the Section III. In Section IV we present the results and in Section V we draw the principle conclusions of this work.

II. Proposed Framework

A. Auto Associative Neural Network

A typical architecture of an AANN is as shown in Fig. 1. The numbers of neurons present in the input and output layer are the same, so that they can both accommodate identical

[1]Sandipan Chakroborty is with Samsung Advanced Institute of Technology India, Bangalore (phone: +91(0)8041819999; fax: +91-80-41819000; e-mail: sandipan.c@ samsung.com).

978-1-4577-0216-7/13/$26.00 ©2013 IEEE

input data. The activation functions involved in those outer layers are linear.

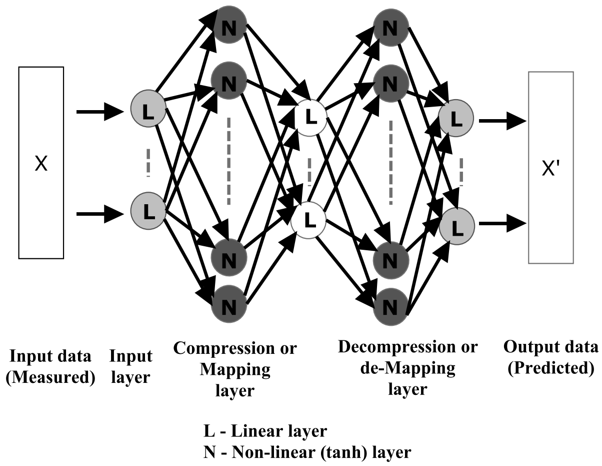

Fig. 1. Typical architecture of an Auto Associative Neural Network

The layers between the input and the output are generally composed of non-linear neurons (sigmoid functions *tanh*(*arg*) [15]) which are the mapping and de-mapping layers respectively. These two layers are chosen to have the same dimension as they contain the same number of neurons. The middle layer is the least complex layer with the lowest dimension and involves linear activation functions. Thus, this layer is called the compression or bottle neck layer from the data dimension's point-of-view.

The idea of choosing this kind of network is to allow self-mapping of the input (it is often called auto-encoder for identity mapping) such that the non-linear relations among the samples could be captured. This is unlike the conventional approach of standard NN, where the input data is accompanied with their respective class labels or targets. The AANN tends to learn in a non-discriminative manner, where the model does not require interacting with the data from other classes (anti-data). Non-discriminative learning can reduce considerably the off-line time as compared to the time taken by a discriminative training method. By off-line time, we refer to the total training time taken for an AANN to process a set of input data. In this problem, for each class, a separate AANN was trained and the weights of those networks were preserved for the testing phase.

B. ECG Data Records

The proposed AANN based Arrhythmia classification technique is validated on the available MIT-BIH public dataset [16]. This database consists of 48 half-hour excerpts of two-channel ambulatory ECG records acquired from 48 subjects. The ECG recordings were collected from 25 men, aged between 32 to 89 years, and 23 women, aged between 23 to 89 years. Each of the ECG records in the database is sampled at 360 samples per second. Each sample of the digitized signal is stored with 11-bit resolution over a 10 mV range. For this work, the signal from the lead II was used, as it shows more prominent R-peak amplitudes compared to the other leads. The database contains ECG beats with different morphologies that give enough variations to the Arrhythmia classification algorithms.

C. Pre-processing of ECG records

Pre-processing of ECG data requires cleaning of several artifacts and noise such as base-line wanderings, and muscle noise. In this work, a Butterworth high-pass filter was used with 0.5 Hz cut-off frequency to remove the low-frequency base-line wandering effect. A low pass filter with a cut-off frequency of 40 Hz is then applied to remove the 50-60 Hz power line interference. It is conjectured that, for an ECG signal, most of the vital information is found within the frequency range of 0.5 to 40 Hz [17].

D. R-peak detection

A number of algorithms [18] are available in the literature to determine location of R-peaks from ECG records. However, in the MIT-BIH database, each recording is accompanied by a cardiologist's annotation [16] that serves as the ground truth. For this work, these prior annotated data were considered as locations of the R-peaks. The R-peak locations help to segment and segregate the individual beats from the ECG records.

