# Heartbeat Case Determination Using Fuzzy Logic Method on ECG Signals

Yun-Chi Yeh, Wen-June Wang, and Che Wun Chiou

## Abstract

**This study proposes Fuzzy Logic Method (FLM) to analyze ECG signals for determining the heartbeat case. The proposed method can accurately classify and distinguish both normal heartbeats (NORM) and abnormal heartbeats. The so called abnormal heartbeats include the left bundle branch block (LBBB), the right bundle branch block (RBBB), the ventricular premature contractions (VPC), and the atrial premature contractions (APC). ECG signal analysis comprises three main stages: (i) the qualitative features stage for qualitative feature selection of an ECG signal; (ii) fuzzy rules base establishment; and (iii) the classification stage for determining patient heartbeat cases. The fuzzy rules base receives four qualitative features of an ECG signal as its inputs and generates one output "heartbeat case". Through fuzzy inference engine and defuzzification operations, we can make a decision to determine the heartbeat case of the patient's heart disease. The ECG records available in the MIT-BIH arrhythmia database are utilized to illustrate the effectiveness of the proposed method. In the experiments, the sensitivities were 95.06%, 91.03%, 90.50%, 92.63% and 93.77% for NORM, LBBB, RBBB, VPC and APC, respectively. The total classification accuracy (TCA) was approximately 93.78%.**

***Keywords: ECG signal, MIT-BIH arrhythmia database, cardiac arrhythmias, Fuzzy Logic.***

## 1. Introduction

An electrocardiogram (ECG) signal is the manifestation of the myocardium electrical activity on the body surface, which appears as a nearly periodic signal. Traditionally, the ECG cycle is labeled using the letters P, Q, R, S, and T for the individual peaks of the whole cycle's waveform (see Fig. 1) [1]. There have been several investigations dealing with the analysis of ECG signals for cardiac arrhythmia. For instance, some of the most popular descriptors which are based on assessment of the QRS complex morphology using pattern recognition methods have been proposed [2, 3]. The paper in [4-6] proposed some signal detection methods for discriminate cardiac arrhythmia in the time or frequency domain. Different transforms such as Hilbert transform [7], Hidden Markov Models [8], cross-distance analysis [9], wavelet transform [10], and Hermite function [11] automatically detect, classify and analyze ECG beat. Methods by using artificial neural networks to discriminate the cardiac arrhythmia are proposed in [12-15]. The paper in [16] proposed the self-organizing maps for classification of cardiac arrhythmias. This study proposes a simple, fast and reliable Fuzzy Logic Method (FLM) to analyze ECG signals for determining the heartbeat case. Fuzzy Logic theory [17] is widely adopted in various fields, such as pole-balancing robot control, electric washing machine control, speech recognition, image retrieval and pattern recognition.

In this study, analyzing the ECG signal using the FLM consists of three main stages: (i) the qualitative features stage for qualitative feature selection of an ECG signal; (ii) fuzzy rules base establishment; and (iii) the classification stage for determining patient heartbeat cases.

The paper is organized as follows. In Section 2, the qualitative feature selection of an ECG signal is introduced. Section 3 describes the fuzzy logic based diagnosis, and the effectiveness of the proposed method is evaluated in Section 4. The paper is briefly concluded in Section 5.

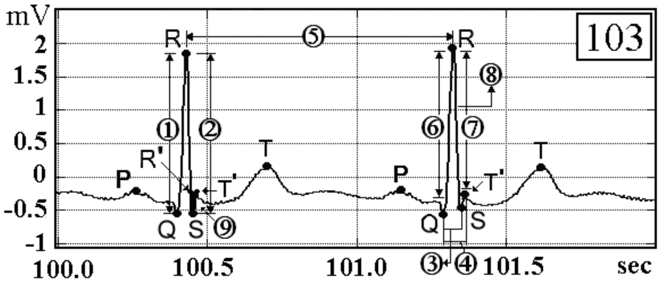


Fig. 1. The PQRST complex features:
(1) $F_1$: H-QR; (2) $F_2$: H-RS; (3) $F_3$: QRS-dur;(4) $F_4$: QTP-int; (5) $F_5$: Ratio-RR; (6) $F_6$: Slope-QR; (7) $F_7$: Slope-RS; (8) $F_8$: Area-QRS; (9) $F_9$: Area-R'ST'.

---

Corresponding Author: Wen-June Wang is with the Department of Electrical Engineering, National Central University, Jhongli 320, Taiwan, R.O.C. E-mail: wjwang@ee.ncu.edu.tw.

Yun-Chi Yeh is with the Department of Electrical Engineering, National Central University, and with the Department of Electronic Engineering, Ching Yun University, Jhongli 320, Taiwan, R.O.C. E-mail: yunchi@cyu.edu.tw.

Manuscript received 27 Feb. 2009; revised 2 Aug. 2009; accepted 3 Sept. 2009.

## 2. Qualitative features stages

This section describes two qualitative features stage in the following, namely PQRST complex feature extraction and the qualitative feature selection.

### *2.1. PQRST Complex Feature Extraction*

The PQRST complex features in an ECG signal are the location, duration, amplitudes and shapes of the waves. These features can be recognized by experienced cardio-doctors for diagnosing human heart diseases [18]. Table 1 lists nine selected PQRST complex features based on many experiments, and Fig. 1 shows their waveforms. Let $F_i$ = 1, 2, …, 9, denote the PQRST complex features “H-QR”, “H-RS”, “QRS-dur”, “QTP-int”, “Ratio-RR”, “Slope-QR”, “Slope-RS”, “Area -QRS” and “Area-R'ST', respectively (see Fig. 1).

