Heart Beat Classification Using Wavelet Feature Based on Neural Network

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Abstract— Arrhytmia is one of the most crucial problem in cardiology. It can be diagnosed by a standard electrocardiogram (ECG). So far, many methode have been develop for arrhytmia detection, recognition and classification But many methode for arrhytmia beat classification have been yet able to solve unknown category data. This paper will discusses about how to determine the type of arrhythmia in computerize way through classification process that able to solve unkown categorical beat. We use FLVQ to solve the weakness of the other methode of calssification such as to classified unknown category beat. This process is divided into three steps: data preprocessing, feature extraction and classification. Data preprocessing related to how the initial data prepared, in this case, we will reduce the baseline noise with cubic spline, then we cut the signal beat by beat using pivot R peak, while for the feature extraction and selection, we using wavelet algorithm. ECG signal will be classified into four classes: PVC, LBBB, NOR, RBBB and one unknown category beat; using two following algorithms Back-Propagation and Fuzzy Neuro Learning Vector Quantization (FLVQ). The classification will be devided on two phase, at ones phase we will find best fitur for out system. At this phase we use known category beat, the best fiture for out study is 50 fitur, it is from wavelet decompotition level 3. Second phase is added unkown category beat on data test, the unknown category beat is not included on data train. Accuracy of FLVQ in our study is 95.5% for data without unknown category beat at testing step and 87.6% for data with unknown category beat.

Key-Words—ECG, Electrocardiogram, Arrhythmia, FLVQ, back-propagation, wavelet transforms, physionet, MIT-BIH.

1 Introduction

Cardiac arrhythmia is a heart disease where the heart beats irregularly. An arrhythmiac heart may beat too slow, too rapid, or in irregular fashion. The symptoms of arrhythmia can be confused with a normal heart, so a patient may or may not aware of its symptoms, like palpitations, vibration heart leap, dizziness, shortness of breath and/or chest pain. Those symptoms can be occurred in normal heart, therefore it is not enough to diagnose arrhythmia only from the symptoms itself.

There are several techniques can be used to diagnose arrhythmias including a standard electrocardiogram (ECG), Blood and urine tests, Holter Monitoring, electro-physiology studies (EPS), Event Recorder, an echo-cardiogram, Chest X-Ray, Tilt-table test ([1] [2]). Using ECG is a common and the best way for diagnosing arrhythmias. Doctors analyze the electrical activity of heart through ECG signal and determine occurrence of arrhythmias. In this research, we will study on how to determine the type of arrhythmia based on the ECG signal. Instead of using manual way using specific expertise like doctors, we use computerized technique based on the pattern contained in the ECG signal.

Various study have been done already for classification of various arrhytmias. There are a lot of works applying artifical neural network (ANN) and it's variant as a detection method ([3], [4], [5]) and some of them are combining wavelet transform (WT) or Principal Component Analysis (PCA) or Fuzzy C-Mean(FCM) with ANN or LVQ-NN for classifing the signal ([6], [7], [8], [9]), and applying bayesian framework [10]. There also researcher applying fuzzy theory on arrhytmia detection([11], [12], [6], [13]). Some of them also applying Support Vector Machine as a classifier ([14], [15]) and combining with Genetic Algorithm, like Nasiri doing [16] or combining with Particle Swarm Optimization (PSO) like Melgani works [17]. Ghongade et.al make a comparation for many

feature extraction method like DFT, PCA, DWT, Morphological based and integrating it with ANN classifier [18]. Philip et.al studies the arrhythmia classification using AAMI standard and apply the morphological feature using linier discriminant (LD) [19].
In this study, we will utilize back-propagation NN and Fuzzy Neuro Learning Vector Quantization (FLVQ) as our classifier and make some comparation at the end. To support this study, we use MIT-BIH arrhythmia database provided online [20] as our dataset. This paper is organized as follows. In section II, we describe preprocessing technique to extract signal in beat basis. Discrete wavelet transformation is used to extract the feature contain in each beat signal in section III. Each beat will be grouped according to the wave pattern that we already define through classification which will be discussed in section IV and section V&VI contain the result and conclusions of this paper and future plans of our study.

