Discrimination of Ventricular Arrhythmias Using NEWFM

Zhen-Xing Zhang, Sang-Hong Lee, and Joon S. Lim

Division of Software, Kyungwon University, Sungnam 461-701, Korea
jjh@ku.kyungwon.ac.kr, shleedosa@kyungwon.ac.kr,
jslim@kyungwon.ac.kr

Abstract. The ventricular arrhythmias including ventricular tachycardia (VT) and ventricular fibrillation (VF) are life-threatening heart diseases. This paper presents a novel method for detecting normal sinus rhythm (NSR), VF, and VT from the MIT/BIH Malignant Ventricular Arrhythmia Database using the neural network with weighted fuzzy membership functions (NEWFM). This paper separates pre-processing into 2 steps. In the first step, ECG beasts are transformed by using Filtering Function [1]. In the second step, transformed ECG beasts produce 240 numbers of probability density curves and 100 points in each probability density curve using the probability density function (PDF) processing. By using three statistical methods, 19 features can be generated from these 100 points of probability density curve, which are the input data of NEWFM. The 15 generalized features from 19 PDF features are selected by non-overlap area measurement method [4]. The BSWFMs of the 15 features trained by NEWFM are shown visually. Since each BSWFM combines multiple weighted fuzzy membership functions into one using bounded sum, the 15 small-sized BSWFMs can realize NSR, VF, and VT detection in mobile environment. The accuracy rates of NSR, VF, and VT is 98.75 %, 76.25 %, and 63.75 %, respectively.

Keywords: fuzzy neural networks, NSR, VT, VF, filtering transform, PDF, weighted fuzzy membership function, feature selection.

1 Introduction

Classifying cardiac arrhythmias using the electrocardiogram (ECG) is in great need of an adaptive decision support tool that can handle noise, baseline drift, and artifacts. Fuzzy neural networks (FNN) can be effectively used for this type of tool as a major pattern classification and predictive rule generation tool for cardiac pattern analysis [2] [6] [9] [10] [11] [13]. Since the ECG signal includes noise, baseline drift, and abnormal behavior, the Filtering Transforms (FT) as filtering process is needed. The filter function, filtfilt function, and butter function are used in the FT filtering process.

Ventricular tachycardia (VT) is a potentially lethal disruption of normal heartbeat (arrhythmia) that may cause the heart to become unable to pump adequate blood through the body. If the VT appears a period of time, VT will induce a Ventricular Fibrillation (VF), the most dangerous type of heart arrhythmia. The VF is represented

H. Li et al. (Eds.): AIRS 2008, LNCS 4993, pp. 176–183, 2008.

by fast rhythm, abnormal and ineffective contractions of the ventricles and it finishes in a systole .The VF within a few minutes or a few days will lead to cardiac sudden death. The survival probability for a human who has a VF attack outside the hospital ranges between 2-25% [14].

This paper presents a set of FT and probability density function (PDF) processing result as common input features for automatic NSR, VF, and VT detection using neural network with weighted membership functions (NEWFM) and the non-overlap area distribution measurement method [5]. The method extracts minimum number of input features each of which constructs an interpretable fuzzy membership function.

Methods of feature extraction of ECG are categorized into four functional groups including direct, transformation, and characteristic parameter estimation methods. FT belongs to the transformation method that filtering process is a reasonable defibrillator method. Chen *et al.* [7] used the PDF of the Blanking Variability and sequential probability ratio test (SPRT) method for detecting arrhythmia classification. Chowdhury *et al.* [3] used Fuzzifier transformation and Fuzzy Rule Base method for detecting arrhythmias classification. This study has quondam accuracy rates of NSR, VF, and VT is 94.3 %, 78.0 %, and 82 %, respectively. But this result doesn't count the classification CT decision (the classification CT implies that no decision can be reached for the interval.)[3], so the recalculated accuracy rates counted of NSR, VF, and VT are 82.5 %, 58 %, and 62.5 %, respectively.

In this paper, the 15 generalized features from 19 PDF features are selected by non-overlap area measurement method [4]. A set of 15 extracted coefficient features are presented to predict NSR, VF, and VT classification using the FT, PDF, and the neural network weighted fuzzy membership functions (NEWFM) [6][5]. The 15 features are interpretably formed in weighted fuzzy membership functions preserving the disjunctive fuzzy information and characteristics, locally related to the time signal, of ECG patterns. Although reducing the number of features is advantageous to computation and complexity, it becomes one of main causes of increasing dependency on data sets or patients.