NORM, LBBB, RBBB, VPC, and APC are symbols for labeling each heart “beat”, which can have different rhythms in different time sections. Table 2 lists annotations of the MIT-BIH database. For instance, Tape No. 103 contains two cases of beats (NORM and APC). This study adopted four records of the NORM case: Tape No. 103 (2083 NORM beats), No.113 (1789 NORM beats), No.123 (1515 NORM beats), and No.234 (2700 NORM beats) (see Table 2) as examples to explain how to calculate the range of each complex feature value. For Tape No.103, 30-minute long ECG signals are selected. The ranges of the PQRST complex feature values are listed in Table 3. The same process is applied to the other three NORM cases, and then nine complex features of these files are united to obtain the results of the four records listed in Table 4. The same process is also applied to the abnormal heart ECG signals, and thus the following records are provided: (1) two records of the left bundle branch block (LBBB) case (Tape No.111 (2123 LBBB beats) and No.214 (2002 LBBB beats)); (2) three records of the right bundle branch block (RBBB) case (Tape No. 118 (2166 RBBB beats), No.212 (675 RBBB beats) and No.231 (562 RBBB beats)); (3) three records of ventricular premature contractions (VPC) case (Tape No.200 (826 VPC beats), No.221 (396 VPC beats) and No. 233(831 VPC beats)); and (4) two records of atrial premature contractions (APC) case (Tape No.222 (209 APC beats) and No.232 (1382 APC beats)). Figure 2 shows the ranges of the PQRST complex feature values for each case.

Table 1. Description of the PQRST complex features.

| Feature’s serial No. | Feature’s symbol | Feature description. | Units. |
|---|---|---|---|
| 1 | H-QR | The amplitude between Q and R in a QRS complex. | mV |
| 2 | H-RS | The amplitude between R and S in a QRS complex. | mV |
| 3 | QRS-dur | The time duration between Q and S in a QRS complex. | ms |
| 4 | QTP-int | The time duration between Q and T' in a QRS complex. | ms |
| 5 | Ratio-RR | The ratio of *RRs* and *RRa, RRs* is the length of a single RR-interval and *RRa* is the average length of all RR-intervals. | – |
| 6 | Slope-QR | The slope between Q and R in a QRS complex. | mV/ms |
| 7 | Slope-RS | The slope between R and S in a QRS complex. | mV/ms |
| 8 | Area-QRS | The area of QRS complex. | mV× ms |
| 9 | Area-R'ST' | The area of R', S, and T' in a QRS complex. The point R' is the previous point which has the same amplitude as the point T'. | mV× ms |

Table 2. Annotations of the MIT-BIH database (“-“represents no such heartbeat case in this Tape).

| Tape No. | beats (30-min long) | Heartbeat case | | | | |
|---|---|---|---|---|---|---|
| | | NORM | LBBB | RBBB | VPC | APC |
| 103 | 2085 | 2083 | - | - | - | 2 |
| 113 | 1795 | 1789 | - | - | - | 6 |
| 123 | 1518 | 1515 | - | - | 3 | - |
| 234 | 2753 | 2700 | - | - | 3 | 50 |
| 111 | 2124 | - | 2123 | - | 1 | - |
| 214 | 2258 | - | 2002 | - | 256 | - |
| 118 | 2278 | - | - | 2166 | 16 | 96 |
| 212 | 2748 | 2073 | - | 675 | - | - |
| 231 | 1571 | 1007 | - | 562 | 2 | - |
| 200 | 2599 | 1743 | - | - | 826 | 30 |
| 221 | 2427 | 2031 | - | - | 396 | - |
| 233 | 3068 | 2230 | - | - | 831 | 7 |
| 222 | 2483 | 2274 | - | - | - | 209 |
| 232 | 1780 | 398 | - | - | - | 1382 |
| Total beats | 31487 | 19843 | 4125 | 3403 | 2334 | 1782 |

Table 3. The ranges of the PQRST complex feature values for Tape No. 103.

| Total beats: 2083 | H-QR | H-RS | QRS -dur | QTP -int | Ratio -RR | Slope -QR | Slope -RS | Area -QRS | Area -R'ST' |
|---|---|---|---|---|---|---|---|---|---|
| Minimum | 2. 125 | 2. 050 | 44.0 | 58.0 | 0. 828 | 0. 061 | 0. 079 | 51. 81 | 2. 70 |
| Maximum | 2. 665 | 2. 625 | 64.0 | 75.0 | 1. 145 | 0. 095 | 0. 156 | 79. 20 | 6. 01 |
| Unit | mV | mV | ms | ms | - | mV/ms | mV/ms | mV× ms | mV× ms |

Table 4. The ranges of the PQRST complex feature values for NORM case.

| Total beats: 8087 | H-QR | H-RS | QRS -dur | QTP -int | Ratio -RR | Slope -QR | Slope -RS | Area -QRS | Area -R'ST' |
|---|---|---|---|---|---|---|---|---|---|
| Minimum | 0. 695 | 0. 800 | 33.0 | 43.0 | 0. 800 | 0. 019 | 0. 017 | 20.0 | 0.00 |
| Maximum | 2. 690 | 3. 645 | 79.0 | 90.0 | 1. 200 | 0. 134 | 0. 214 | 82.0 | 24.50 |
| Unit | mV | mV | ms | ms | - | mV / ms | mV / ms | mV × ms | mV × ms |