2. Data preprocessing

In this research, we use MIT-BIH arrhythmia database from physionet [20]. This database contains 48 recordings from 47 subjects studied by the BIH Arrhythmia Laboratory between 1975 and 1979. Each record contains two 30-min ECG lead signal, mostly MLII lead and lead V1/V2/V4/V5. The frequency of the ECG data was 360Hz.
For this research, we only use the MLII lead as our source data. The groups/classes that we will to consider in this research are Left Bundle Branch Block beat (LBBB),normal beat (NOR), right bundle branch block beat (RBBB), premature ventricular contraction (PVC).
The first step of ECG data preprocessing is baseline noise reduction. In our study we use cubic splines that generated exclusively from PR_segment sample to estimate and remove noise from the baseline ecg. The baseline noise is estimated from the ECG using PR-interval knot by cubic splines method. The baseline noise is reduced by simply subtracting the estimate from the raw data. For the detail please see fig 1.
After baseline noise reduction the we will do the segmentation ECG beat. In this step, the continuous ECG signals will be transformed into individual ECG beats. We approximate the width of individual beat to 300 sample data and the extracted beat is centered around R peak.
For this purpose we utilize the annotation provided by the database to do the transformation. We use the R peak annotation as the pivot point for each beat. For each R-peak, we cutoff the continuous signal for each beat start at R-150 pos until R+149 pos, as you can see in Fig.2, therefore we will get a beat with 300 sample data in width.

3. Feature extraction

As part of the pattern recognition system, feature is an important part to make the classification process work well. Good feature will lead the process to the better result as expected, but if the feature is not appropriate, it will yield to negative result.

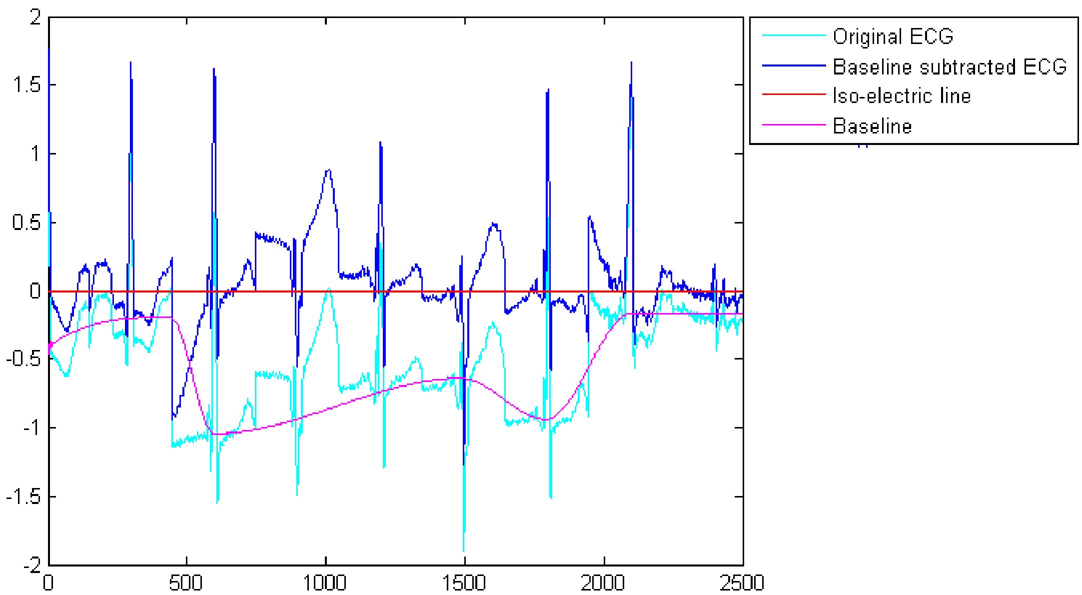

Fig. 1: Performance of thechnique on ECG baseline wander removal

There are many way to do a feature extraction process, in this step, we use discrete wavelet transformation to extract the feature contained in the individual signal beat. The Wavelet Transform (WT) of a signal f(x) is defined as:

$$W_s f(x) = f(x) * \psi_s(x) = \frac{1}{s}\int_{-\infty}^{+\infty} f(t)\psi\left(\frac{x-t}{s}\right) dt \quad (1)$$