2 Pre-process of ECG Signals

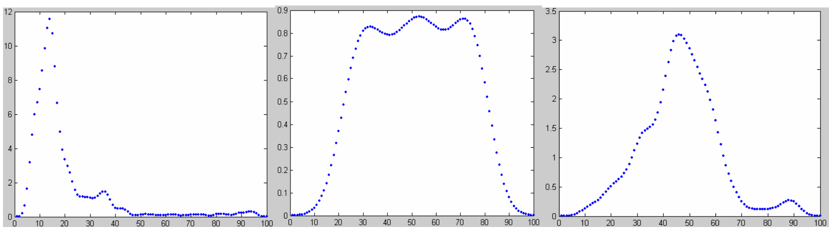
2.1 Filtering Transformation

NEWFM uses the same filtering transformation in Amann et al [1]. The filtering transformation process contained a filtering function file. The filtering function works in four steps as follows:

A. Remove the average value of the signal from the signal.
B. Apply a moving averaging filter in order to remove high frequency noise.
C. Carry out the drift suppression. It removes slow signal changes, which are not produced by the heart and originate from external sources.
D. Make a butterworth filter with a remove frequency of 30 Hz eliminates frequencies higher than 30 Hz, which seem to be of no relevance in our simulations. By applying this filtering process, the behavior of the signal acquisition by a defibrillator is reasonably simulated.

2.2 Probability Density Function (PDF) Transformation

This PDF process is based on sampling the amplitude distribution of the same baseline cardiac rhythm signal. The distinct NSR, VT, and VF rhythm signal probability density curve has been shown in Fig.1. There are eight ranges in Y coordinate of the curve like [0,0.5],[0.5,1],[1,2],[2,3],[3,4],[4,5],[5,6],[6, +∞]. The number of Y coordinates in the every interval of the eight ranges are counted and then the every interval's average of the eight ranges are counted as all Y coordinates divided by the number of Y coordinates. The number of Y coordinates in the [0.5, +∞], [1, +∞] interval and maximum value of the curve are counted. The appearing 19 data are selected after some tests and are used as the NEWFM input data.



NSR VT VF

Fig. 1. NSR, VT, and VF probability density curves

3 Neural Network with Weighted Fuzzy Membership Function (NEWFM)

3.1 The Structure of NEWFM

Neural network with weighted fuzzy membership function (NEWFM) is a supervised classification neuro-fuzzy system using bounded sum of weighted fuzzy membership functions (BSWFM in Fig. 3) [5][6]. The structure of NEWFM, illustrated in Fig. 2, comprises three layers namely input, hyperbox, and class layer. The input layer contains n input nodes for an n featured input pattern. The hyperbox layer consists of m hyperbox nodes. Each hyperbox node B_l to be connected to a class node contains n BSWFMs for n input nodes. The output layer is composed of p class nodes. Each class node is connected to one or more hyperbox nodes. An h-th input pattern can be recorded as $I_h=\{A_h=(a_1, a_2, \ldots , a_n), class\}$, where class is the result of classification and A_h is n features of an input pattern.

The connection weight between a hyperbox node B_l and a class node C_i is represented by w_{li}, which is initially set to 0. From the first input pattern I_h, the w_{li} is set to 1 by the winner hyperbox node B_l and class i in I_h. C_i should have one or more than one connections to hyperbox nodes, whereas B_l is restricted to have one connection to a corresponding class node. The B_l can be learned only when B_l is a winner for an input I_h with class i and $w_{li} = 1$.