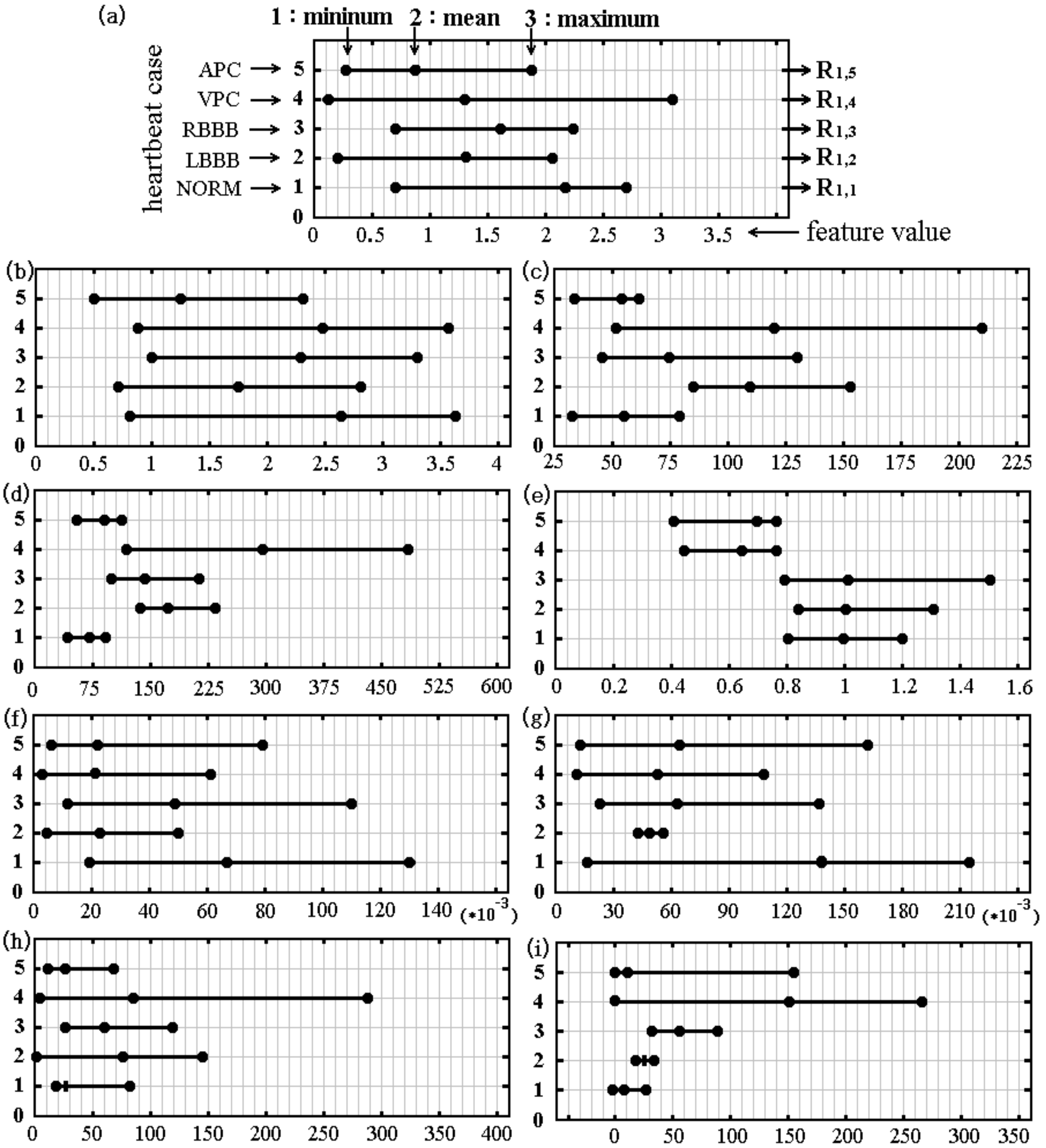


Fig. 2. The feature value range of each PQRST complex feature for each heartbeat case of the corresponding feature range: (a) $R_1$: H-QR; (b) $R_2$: H-RS; (c) $R_3$: QRS-dur (d) $R_4$: QTP-int; (e) $R_5$: Ratio-RR; (f) $R_6$: Slope-QR; (g) $R_7$: Slope-RS; (h) $R_8$: Area –QRS; (i) $R_9$: Area-R'ST'. (Note: 1: minimum value, 2: mean value, 3: maximum value)

### *2.2. Qualitative Feature Selection*

After providing the PQRST complex features, the next important task is the qualitative feature selection. The goal of qualitative feature selection is to find the optimal subset consisting of *m* selected features among a total *n* features, where $m \le n$. The procedure for performing QFS (qualitative feature selection) is depicted as follows.

*Procedure-QFS:*

Step 0: Define $R_{i,j}$

Let $R_{i,j}$ denote the feature value range of the ith PQRST complex feature for the jth heartbeat case. The sub-index i is defined as the same as that of $F_i$. The sub-index j = 1, 2, 3, 4, 5 denotes the case of "NORM", "LBBB", "RBBB", "VPC" and "APC", respectively (see Fig. 2). For instance, $R_{1,1}$ = [0.695, 2.69] mV, $R_{1,2}$ = [0.205, 2.06] mV, $R_{1,3}$ = [0.695, 2.24] mV, $R_{1,4}$ = [0.105, 3.095] mV, and $R_{1,5}$ = [0.275, 1.870] mV in Fig. 2(a).

Step 1: Obtain feature $F_i$ using the following algorithm:

If $\tilde{R} = 1$, then feature $F_i$ (see Fig. 1) is obtained for $1 \le i \le 9$, $1 \le k \le 5$, $1 \le j \le 5$, $k \neq j$, where $\tilde{R} = R_{i,k} \cap R_{i,j}$, and the index *i*, *j* (or *k*) is defined as the same as that of $R_{i,j}$.

Remark Step 1: Let $\tilde{R} = R_{i,k} \cap R_{i,j} = 1$ if the two feature value ranges $R_{i,k}$ and $R_{i,j}$ do not overlap. Thus, feature $F_i$ is obtained to discriminate heartbeats case-k and case-j, and $NF_i$ is increased by 1, where $NF_i$ denotes the total number of cases in which feature $F_i$ can discriminate two disjoint heartbeats case-k and case-j. For instance, if $R_{3,1}$ = [33, 79] msec, $R_{3,2}$ = [86, 153] msec (see Fig. 2(c)), then $\tilde{R} = R_{3,1} \cap R_{3,2} = 1$, meaning that feature $F_3$ ("QRS-dur") can discriminate heartbeats case-1 (NORM case) and case-2 (LBBB case). Similarly, let $\tilde{R} = R_{i,k} \cap R_{i,j} = 0$ if $R_{i,k}$ and $R_{i,j}$ overlap, that is, feature $F_i$ is not obtained and heartbeats case-k and case-j cannot be discriminated. In this case, the value of $NF_i$ remains unchanged. For instance, if $R_{1,1}$ = [0.695, 2.69] mV, $R_{1,2}$ = [0.205, 2.06] mV (see Fig. 2(a)), then $\tilde{R} = R_{1,1} \cap R_{1,2} = 0$, meaning that feature $F_1$ ("H-QR") cannot discriminate heartbeats case-1 (NORM case) and case-2 (LBBB case).