where s is scale factor, $\Psi_s(x) = \frac{1}{s}\Psi\left(\frac{x}{s}\right)$ is the dilation of a basic wavelet $\Psi(x)$ by the scale factor s. Let $s = 2j$ (j ∈ Z,Z is the integral set), then the WT is called dyadic WT [21]. The dyadic WT of a digital signal $f(n)$ can be calculated with Mallat algorithm as follows:

$$S_{2j} f(n) = \sum_{k \in Z} h_k S_{2j-1} f(n - 2^{j-1}k) \quad (2)$$

$$W_{2j} f(n) = \sum_{k \in Z} g_k S_{2j-1} f(n - 2^{j-1}k) \quad (3)$$

where S_{2j} is smoothing operator, $S_{2j} f(n) = a_j$. a_j is the low frequency coeficients that is approximation of original signal while $W_{2j} f(n) = d_j$, d_j is high frequency coeficients that is the detail of original signals [22].

In wavelet theory, selecting the appropriate mother wavelet and the number of decomposition level is an important part. The proper selection aims to retain the important part of information and still remain in the wavelet coefficients. The Mother wavelet that we used in this research is one member of the Daubechies families : Daubechies order 8, adapted from the Senhadji research [28], who concluded that the Daubechies wavelet provide the best performance. through out this research, we will try to decompose our individual beats data from level 1 until level 3. Thus, the individual beat will be decomposed into details d1- d3, and one of the approximation a1- a3, depending on the level we choose.

In all the information generated after the decomposition process, for example, decomposition at level 3, namely a3 , d1- d3 , then we chose the proper coefficient that represent the signal well. For each individual beat, the detail d1 is usually noise signals and have to eliminated and the d2, d3, represent the high frequency coefficient of the Signal. Since a3 represent the approximation of the signal, it meant that it contained the main feature of the signal, thus we choose a3 as a feature for each individual beat. For each individual beat, we have 300 sample data, after the decomposition using wavelet db8 level 3, we have a3 contains 50 points, as we can see in Fig.3 show the original signal beat, and the wavelet coefficient of that signal after decomposition.

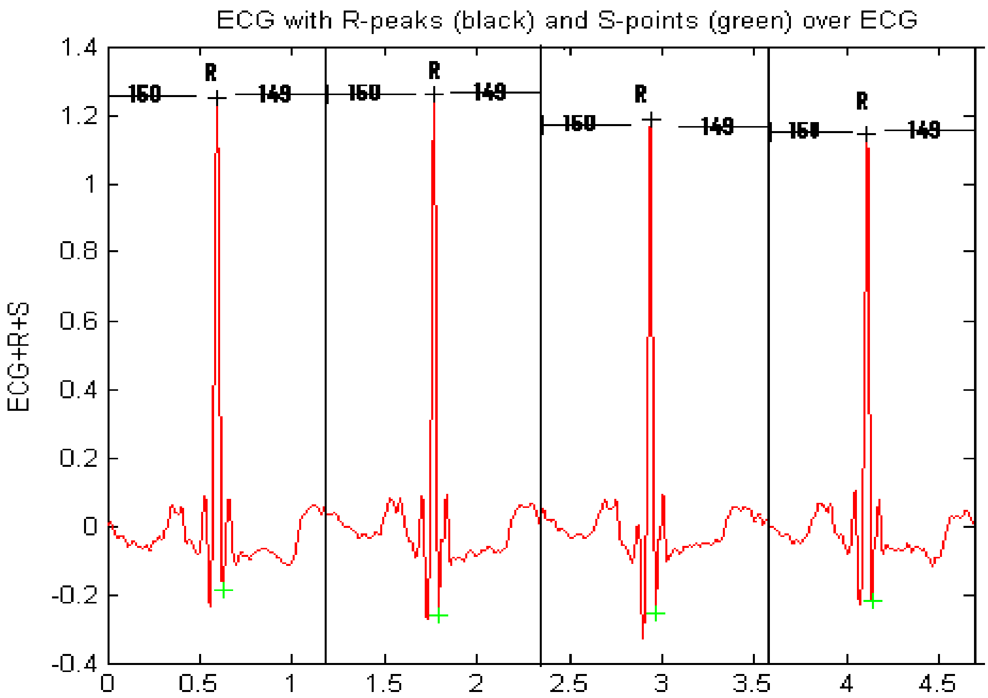

Fig. 2: cutoff technique used in this transformation process.