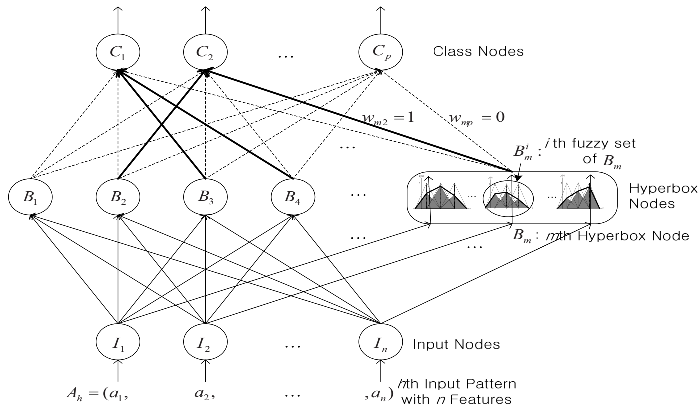


Fig. 2. Structure of NEWFM

3.2 Learning Scheme

A hyperbox node B_l consists of n fuzzy sets. The ith fuzzy set of B_l, represented by B_l^i, has three *weighted fuzzy membership functions* (WFM, grey triangles $\omega_{l1}^i, \omega_{l2}^i$, and ω_{l3}^i in Fig. 3) which randomly constructed before learning. Each $\omega_{l\,j}^i$ is originated from the original membership function $\mu_{l\,j}^i$ with its weight $W_{l\,j}^i$ in the Fig. 3. The *bounded sum of three weighted fuzzy membership functions* (BSWFM, bold line in Fig. 3) of B_l^i combines the fuzzy characteristics of the three WFMs. The BSWFM value of B_l^i, denoted as $BS_l^i(.)$, and is calculated by formulas (1) where a_i is an ith feature value of an input pattern A_h for B_l^i.

$$BS_l^i(a_i) = \sum_{j=1}^{3} \omega_{l\,j}^i(a_i), \tag{1}$$

The winner hyperbox node B_l is selected by the *Output* (B_l) operator. Only the B_l, that has the maximum value of *Output* (B_l) for an input I_h wtih class i and w_{li} = 1, among the hyperbox nodes can be learned. For the hth input A_h= (a_1, a_2… a_n) with n features to the hyperbox B_l, output of the B_l is obtained by formulas (2)

$$Output\ (B_l) = \frac{1}{n}\sum_{i=1}^{n} BS_l^i(a_i). \tag{2}$$

Then, the selected winner hyperbox node B_l is learned by the *Adjust* (B_l) operation. This operation adjusts all B_l^i s according to the input a_i, where i=1, 2… n. The membership function weight $W_{l\,j}^i$ (where 0≤ $W_{l\,j}^i$ ≤1 and j=1, 2, 3) represents the strength of $\omega_{l\,j}^i$. Then a WFM $\omega_{l\,j}^i$ can be formed by ($v_{l\,j-1}^i, W_{l\,j}^i, v_{l\,j+1}^i$). As a result of *Adjust* (B_l) operation, the vertices $v_{l\,j}^{i}$ and weights $W_{l\,j}^{\,i}$ in Fig. 4 are adjusted by the following expressions:

$$
\begin{aligned}
v_{l\,j}^{i} &= v_{l\,j}^{i} + s\times\alpha\times E_{l\,j}^{i}\times\omega_{l\,j}^{i}(a_i) \\
&= v_{l\,j}^{i} + s\times\alpha\times E_{l\,j}^{i}\times\mu_{l\,j}^{i}(a_i)\times W_{l\,j}^{\,i},\ where \\
&\begin{cases}
s=-1, E_{l\,j}^{i}=\min(\left|v_{l\,j}^{i}-a_i\right|,\left|v_{l\,j-1}^{i}-a_i\right|),\ \ if\ v_{l\,j-1}^{i}\le a_i< v_{l\,j}^{i} \\
s=1, E_{l\,j}^{i}=\min(\left|v_{l\,j}^{i}-a_i\right|,\left|v_{l\,j+1}^{i}-a_i\right|),\ \ if\ v_{l\,j}^{i}\le a_i< v_{l\,j+1}^{i} \\
E_{l\,j}^{i}=0,\ \ otherwise
\end{cases} \\
W_{l\,j}^{\,i} &= W_{l\,j}^{\,i} + \beta\times(\mu_{l\,j}^{\,i}(a_i)-W_{l\,j}^{\,i})
\end{aligned}
\tag{3}
$$

where the α and β are the learning rates for $v_{l\,j}^{i}$ and $W_{l\,j}^{\,i}$ respectively in the range from 0 to 1 and j=1,2,3.

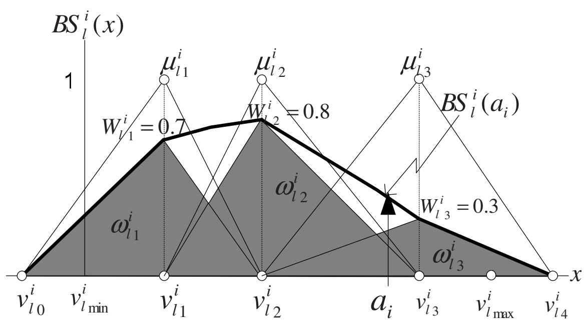


Fig. 3. An Example of Bounded Sum of Weighted Fuzzy Membership Functions (BSWFM, Bold Line) of $B_l^{\,i}$ and $BS_l^i(a_i)$