Step 2: Sort $NF_i$, $i = 1, 2, \cdots, 9$, with the order of decreasing values, and then select the index with the highest value, that is,

$$i = arg\{Max(NF_i),\ i = 1, 2, \cdots, 9\} \qquad (1)$$

For instance, suppose that $NF_1$ = 6, $NF_2$ = 1, $NF_3$ = 3, the sorted sequence becomes $NF_1$, $NF_3$ and $NF_2$. Thus, the index with the biggest value is $NF_1$ and the sequence of sub-indexes $NF_i$ with the order of decreasing values of $NF_i$ is 1, 3, and 2.

Step 3: Obtain qualitative feature $F_i$.

A feature $F_i$ is selected as a qualitative feature if it satisfies both the following conditions:

Condition 1: Feature $F_i$ can discriminate heartbeats case-k and case-j, where sub-indexes *i* are obtained from Step 2.

Condition 2: The qualitative feature for discriminate between heartbeats case-k and case- j is not found yet, where $k, j$ = 1, 2, 3, 4, 5, and $k \neq j$.

If the feature $F_i$ is selected as qualitative feature, then both heartbeat cases *k* and *j* are recorded in data items for the feature $F_i$ and OUT $F_i$ (that is, $F_i$ is a qualitative feature). If the feature $F_i$ can not be selected as qualitative feature, then go to Step 4.

Remark Step 3: Index *k* and *j* = 1, 2, 3, 4, 5 denote the heartbeat cases of "NORM", "LBBB", "RBBB", "VPC" and "APC", respectively.

Step 4: Obtain the next qualitative feature.

If the qualitative features obtained from Step 3 are enough to discriminate each heartbeat case, and then go to Step 5, otherwise go to Step 3.

Step 5: End QFS.

Four qualitative features QRS-dur, QTP-int, Ratio-RR, and Area-R'ST' were selected after performing the above procedure QFS. Each heartbeat case had its own range of values for each qualitative feature, as shown in Fig. 2(c), 2(d), 2(e) and 2(i). Thus, these specific value ranges can be adopted to determine whether the patient has the case of cardiac arrhythmia by the FLM.

## 3. Fuzzy Logic Based Diagnosis

In this section, a fuzzy logic for the diagnosis of the cardiac arrhythmia is introduced. The fuzzy logic includes four parts: fuzzy sets definition, fuzzy rule base establishment, fuzzy inference engine design, and defuzzification (see Fig. 3) [17, 19, 20]. The input variables of the fuzzy rule base are four qualitative features such as “QRS-dur”, “QTP-int”, “Ratio-RR”, and “Area-R'ST' “(see Fig. 2(c), 2(d), 2(e) and 2(i)). The output variable is “heartbeat case” which has five cases of NORM, LBBB, RBBB, VPC, and APC.

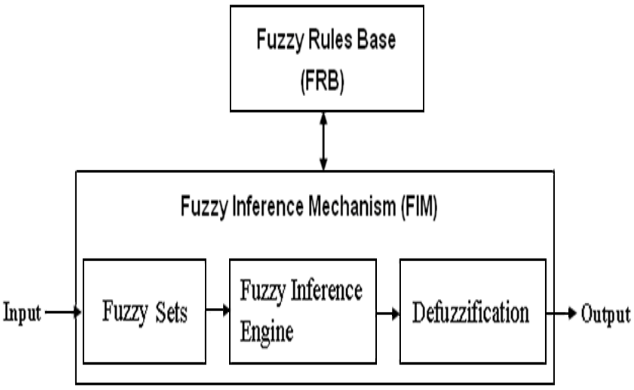


Fig. 3. Block diagram of fuzzy logic system.

Table 5. Fuzzy rules Table (According to the order of the mean values in Fig. 2(c), 2(d), 2(e) and 2(i)).

| Heartbeat case | Qualitative Features | | | |
|---|---|---|---|---|
| | QRS-dur | QTP-int | Ratio-RR | Area-R'ST' |
| NORM | PM | PS | PB | PM |
| LBBB | PE | PE | PE | PB |
| RBBB | PB | PB | PV | PE |
| VPC | PV | PV | PS | PV |
| APC | PS | PM | PM | PS |

First, let us define the fuzzy sets for the four features. According to the order of the mean values in Fig. 2(c), 2(d), 2(e) and 2(i), we set five fuzzy sets, termed “positive small (PS)”, “positive median (PM)”, “positive big (PB)”, “positive very-big (PV)”, and “positive enormous (PE)” for each heartbeat case as shown in Table 5. The core and the support of each fuzzy set are the corresponding mean value and the interval [*u, v*], respectively, where *u* (v) is the smallest (largest) value of the corresponding feature range in Fig. 2(c), 2(d), 2(e) and 2(i). The X-axis of each figure is the feature value and the Y-axis represents the membership degree (see Fig. 4). The triangular shape membership functions are chosen because of their simple calculation in the fuzzy inference engine. The membership functions of the input variable “QRS-dur” (see Fig. 4(a)) are presented as Eqs. (2-6), respectively. The fuzzy sets’ membership function is defined as follows:

(a) “PS” (APC case): (see $R_{3,5}$: Mean value: 54.3, Range: 34.0-61.0 in Fig. 2(c))

$$A_1(x)=\begin{cases}\dfrac{x-34.0}{54.3-34.0}=\dfrac{x-34.0}{20.3}, & \mathit{if}\ 34.0<x\le 54.3\\ \dfrac{61.0-x}{61.0-54.3}=\dfrac{61.0-x}{6.7}, & \mathit{if}\ 54.3<x\le 61.0\\ 0, & \mathit{otherwise}\end{cases} \tag{2}$$

Based on Eq. (2), Table 5, and Fig. 2(c), “PS” is derived and shown in Fig. 4(a). In Fig. 4(a), values 34.0, 61.0 and 54.3 are the smallest, largest, and mean value for the APC case, respectively.