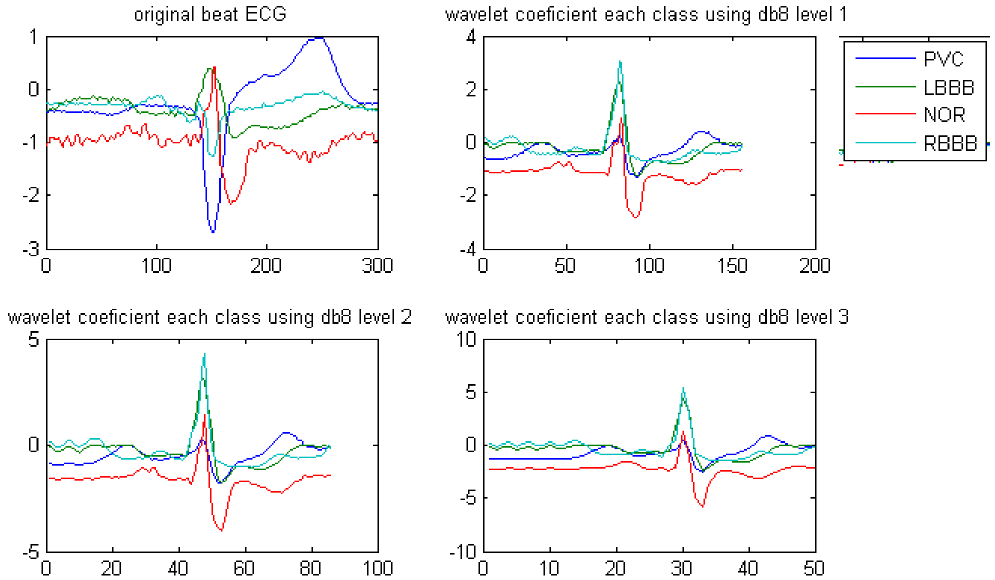

Fig. 3: Original Signal, 300 sample data, Wavelet Coeficient after each level of decomposition using db8, level 1-157 point, level 2-86 point, level 3-50 point (left to right respectively)

4. Fuzzy Neuro Learning Vector Quantization (FLVQ)

Fuzzy learning vector quantization (FLVQ) is developed based on learning vector quantization and extended by using fuzzy theory. In this FLVQ, neuron activation is expressed in terms of fuzzy number for dealing with the fuzziness caused by statistical measurement error. Fuzzification of all components of the reference and the input vectors is done through a normalized triangular fuzzy numbers process; with the maximum membership value is equal to *1*. A normalized triangular fuzzy number *F* s designated as [8],[9]:

$$F = (f, f_l, f_r) \tag{4}$$

Where f the center-peak position of F, f_l left part fuzziness and f_r right part one. Fuzziness is expressed by the skirt width of the membership function. For ECG heart beat signal, we get membership function by grouping the train data into five groups, then we get minimum column value for f_l, mean column value for f and maximum column for f_r. Triangular fuzzy numbers is shown at Figure 4 Triangular fuzzy numbers present fuzzy membership function, with the value of membership function of f is 1 and 0 for f_l and f_r.

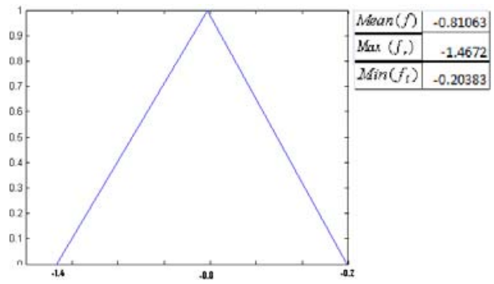

Fig. 4: Triangular fuzzy member

As the neuron of FLVQ deals directly with a fuzzy quantity, the concept of Euclidean distance in the conventional LVQ is modified by a fuzzy similarity that is calculated by using max-min operation over its input and the reference vectors. As a consequence, the network architecture should also be modified to accommodate the max-min operation of the two vectors [26]

The architectural network of FLVQ is depicted in figure 5, which consists of one input layer, one cluster layer as a hidden layer and one output layer. Neurons in the input layer are connected to a cluster-of-neurons in the hidden layer, which is grouped according to the odor-category of the input data. Thus, the number of cluster-of-neurons in the hidden layer is as many as the odor categories, while each cluster composes of neurons, which corresponds to each of the used sensors. Each cluster has a fuzzy codebook vector as a reference vector for its known-category that should be represented.