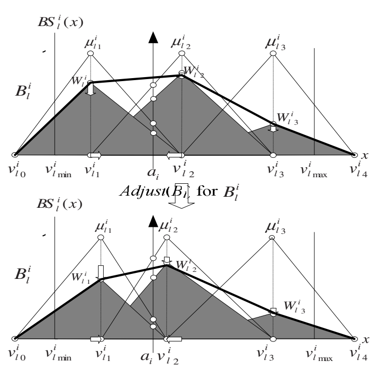


Fig. 4. An Example of Before and After Adjust (B_l) Operation for B_l^i

Fig. 4 shows BSWFMs before and after *Adjust* (B_l) operation for B_l^i with an input a_i. The weights and the centers of membership functions are adjusted by the *Adjust* (B_l) operation, e.g., $W_{l\,1}^{\,i}$, $W_{l\,2}^{\,i}$, and $W_{l\,3}^{\,i}$ are moved down, v_{l1}^{i} and v_{l2}^{i} are moved toward a_i, and $v_{l\,3}^{\,i}$ remains in the same location.

The Adjust (B_l) operations are executed by a set of training data. If the classification rate for a set of test data is not reached to a goal rate, the learning scheme with Adjust(B_l) operation is repeated from the beginning by randomly reconstructing all WFMs in B_l s and making all connection weights to 0 (w_{li} = 0) until the goal rate is reached.

4 Experimental Results

In this section, the NSR, VF, and VT data sets, which were used in Chowdhury [3], are used to evaluate the accuracy of the proposed NEWFM. The 15 generalized features among 19 generalized features are selected by non-overlap area measurement method [4].

The analyzed data set is taken from MIT/BIH Malignant Ventricular Arrhythmia Database [8]. This data base consists of 22 thirty-five-minute records and 80 four-second samples of each NSR, VT, and VF episodes in the 22 records are selected at random. Fig. 5 shows BSWFMs of the generalized 6 features among the generalized 15 features. The solid lines, broken lines and dotted lines represent NSR, VF, and VT characteristics of ECG visually, which enables the features to interpret explicitly.

Chowdhury has quondam accuracy rates of NSR, VF, and VT is 94.3 %, 78.0 %, and 82 %, respectively. But this result doesn't count the classification CT decision (the classification CT implies that no decision can be reached for the interval.) [3], so the recalculated accuracy rates of NSR, VF, and VT is 82.5 %, 58 %, and 62.5 %, respectively. Table 1 shows the recalculated accuracy rates. The average accuracy rate is 67.5%.

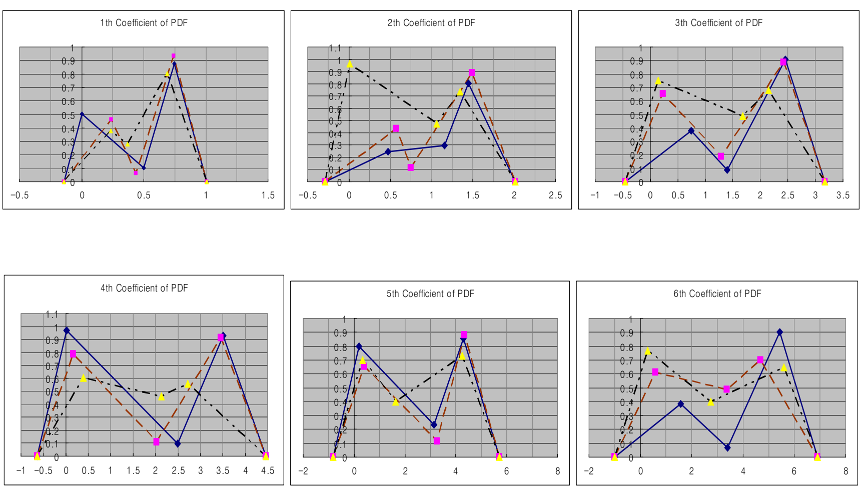


Fig. 5. Trained BSWFMs of the 1- 6th Features for NSR, VF, and VT Classification

Table 1. Chowdhury's results of evaluating the NSR, VT, and VF detection algorithm using the MIT/BIH Malignant Ventricular Arrhythmia ECG DATABASE

True Events& Tot.NO.of Samples	NSR	VT	VF	CT	Accuracy Rate
NSR(80)	66	4	0	10	82.5
VT(80)	1	50	10	19	62.5
VF(80)	0	13	46	21	58

Table 2. Comparisons of performance results for NEWFM with CHOWDHURY'S

True Events& Tot.NO.of Samples	NSR	VT	VF	Accuracy Rate
NSR(80)	79	1	0	98.75
VT(80)	22	51	7	63.75
VF(80)	7	12	61	76.25

Table 2 shows the performance results of NEWFM using the generalized 15 features. In this paper, there is no CT decision. NEWFM classifies NSR, VF, and VT on all data sets. The accuracy rates of NSR, VF, and VT are 98.75 %, 76.25 %, and 63.75 %, respectively and the average accuracy rate is 79.16%.