(b) “PM” (NORM case): (see $R_{3,1}$: Mean value: 55.0, Range: 33.0-79.0 in Fig. 2(c))

$$A_2(x)=\begin{cases}\dfrac{x-33.0}{55.0-33.0}=\dfrac{x-33.0}{22.0}, & \mathit{if}\ 33.0<x\le 55.0\\ \dfrac{79.0-x}{79.0-55.0}=\dfrac{79.0-x}{24.0}, & \mathit{if}\ 55.0<x\le 79.0\\ 0, & \mathit{otherwise}\end{cases} \tag{3}$$

Based on Eq. (3), Table 5, and Fig. 2(c), “PM” is derived and shown in Fig. 4(a). In Fig. 4(a), values 33.0, 79.0 and 55.0 are the smallest, largest, and mean value for the NORM case, respectively.

(c) “PB” (RBBB case): (see $R_{3,3}$: Mean value: 74.6, Range: 46.0-130.0 in Fig. 2(c))

$$A_3(x)=\begin{cases}\dfrac{x-46.0}{74.6-46.0}=\dfrac{x-46.0}{28.6}, & \mathit{if}\ 46.0<x\le 74.6\\ \dfrac{130.0-x}{130.0-74.6}=\dfrac{130.0-x}{55.4}, & \mathit{if}\ 74.6<x\le 130.0\\ 0, & \mathit{otherwise}\end{cases} \tag{4}$$

Based on Eq. (4), Table 5, and Fig. 2(c), “PB” is derived and shown in Fig. 4(a).

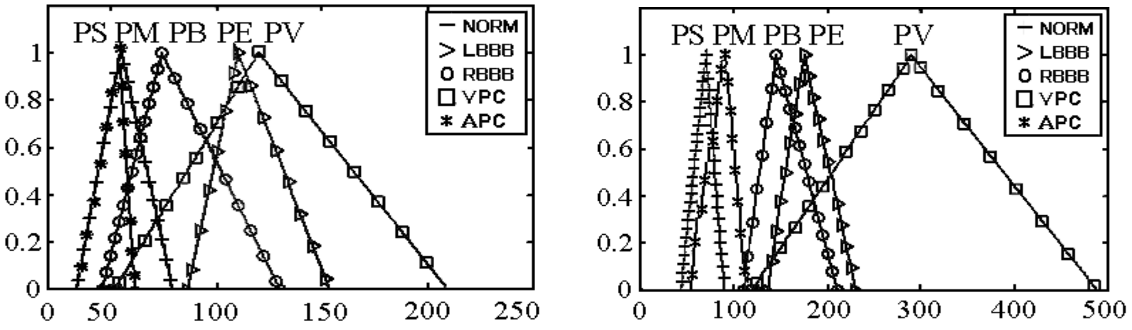
(d) “PE” (LBBB case): (see $R_{3,2}$: Mean value: 109.2, Range: 86.0-153.0 in Fig. 2(c))

$$A_4(x)=\begin{cases}\dfrac{x-86.0}{109.2-86.0}=\dfrac{x-86.0}{23.2}, & \mathit{if}\ 86.0<x\le 109.2\\ \dfrac{153.0-x}{153.0-109.2}=\dfrac{153.0-x}{43.8}, & \mathit{if}\ 109.2<x\le 153.0\\ 0, & \mathit{otherwise}\end{cases} \tag{5}$$

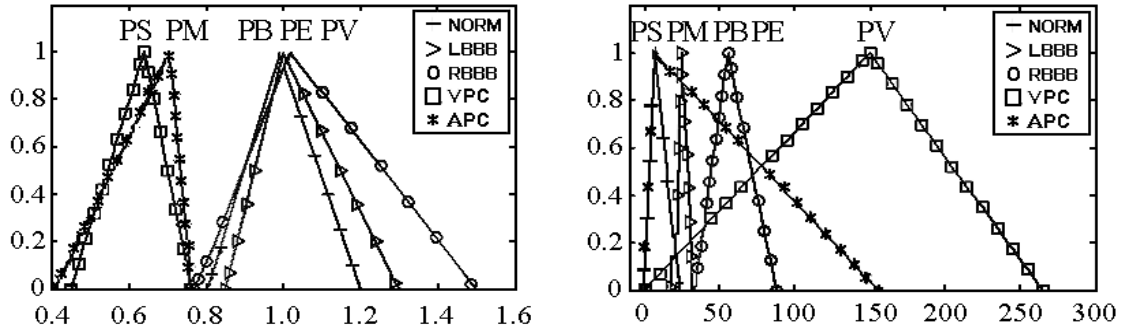
Based on Eq.(5) , Table 5, and Fig. 2(c), “PE” is derived and shown in Fig. 4(a).

(e) “PV” (VPC case): (see $R_{3,4}$: Mean value: 120.4, Range: 52.0-210.0 in Fig. 2(c))

$$A_5(x)=\begin{cases}\dfrac{x-52.0}{120.4-52.0}=\dfrac{x-52.0}{68.4}, & \mathit{if}\ 52.0<x\le 120.4\\ \dfrac{210.0-x}{210.0-120.4}=\dfrac{210.0-x}{89.6}, & \mathit{if}\ 120.4<x\le 210.0\\ 0, & \mathit{otherwise}\end{cases} \tag{6}$$



(a) QRS-dur (b) QTP-int



(c) Ratio-RR (d) Area-R’ST’

Fig.4. The fuzzy sets of input variables: (a) QRS-dur; (b) QTP-int; (c) Ratio-RR; (d) Area-R'ST'.

Based on Eq. (6), Table 5, and Fig. 2(c), “PV” is derived and shown in Fig. 4(a).
By repeating the same process, the triangles of all other input variables can be revealed (see Fig. 4(b)-4(d)).