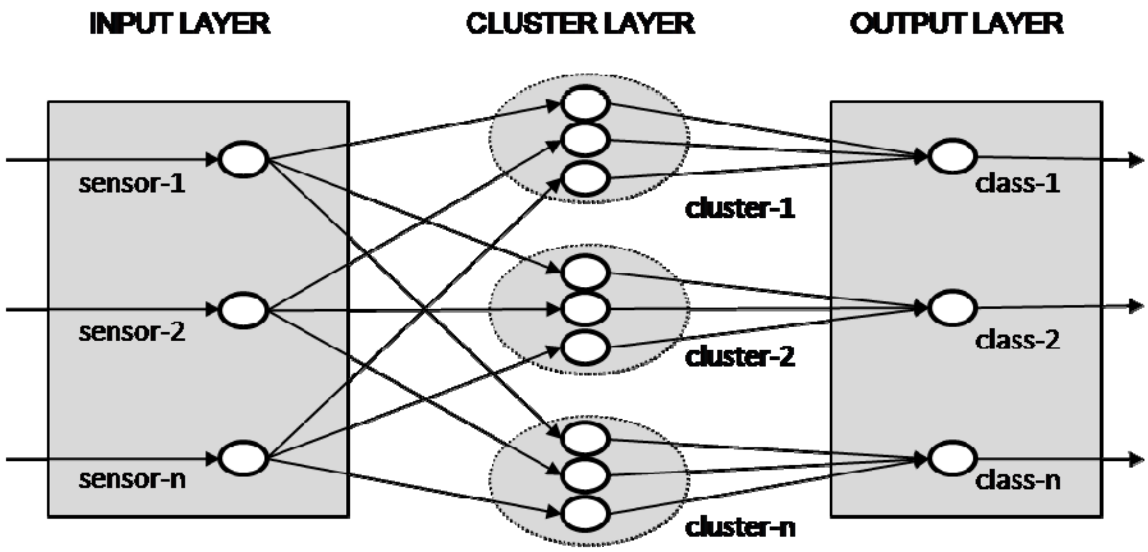

Figure 5. Architecture of the FLVQ that is used as the discrimination system in the artificial nose system.

When an input vector is fetched to the neural system, each cluster performs the similarity calculation of fuzziness between input vector and the reference vector through max operation. Output of each cluster is then propagated to output neuron that performs the minimum operation. Output neuron that has the maximum similarity value is then determined as the winning-reference vector. It is easy to notice that fuzziness of the input vector depend on the statistical distribution of the input data, while fuzziness of the reference vector is adaptively determined during learning process.

Let vector $x(t)$ denote an input vector in an n-dimensional sample space with T as the known-target category, that can be expressed by:

$$x(t) = (x_1(t), x_2(t),......., x_n(t)) \qquad (5)$$

Where n number of sensors, t denotes the time instance, and x_1 is a normalized triangular fuzzy number of the sensor 1 (see Fig.1). The membership function of $x(t)$ can be expressed by:

$$hx(t) = (hx_1(t), hx_2(t),......., hx_n(t)) \qquad (6)$$

Suppose the fuzzy reference vector for category i is w_i that can be expressed by:

$$w_i(t) = (w_{i1}(t), w_{i2}(t),......., w_{in}(t)) \qquad (7)$$

And the membership functions of w_i can be expressed by:

$$hw_i(t) = (hw_{i1}(t), hw_{i2}(t),......., hw_{in}(t)) \qquad (8)$$

Each cluster in the hidden layer then determines the similarity between the two vectors by calculating the fuzzy similarity $\mu_i(t)$ between fuzzy number of $x(t)$ and $w_i(t)$ for all of the axial components through a max operation, defined by

$$\mu_i(t) = max(h_x(t)\ , h_{wi}(t)) \qquad (9)$$

Where $i = 1,2, . . ., m$ number of the category of the odors.