E. Beat selection and normalization

Once the locations of the R-peaks are marked, the start and the end of a beat are determined by moving forward and backward from the R-peak location as shown in the Figure 2. Note that a beat represents one entire cardiac cycle that includes P wave, QRS complex, and T wave. We used 351 sample points, from *R-peak position* - 150 samples to *R-peak position* + 200 samples, which corresponds to one complete cardiac cycle. The period of the cardiac cycle was chosen from the ground truth average RR interval, which is defined as the interval between one R-peak and the adjacent R-peak location. This single beat is normalized by subtracting the beat mean and divided by the beat variance giving a zero mean and unit variance as:

$$\bar{x} = \frac{x-\mu}{\sigma} \tag{1}$$

where, x, $\bar{x}$, μ and σ are respectively the original beat, the normalized beat, the mean and the variance calculated from original beat. This normalization was done so that the AANN does not need to operate on a wide dynamic range of input data.

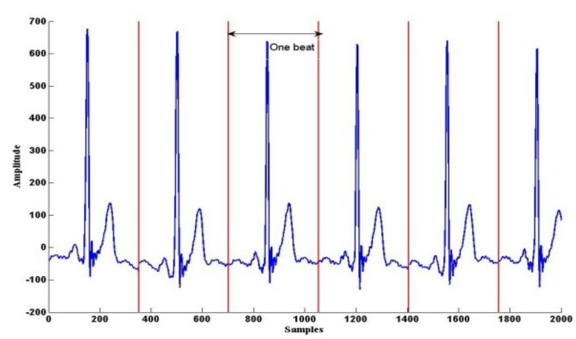

Fig. 2. ECG beat selection procedure in continous stream of data

Since each beat carries the same number of samples, the time axis was not normalized. Here, the same number of samples, that is 351, was used across all the classes of Arrhythmia and normal beats. Note that the same normalization method was applied during both the training and the testing phases. Depending on the origin of the Arrhythmia, the morphologies of ECG beats are widely varied. Hence, it would be more intuitive to include PQRST waves as a single beat. Care was taken during the beat selection process to include all the waves in a beat. The name of the Arrhythmia classes that have been considered for the experiments are Left bundle branch block (LBBB), Right bundle branch block (RBBB), Premature ventricular contraction (PVC), and Atrial premature contraction (APC). The symbol N is used to represent the Normal Sinus Rhythm class.

III. Experimental Setup

The numbers of training and test beats for each of the five classes are shown in Table I below.

TABLE I. NUMBER OF BEATS INVOLVED IN TRAINING AND TESTING

Class labels	No. of Training Beats	No. of Test Beats
N	1240	8700
LBBB	1151	8069
RBBB	965	6769
PVC	450	3167
APC	351	2078

In this work, the AANN structure with 351-20-20-20-351, were chosen, where 351 is the length of one beat. The values 20 for hidden layers are experimentally chosen for better performance without a scope for over fitting. The sequences of activation functions used for the five layers are linear, non-linear, linear, non-linear, and linear respectively. For each of the pattern classes (here Arrhythmia), the AANN was trained using a back-propagation [19] (BP) algorithm. An AANN uses the BP algorithm in batch mode till either the number of epochs reach 3000 or the error change is less than 0.001. After the training, the weights of all the NN are preserved so that they can be used for the testing stage.

Note that the direct input of the beat signal to the AANN saves much on the computation time necessary for feature extraction (either time or frequency domain features). At the time of classification, an unknown beat is submitted to all the AANNs' inputs and the output beats are computed (or predicted) through their stored weights. Then, the sum of the squared difference was calculated between the input beat ($Beat_{in}$) and the beat generated ($Beat_{pred}$) from output for each of the network models as in Eq. (2) below:

$$D_i = \sum_{k=0}^{N-1} \left(Beat_{in}(k) - Beat_{pred}(k) \right)^2 \qquad (2)$$

Where, D_i is the i^{th} distance for the i^{th} AANN and $i = 1$ to 5. N is the data length and the other symbols have their usual meanings. Finally, the ANNN that shows the lowest score (that is highest proximity) among all the scores, the class label (i^*) corresponding to that AANN, is the final verdict for the unknown class label (see Eq. (3)):

$$i^* = \min_{1 \le i \le 5} D_i \qquad (3)$$

Figure 3 gives an example of how the trained AANN could approximate the unknown input with its generated output through the network. The red line shows the input to the network while the blue one is the approximated signal from the same network. The low score (0.0018 in normal class) as sum-of-squared error indicates the ability of auto encoding to provide a good approximation. When viewed differently, the score or error will be higher, if the class label of unknown beat and that of the trained AANN are different. This also shows the AANN's capability of capturing generalized wave morphology from a training corpus with similar waves.