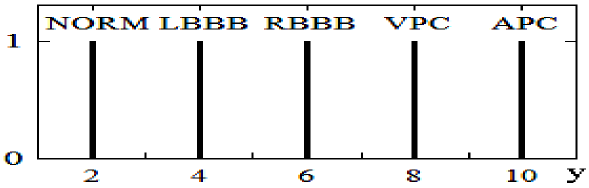


Fig. 5. The membership functions of the output y.

The membership functions of the output y (“heartbeat case”) with labels “NORM”, “LBBB”, “RBBB”, “VPC”, and “APC” are all singletons as shown in Fig. 5. According to the fuzzy rules Table (see Table 5), the five fuzzy rules for the diagnosis of the cardiac arrhythmia can be constructed as follows:

Rule 1: IF QRS-dur is PM, and QTP-int is PS, and Ratio-RR is PB, and Area-R'ST' is PM, THEN Heartbeat case is NORM (see NORM case in Table 5).

Rule 2**:** IF QRS-dur is PE, and QTP-int is PE, and Ratio-RR is PE, and Area-R'ST' is PB, THEN Heartbeat case is LBBB (see LBBB case in Table 5).

Rule 3**:** IF QRS-dur is PB, and QTP-int is PB, and Ratio-RR is PV, and Area-R'ST' is PE, THEN Heartbeat case is RBBB (see RBBB case in Table 5).

Rule 4**:** IF QRS-dur is PV, and QTP-int is PV, and Ratio-RR is PS, and Area-R'ST' is PV, THEN Heartbeat case is VPC (see VPC case in Table 5).

Rule 5**:** IF QRS-dur is PS, and QTP-int is PM, and Ratio-RR is PM, and Area-R'ST' is PS, THEN Heartbeat case is APC (see APC case in Table 5).

By using minimum fuzzy inference engine, we have the following result [19, 20].

$$B^1(y) = \text{QRS-dur}_{PM}(x_1) \wedge \text{QTP-int}_{PS}(x_2) \wedge \text{Ratio-RR}_{PB}(x_3) \wedge \text{Area-R'ST'}_{PM}(x_4) \wedge \text{NORM}(y) \quad (7)$$

$$B^2(y) = \text{QRS-dur}_{PE}(x_1) \wedge \text{QTP-int}_{PE}(x_2) \wedge \text{Ratio-RR}_{PE}(x_3) \wedge \text{Area-R'ST'}_{PB}(x_4) \wedge \text{LBBB}(y) \quad (8)$$

$$B^3(y) = \text{QRS-dur}_{PB}(x_1) \wedge \text{QTP-int}_{PB}(x_2) \wedge \text{Ratio-RR}_{PV}(x_3) \wedge \text{Area-R'ST'}_{PE}(x_4) \wedge \text{RBBB}(y) \quad (9)$$

$$B^4(y) = \text{QRS-dur}_{PV}(x_1) \wedge \text{QTP-int}_{PV}(x_2) \wedge \text{Ratio-RR}_{PS}(x_3) \wedge \text{Area-R'ST'}_{PV}(x_4) \wedge \text{VPC}(y) \quad (10)$$

$$B^5(y) = \text{QRS-dur}_{PS}(x_1) \wedge \text{QTP-int}_{PM}(x_2) \wedge \text{Ratio-RR}_{PM}(x_3) \wedge \text{Area-R'ST'}_{PS}(x_4) \wedge \text{APC}(y) \quad (11)$$

where $x_j$, $j = 1, 2, 3, 4,$ represent the values of four qualitative feature values, respectively. Let us union all $B^i(y)$, i = 1, 2, 3, 4, 5, to obtain the final output fuzzy set B'(y) with maximum operation as follows

$$B'(y) = \max_{i=1}^{5} B^i(y) \quad (12)$$

Finally, the defuzzification of the center of gravity (COG) is applied to get the final output $y^*$

$$y^* = \frac{\sum_{i=1}^{5} y_i \cdot B'(y_i)}{\sum_{i=1}^{5} B'(y_i)} \quad (13)$$

Checking the value $y^*$ corresponding to the heartbeat's case in Fig. 5, the heartbeat's label, which is the most close to $y^*$, will be the heartbeat case of the patient.

Figure 6 shows a flowchart of the proposed method, which consists of three main stages: (i) QRS extraction stage for detecting QRS waveform (points R, Q, S, P and T) using the Difference Operation Method (DOM), the paper [21] presents that DOM is effective to find QRS complexes correctly; (ii) qualitative features stage for qualitative feature selection on ECG signals and (iii) classification stage for determining patient's heartbeat cases.

The ECG signals in the MIT-BIH arrhythmia database [22] are adopted as the reference data for accomplishing the first two stages, and the FLM is used to determine the heartbeat cases for the patient.

## 4. Evaluation

This study is focused on classifying the five largest heartbeat cases in the MIT-BIH arrhythmia database [22], including (i) NORM – about 68.5% of total beats; (ii) LBBB – about 7.4% of total beats; (iii) RBBB – about 6.6% of total beats; (iv) VPC – about 6.5% of total beats; (v) APC – about 2.3% of total beats. Two experiments were performed to evaluate the performance of the proposed method. In these experiments, the proposed method was implemented by MATLAB software on a personal computer. These experiments are described in the following subsections.

### *4.1. Experiment 1: Single heartbeat*

In the first experiment, a single heartbeat is randomly and individually selected as a sample from the NORM, LBBB, RBBB, VPC, and APC cases. In Fig.7, features $x_1, x_2, x_3,$ and $x_4$ are as inputs of our proposed method and their classified results are also shown. In this figure, different output values will represent different cases as follows:

(i) Sample 1: the output value is $y^* = 2$ (that is, NORM case, see Fig.5);
(ii) Sample 2: the output value is $y^* = 4$ (that is, LBBB case);
(iii) Sample 3: the output value is $y^* = 6$ (that is, RBBB case);
(iv) Sample 4: the output value is $y^* = 8$ (that is, VPC case);
(v) Sample 5: the output value is $y^* = 10$ (that is, APC case).