Schematic diagram of fuzzy similarity calculation between inputs vectors with a reference vector in each cluster is depicted in figure 3. Neuron in the output layer received the fuzzy similarity μ_i from hidden layer, and, as in LVQ, determines the minimum one among all the axial similarity components by,

$$\mu(t) = min(\mu_i(t)) \qquad (10)$$

Which is the output from the i^{th} output neuron. The winning-neuron of the output layer is determined by which its $\mu(t)$ is maximum, and the reference vector of the cluster of neurons in the hidden layer which corresponds to that winning-neurons could also be determined. When the winning-neuron has a similarity value of $\mu(t)$ is one, the reference vector and the input vector exactly resemble; while if the $\mu(t)$ is zero, the reference vector and the input vector do not resemble at all.

Learning in FLVQ is accomplished by presenting a sequence of learning vector with its known category, and the similarity value between the learning vector and the reference vectors for all categories are calculated. After the winning-neuron and its cluster of neurons in the hidden layer could be determined, both the winning and the non-winning reference vectors are updated repeatedly for reducing the difference between the output and the target. During learning, two steps of updating procedure are done. The first step is done, by shifting the central position of the fuzzy reference vector toward, or moving away from, the input vector. The second step is called fuzziness modification, which is done by increasing or decreasing the fuzziness of the reference vector. The purpose of this fuzzy modification is to increase the possibility of making intersect between an input vector and the winning-reference vector, which in turn will increase the similarity value between those vectors. We developed two types of this fuzziness modification; the first is by multiplying the fuzziness with a constant factor [25], while the second is by multiplying it with a variable factor [25],[26].

By using these procedures, FLVQ has three cases that are possibly occurred; the first is when the network outputs the right answer, and the second is when the network outputs the wrong answer, while the third is when the reference and the output vector has no intersection of their fuzziness. For the first case, when the network outputs the category of the learning vector *Cx* is the same as the target category *T*, the reference vector of the winning cluster is updated according to [25]:

Step 1. The central position of the reference vector is shifted toward the input vector

$$w_i(t+1)= w_i(t) + \alpha(t)\{(1- \mu_i(t))*(x(t)-w_i(t))\} \quad (11)$$

Step 2. Increase the fuzziness of the reference vector for the next learning steps:

a. Modific ation by constant factor

$$f_l(t+1)= f_l(t) - (1+\beta)*\{f(t) - f_l(t)\}$$

$$f_r(t+1)= f_r(t) + (1+\beta)*\{f_r - f(t)\} \quad (12)$$

$$f(t+1)= w_i(t+1)$$

b. Modification by a variable factor

$$f_l(t+1)= f_l(t) - (1-\mu)*\{(1+\eta)*\{f(t)- f_l(t)\}$$

$$f_r(t+1)= f_l(t) + (1+\mu)*\{(1+\eta)*\{f_r(t)- f(t)\} \quad (13)$$

$$f(t+1)= w_i(t+1)$$

For the second case, when the network outputs the category of the learning vector *Cx* that is not the same as the target-category *T*, the reference vector of the winning cluster should be moved away, and is updated according to:

Step 1. The reference vector is shifted away from the input vector

$$w_i(t+1)= w_i(t) - \alpha(t)\{(1- \mu_i(t))*(x(t)-w_i(t))\} \quad (14)$$

Step 2. Decrease the fuzziness of the reference vector for the next learning step:

a. Modification by constant factor

$$f_l(t+1)= f_l(t) + (1+\gamma)*\{f(t)- f_l(t)\}$$

$$f_r(t+1)= f_r(t) - (1+\gamma)*\{f_r(t)- f(t)\} \quad (15)$$

$$f(t+1)= w_i(t+1)$$

b. Modification by a variable factor

$$f_l(t+1)= f_l(t) + (1-\mu)*\{(1-\kappa)*\{f(t)- f_l(t)\}$$

$$f_r(t+1)= f_r(t) - (1-\mu)*\{(1-\kappa)*\{f_r(t)- f(t)\} \quad (16)$$

$$f(t+1)= w_i(t+1)$$

For the third case, when the reference vector and the input vector has no intersection of their fuzziness, the fuzziness of the reference vector is updated in order to have the possibility of being crossed the input vector, according to:

$$w_i(t+1)= \xi(t) * w_i(t) \quad (17)$$

The nomenclature we use is as follows:

$w_i(t+1)$ = the winner reference vector after being shifted

$w_i(t)$ = the winner reference vector before being shifted

$\alpha(t)$ = learning rate, a monotonically decreasing scalar gain factor ($0<\alpha\leq1$), that is defined as

$$\alpha(t+1) = 0.9999\ \alpha(t)$$

$$\alpha(0) = 0.05 \quad (18)$$

β,γ = constant value of increasing or decreasing the fuzziness within interval of [0,1]

η,κ = variable value of increasing or decreasing the fuzziness through

$$\eta(t+1) = 1/100\ \{1-\alpha(t+1)\}$$

$$\kappa(t+1) = 1-\alpha(t+1) \quad (19)$$

ξ = constant value of *1.1*

4.1 Performance Evaluation

The performance evaluation of the classification algorithm are evaluated using classification accuracy. The accuracy of ECG classifier is defined as:

$$Accuracy = \frac{nC}{N} \qquad (20)$$

Where nC = Number of beats correctly classified, and N = the Total number of beats tested

5. Result & Discussion

The experiment was performed using MIT-BIH arrhythmia database from physionet [20]. After we do the transformation process,as in section II, we have groups of individual beats as follows; 500 beats for LBBB, 1000 beats for RBBB, 500 beats for NOR, and 500 beats for PVC, contain 300 sample each as a raw feature for the signal.

Then we apply decomposition on the raw feature (300 sample) using wavelet transform with Daubechies order 8 (db8) in any level started from level 1 until level 3. As describe in section III, we will using the approximation part of the decomposition result. Each decomposition generate different number of coefficient depend on the level. level 1 generate 157 coefficients on a1 , level 2 generate 86 coefficients on a2 , and level 3 generate 50 coefficients on a3.

5.1 ECG arrhythmias beat classification without unknown category

The studies proposed here are to clasify the dataset using back-propagation neural network and Fuzzy neuro learning vector quantization (FLVQ). After passing a series of tests, we configure the training parameter of back-propagation neural network as follows: epoch = 10000, α = 0.001 using 5 hidden layer. And For the FLVQ training parameter as follows : epoch = 1000, cluster = 5, α = 0.002 and threshold 0.9.

We did our experiments in two stages. The first stage is to find the best number of features that can produce the best classification among the dataset. In this stage, we do 10 times of experiments for each group of feature number including the original one (300, 157, 86, 50). Our experiments involving the dataset ratio 50:50 as train and test data. Classification result on this stage can be seen on fig 6.

Based on fig. 6, show that the best accuracy of our experiment is using 50 features, it's the best features for use FLVQ and Back-propagation

5.2 ECG arrhythmias beat classification without unknown category

Experiments in stage I show that more over number of features that used, not always produces better accuracy. Because too much features used, the possibility of information redundancy that would obscure the more important information from the data.

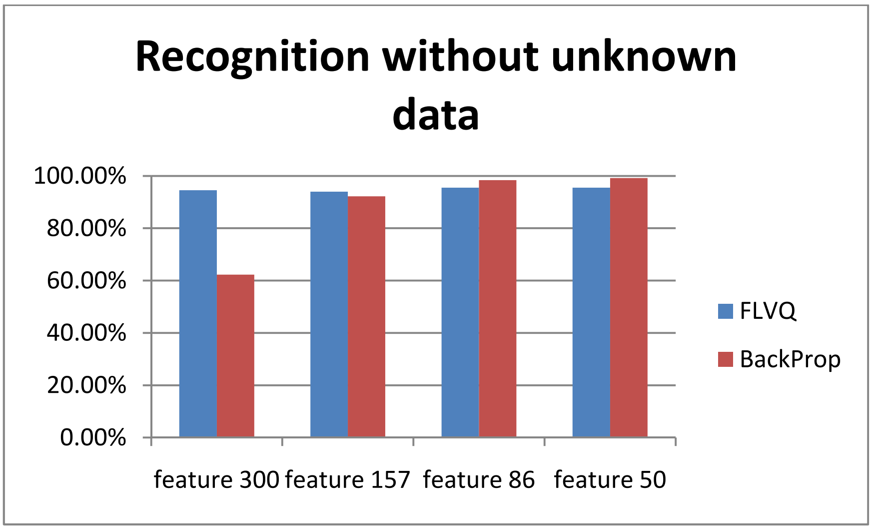

Fig. 6: histogram between back-propagation and FLVQ

Table I: Back-propagation experiment on stage 2

	PVC	LBBB	NOR	RBBB	Unknown
PVC	99.20%	0.40%	0.00%	0.40%	0.00%
LBBB	0.00%	100.00%	0.00%	0.00%	0.00%
NOR	0.00%	0.00%	100.00%	0.00%	0.00%
RBBB	0.00%	0.00%	0.80%	99.20%	0.00%
Unknown	42.40%	14.80%	0.00%	42.80%	0.00%