5 Concluding Remarks

The BSWFMs of the 15 features trained by NEWFM are shown visually, which makes the features interpret explicitly. Since each BSWFM combines multiple weighted fuzzy membership functions into one using bounded sum, the 15 small-sized BSWFMs can realize real-time NSR, VT, and VF detection in mobile environment. These algorithms are pivotal component in Automated External Defibrillators (AED). To improve the accuracy rates of NSR, VF, and VT, some kinds of mathematics' method instead of PDF will be needed to study in real application of AED. On the other hand, some good results are achieved on economy index and stock forecasting which using NEWFM.

References

1. Amann, A., Tratnig, R., Unterkofler, K.: Detecting Ventricular Fibrillation by Time-Delay Methods. IEEE Trans. on Biomedical Engineering 54(1), 174–177 (2007)
2. Engin, M.: ECG beat classification using neuro-fuzzy network. Pattern Recognition Letters 25, 1715–1722 (2004)
3. Chowdhury, E., Ludeman, L.C.: Discrimination of cardiac arrhythmias using a fuzzy rule-based method. Computers in Cardiology, 549–552, September 25-28 (1994)

4. Lim, J.S., Gupta, S.: Feature Selection Using Weighted Neuro-Fuzzy Membership Functions. In: The 2004 International Conference on Artificial Intelligence(IC-AI 2004), Las Vegas, Nevada, USA, June 21-24, vol. 1, pp. 261–266 (2004)
5. Lim, J.S., Ryu, T.-W., Kim, H.-J., Gupta, S.: Feature Selection for Specific Antibody Deficiency Syndrome by Neural Network with Weighted Fuzzy Membership Functions. In: Wang, L., Jin, Y. (eds.) FSKD 2005. LNCS (LNAI), vol. 3614, pp. 811–820. Springer, Heidelberg (2005)
6. Lim, J.S., Wang, D., Kim, Y.-S., Gupta, S.: A neuro-fuzzy approach for diagnosis of antibody deficiency syndrome. Neurocomputing 69(7-9), 969–974 (2006)
7. Clarkson, S.-W.C., Clarkson, P.M., Fan, Q.: A robust sequential detection algorithm for cardiac arrhythmia classification. IEEE Transactions on Biomedical Engineering 43(11), 1120–1124 (1996)
8. MIT-BIH Malignant Ventricular Arrhythmia database directory, Document BMEC TR010, Mass. Inst. Technol, Cambridge, July (1992)
9. Minami, K., Nakajima, H., Toyoshima, T.: Real-Time Discrimination of Ventricular Tachyarrhythmia with Fourier-Transform Neural Network. IEEE Trans. on Biomedical Engineering 46(2), 176–185 (1999)
10. Linh, T.H., Osowski, S., Stodolski, M.: On- Line Heart Beat Recognition Using Her8e Polynomials and Neuro-Fuzzy Networks. IEEE Trans. on Instrumentation and Measurement 52(4), 1224–1231 (2003)
11. Osowski, S., Linh, T.H.: ECG beat recognition using fuzzy hybrid neural network. IEEE Trans. on Biomedical Engineering 48(4), 1265–1271 (2001)
12. Ramirez-Rodriguez, C., Hernandaz-Silveria, M.: Multi-Thread Implementation of a Fuzzy Neural Network for Automatic ECG Arrhythmia Detection. Proceedings in Computers in Cardiology 2001, 297–300 (September 2001)
13. Silipo, R., Marchesi, C.: Artificial Neural Networks for Automatic ECG Analysis. IEEE Trans. on Signal Processing 46(5), 1417–1425 (1998)
14. Fernandez, A.R., Folgueras., J., Colorado., O.: Validation of a set of algorithms for ventricular fibrillation detection: experimental results. In: Proceedings of the 25th Annual International Conference of the IEEE, September 17-21 2003, vol. 3, pp. 2885–2888 (2003)