It is seen that the single heartbeat is correctly classified.

### *4.2. Experiment 2: Multiple heartbeats*

Various approaches were adopted to evaluate the classifier configurations. Table 6 shows the full classification matrix is used to calculate the performance measures. The heartbeat classification abilities are compared using the five statistical indices: sensitivity (Se), specificity (Sp), positive predictive value (PPV), negative predictive value (NPV), and total classification accuracy (TCA), which are defined in Eqs. (14-18), respectively [2, 13, 23].

(i) $$Se_i = \frac{TP_i}{TP_i + FN_i} \quad (14)$$

(ii) $$Sp_i = \frac{TN_i}{TN_i + FP_i} \quad (15)$$

(iii) $$PPV_i = \frac{TP_i}{TP_i + FP_i} \quad (16)$$

(iv) $$NPV_i = \frac{TN_i}{TN_i + FN_i} \quad (17)$$

(v) $$TCA = \sum_{i=1}^{5} \frac{TP_i}{T_r} \quad (18)$$

where $TP_i$ (true positives) denotes the number of heartbeats of the *i*th class that are correctly classified (that is, NORM classified as NORM, see Table 6); $FN_i$ (false negatives) represents the number of heartbeats of class *i* but that are misclassified (that is, NORM not classified as NORM); $TN_i$ (true negatives) is the number of heartbeats not belonging to the number of the *i*th class and not classified in the *i*th class (that is, LBBB, RBBB, VPC, and APC not classified as NORM); $FP_i$ (false positives) denotes the number of heartbeats classified erroneously in the *i*th class (that is, LBBB, RBBB, VPC, and APC classified as NORM); and $T_r$ represents the total number of heartbeats listed in Table 2.

The second experiment was performed on several 30-min long records of ECG signals in the MIT-BIH arrhythmia database (see Table 2). Figure 8(a) lists the beat-by-beat testing results of this experiment for Tape No. 103, revealing that the proposed method misidentified 6 NORM beats as VPC beats, and 15 NORM beats were as APC beats. Figure 8(b) and 8(c) (see Table 2 and 6) present the final decision results obtained by the proposed method in the second experiment. The sensitivities were 95.06%, 91.03%, 90.50%, 92.63% and 93.77% for NORM, LBBB, RBBB, VPC and APC, respectively (see Fig. 9). The total classification accuracy (TCA) was approximately 93.78%.

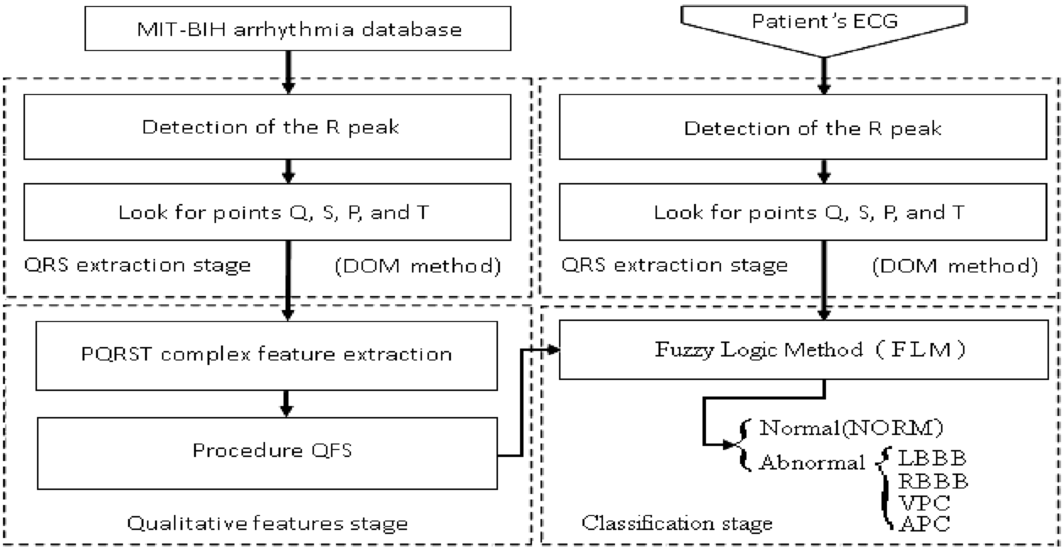


Fig. 6. A flowchart of the proposed method.