Table II: FLVQ experiment on stage 2

	PVC	LBBB	NOR	RBBB	Unknown
PVC	98.00%	0.00%	0.00%	0.00%	2.00%
LBBB	0.00%	88.00%	0.00%	0.00%	12.00%
NOR	0.00%	0.00%	96.00%	0.00%	4.00%
RBBB	4.00%	0.00%	0.00%	88.00%	8.00%
Unknown	4.00%	0.00%	0.00%	0.00%	96.00%

Then we continue to second stage. The purposed of this stage was investigates the ability of FLVQ to classified data that contains of unknown category. Based on previous stage we decide to chose the 50 features and added 50 data unknown category at data test. For unknown data category classification, we modified the FLVQ with added threshold parameter to be the boundary similarity between known category and unknown categorical data. We can see on table I and table II result of this experiment stage that FLVQ is more stable than back-propagation although we add unknown category data. Back-propagation accuracy decreased sharply when we added unknown category data to the data test. Figure 7 shows the accuracy of FLVQ tested with unknown data for date feature 300 to 50. The Accuracy of FLVQ is 95.5% for data without unknown category beat at testing step and 87.6% for data with unknown category beat.

6. Conclusion

The experiments of recognition of 4 types of arrhythmia: 4 types known category, 1 type of unknown category and normal beat were carried out on MIT- BIH arrhythmia database. We train our classification methods, Back-propagation and FLVQ, with extracted features using Wavelet Transforms, daubechies order 8. We conduct 2 stage of experiments, firstly for finding the best number of features, it's related to how many level we will decompose the signal, and secondly is for testing the stability of our classification system for unknown category. From the experiments, we found that the best number of features for our system are 50 features, by considering the computational cost and the classification result. It means that we have to decompose our dataset for 3 level. Our experiment produces an average accuracy 99.20% using Back-Propagation and 95.50% for FLVQ. The result show that back-propagation leading than FLVQ but, as we know back-propagation has disadvantages to classified unknown category beat but not for FLVQ. FLVQ has stable accuracy although contain unknown category beat. The Accuracy of FLVQ is 95.5% for data without unknown category beat at testing step and 87.6% for data with unknown category beat.

Because of only using single-lead ECG, MLII, and not using all available beats and classes, for further work, we will try to increase the number of beats used also the classification class and more ECG-lead for more accuracy. It is not impossible also to use AAMI standard as our base classification class refer to Philip de Chazal works [19]

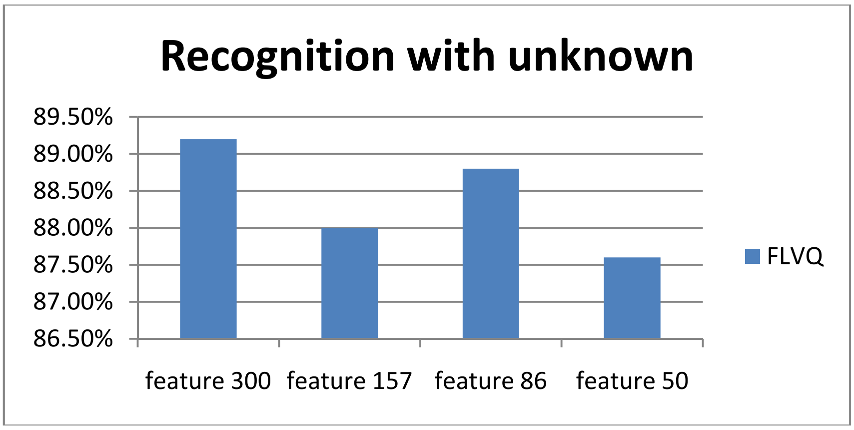

Figure 7: Histogram of FLVQ recognition rate with unknown data

7. Acknowledgement

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