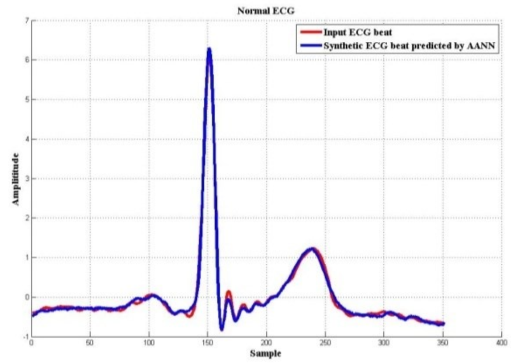

Fig. 3. The approximation capability of a trained AANN for Normal class

IV. Results and Discussions

Arrhythmia classification results using MIT-BIH are shown in Table II and III given below;

TABLE II. CLASSIFICATION ACCURACIES (TRUE POSITIVITY)

Class Label	Dynamic Time-Warping		Proposed (AANN based)
	Euclidean Distance	Cosine Similarity measure	
N	93.68	94.63	**97.50**
LBBB	95.67	95.68	**98.66**
RBBB	95.78	95.82	**99.35**
PVC	95.79	95.17	**97.10**
APC	91.17	92.32	**95.62**

TABLE III. CONFUSION MATRIX FOR ANNN BASED PARADIGM

Class labels of Neural Net / Class labels of Test sample	N	LBBB	RBBB	PVC	APC	Total Test data
N	8482	42	9	134	33	8700
LBBB	56	7961	1	50	1	8069
RBBB	9	5	6725	28	2	6769
PVC	34	42	3	3075	13	3167
APC	73	10	2	6	1987	2078

The results given in the Table II illustrates the fact that the AANN outperforms considerably in terms of true positivity, when compared with similar approaches like Dynamic Time Warping (DTW)-based template matching method [17, 20]. In DTW paradigm, the original training templates need to be stored for comparison. On the same test dataset, DTW-based distance measure was used to compare the distance with the templates (here, the ECG beats) stored in the training corpus. For any unknown test sample, the DTW distances between the test beat and all the training samples from a particular class are determined first. The lowest distance among all the computed distances is then stored temporarily for future use. The process of one-to-all distance calculation is done for all the five classes. Finally, the class label corresponding to the minimum distance among the lowest distances from all the pattern class would be the final class label for the DTW-based technique. No normalization was required for the distances, as the beats were already normalized in Eq. (1). Like the AANN, the DTW too [17, 20] does not involve feature extraction techniques while classifying the Arrhythmias. However, DTW is computationally expensive at the time of testing, as it involves dynamic programming. Contrary to that, the proposed method's requirement is to store only the weights of AANN to represent the training dataset. In this work, the R-peak locations were chosen from the ground truth data, which is hand labeled and considered to be of gold standards. However, the performance of the proposed algorithm may reduce depending on the performance of the automatic R-peak detection algorithm [18] used.

In Table III, we have shown the confusion matrix for the proposed technique. It can be observed that the inter class confusions are (see the off-diagonal elements) significantly less than those of intra classes. This indicates the AANN's ability to discriminate one class from another although the training was done in a non-discriminative manner. Table IV shows the compression ratio of the size of AANN weights to the size of original training data which was found to be **18.9: 1** or **94.72%**.

TABLE IV. RELATIVE COMPRESSION

Data	Size (in KB)	Relative Compression (Size of Total Train Data – Size of Weights of NNet)/Size of Total Train Data *100
Total Train data	10925	-
Weights of Neural Nets	576	94.72%

V. CONCLUSION AND FUTURE SCOPE

An Auto Associative Neural Network-based Arrhythmia classification technique is presented in this paper. The weights of the Neural Network are saved for posterity instead of storing the reference template of beats. Hence, the storage requirement is reduced drastically. The AANN also does not involve any feature extraction step, which gives it an advantage of lower complexity at the time of testing. We have presented our results on four different Arrhythmia classes and Normal Sinus Rhythm. This shows the considerable improvement of this algorithm, in terms of classification accuracy, over the state-of-the-art technique such as Dynamic Time-Warping.

The neural network was trained here in a non-discriminative way. For the future, it would be interesting to also investigate the training of the AANN in a discriminating manner. Also the AANN were trained for a particular size of the beat. It might be also worth investigating the network's performance on beat of various sizes and that are drawn from different Arrhythmia classes.

ACKNOWLEDGEMENT

The author would like to sincerely thank Dr. Kyoung-Gu Woo and Dr. Hyougmin Park from Samsung Advanced Institute of Technology (SAIT), Korea for the initial discussions of this work and to Dr. Heasoo Wang (formerly with SAIT Korea).

REFERENCES

[1] L. Glass, "Cardiac oscillations and arrhythmia analysis," Complex Systems Science in Biomedicine, 2006, Springer US.

[2] E. Braunwald, D. P. Zipes, P. Libby, and R. Bonow, "Braunwald's Heart Disease: A Textbook of Cardiovascular Medicine, "Elsevier, 9th Edition, 2011.

[3] M. G. Tsipouras, D. I. Fotiadis, and D. Sideris, "An arrhythmia classification system based on the RR-interval signal," Artificial Int. in Medicine, vol. 33, no. 3, pp. 237-250, 2005.

[4] A. R. Naghsh-Nilchi and A. R. Kadkhodamohammadi, "Cardiac arrhythmias classification method based on MUSIC, morphological descriptors, and neural network," EURASIP J. on Advan. in Sig. Proc., vol. 2008.

[5] V. X. Afonso, W. J. Tomkins, T. Q. Nguyen, and S. Luo, "ECG beat detection using filter banks," IEEE Trans. Biomed. Eng., vol. 46, no. 2, pp. 192-202, 1999.

[6] M. G. Tsipouras and D. I. Fotiadis, "Automatic arrhythmia detection based on time and time–frequency analysis of heart rate variability," Comput. Meth. Prog. Biomed, vol. 74, no. 2, pp. 95-108, 2004.

[7] C. W. Li, C. X. Zheng, and C. F. Tai, "Detection of ECG characteristic points using wavelet transform," IEEE Trans. Biomed. Eng., vol. 42, no. 1, pp. 21-28, 1995.

[8] D. Ge, N. Srinivasan, and S. M. Krishnan, "Cardiac arrhythmia classification using autoregressive modeling," BioMedical Eng. Online, vol. 1, no. 5, 2002.

[9] F. M. Ham and S. Han, "Classification of cardiac arrhythmias using fuzzy ARTMAP," IEEE Trans. Biomed. Eng., vol. 43, no. 4, pp. 425-430, 1996.

[10] P. Laguna, R. Jane, S. Olmos, N. V. Thakor, H. Rix and P. Caminal, "Adaptive estimation of QRS complex wave features of ECG signal by the Hermite model," Med. Biol. Eng. Comput., vol. 34, no. 1, pp. 58-68, 1996.

[11] D. Benietz, P. A. Gaydecki, A. Zaidi and A. P. Fitzpatrick, "The use of the Hilbert transform in ECG signal analysis," Comput. Biol. Med., vol. 31, no. 5, pp. 399-406, 2001.

[12] N. V. Thakor, Y-S. Zhu and K-Y. Pan, "Ventricular tachycardia and fibrillation detection by a sequential hypothesis testing algorithm," IEEE Trans. Biomed. Eng., vol. 37, no. 9, pp. 837-843, 1990.

[13] S. M. Jadhav, S. L. Nalbalwar and A. Ghatol, "Artificial neural network based cardiac arrhythmia classification using ECG signal data," Int Conf. on Electronics and Info. Eng., Kyoto, vol. 1, pp. 228-231, 2010.

[14] Y-C. Yeh, W-J. Wang and C. W. Chiou, "Cardiac arrhythmia diagnosis method using linear discriminant analysis on ECG signals," Measurement, vol. 42, no. 5, pp. 778-789, 2009.

[15] B. Yegnanarayana and S. P. Kishore "AANN: an alternative to GMM for pattern recognition", Neural networks, vol. 15, no. 3, pp. 459-469, 2002.

[16] R.G Mark, P.S Schluter, G.B. Moody, P.H. Moody, and D. Chernoff, "An annotated ECG database for evaluating arrhythmia detectors". IEEE Trans. Biomed. Eng.., vol. 29, no. 8, pp. 600, 1982.

[17] B. S. Raghavendra, D. Bera, A. S. Bopardikar, and R. Narayanan, "Cardiac arrhythmia detection using dynamic time warping of ECG beats in e-healthcare systems", in Proc WOWMOM, pp. 1-6, 2011.

[18] J. Pan and W. J. Tompkins. "A real-time QRS detection algorithm," IEEE Trans. Biomed Eng., vol. BME-32, no. 3, pp. 230-236, 1985.

[19] P. J. Werbos. Beyond Regression: New Tools for Prediction and Analysis in the Behavioral Sciences. PhD thesis, Harvard University, 1974.

[20] B. Huang and W. Kinser, "ECG frame classification using dynamic time warping," Proc. IEEE Canadian Conf. on Electrical & Comput. Eng., vol. 2, pp. 1105-1110, 2002