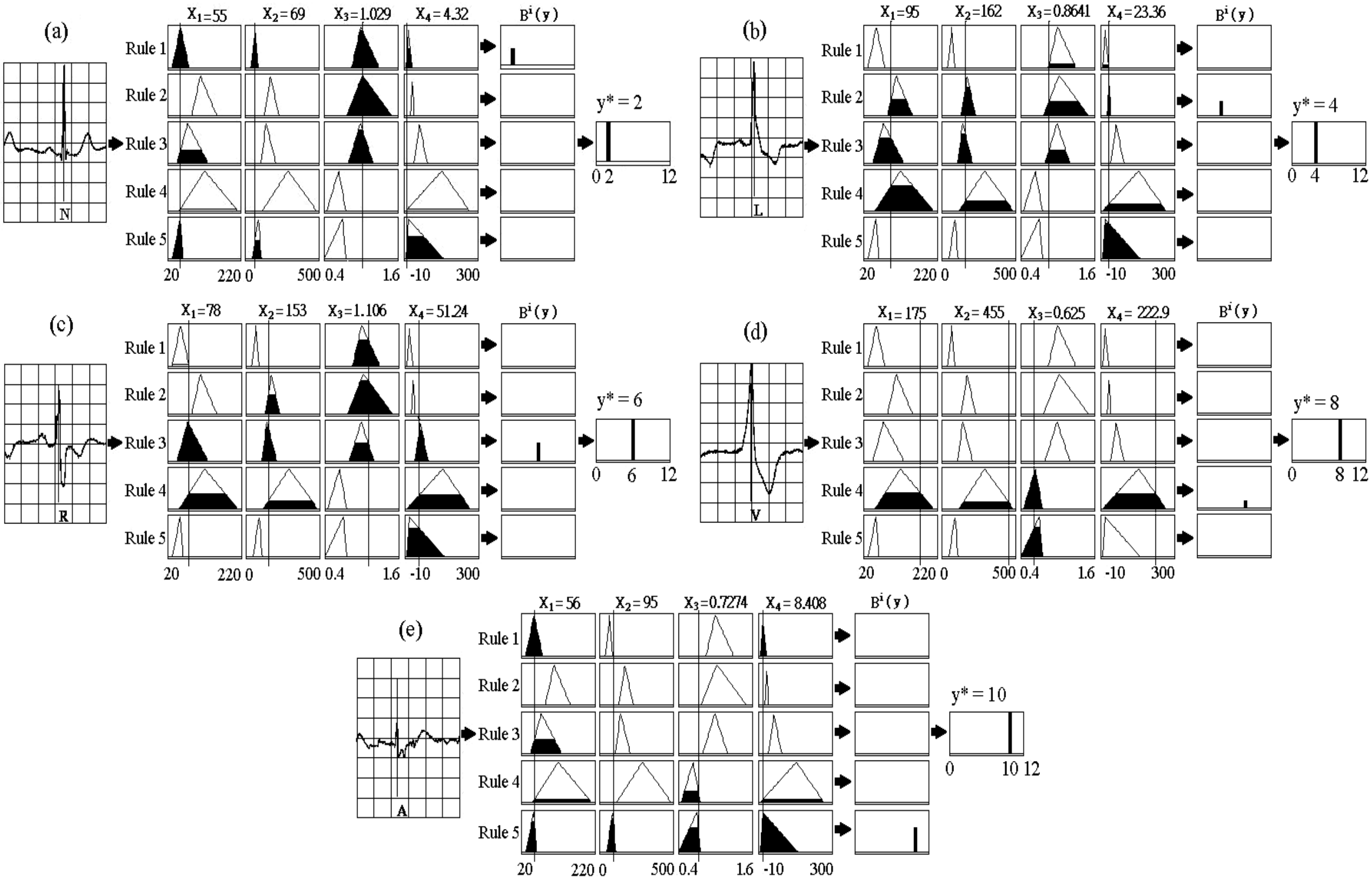
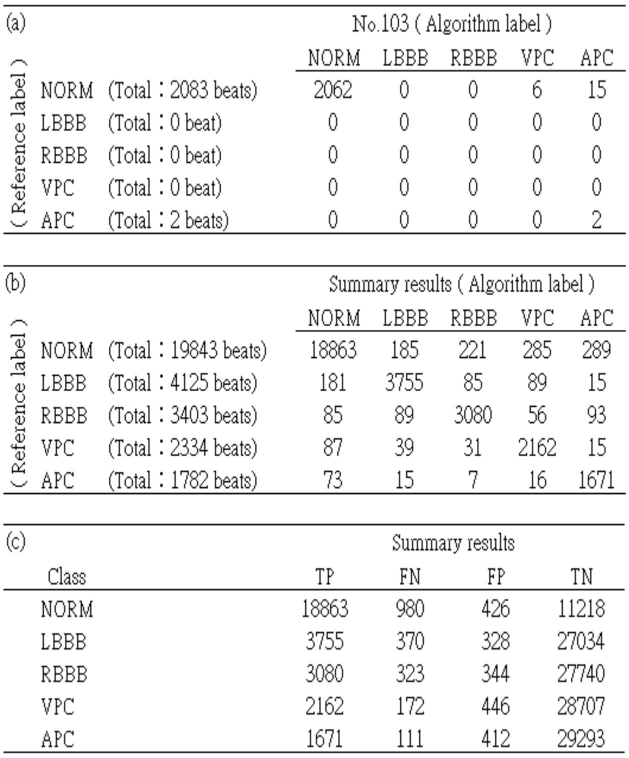


Fig. 7. The classified results of the first experiment (single heartbeat): (a) Sample 1: NORM case; (b) Sample 2: LBBB case; (c) Sample 3: RBBB case; (d) Sample 4: VPC case; (e) Sample 5: APC case.

Table 6. Performance measures used in this study for (i) NORM case; (ii) LBBB case; (iii) RBBB case; (iv) VPC case; and (v) APC case.

| | | Algorithm label | | | | |
|---|---|---|---|---|---|---|
| | | NORM | LBBB | RBBB | VPC | APC |
| Reference label | NORM | NN | NL | NR | NV | NA |
| | LBBB | LN | LL | LR | LV | LA |
| | RBBB | RN | RL | RR | RV | RA |
| | VPC | VN | VL | VR | VV | VA |
| | APC | AN | AL | AR | AV | AA |

(i) NORM case: TP=NN; FN=NL+NR+NV+NA; FP=LN+RN+VN+AN;TN=LL+LR+LV+LA+RL+RR+RV+RA+VL+VR+VV+VA+AL+AR+AV+AA.
(ii) LBBB case: TP=LL; FN=LN+LR+LV+LA; FP=NL+RL+VL+AL;TN=NN+NR+NV+NA+RN+RR+RV+RA+VN+VR+VV+VA+AN+AR+AV+AA;
(iii) RBBB case: TP=RR; FN=RN+RL+RV+RA; FP=NR+LR+VR+AR;TN=NN+NL+NV+NA+LN+LL+LV+LA+VN+VL+VV+VA+AN+AL+AV+AA.
(iv) VPC case:TP=VV; FN=VN+VL+VR+VA; FP=NV+LV+RV+AV;TN=NN+NL+NR+NA+LN+LL+LR+LA+RN+RL+RR+RA+AN+AL+AR+AA.
(v) APC case: TP=AA; FN=AN+AL+AR+AV; FP=NA+LA+RA+VA;TN=NN+NL+NR+NV+LN+LL+LR+LV+RN+RL+RR+RV+VN+VL+VR+VV.



(a)

| ( Reference label ) | | No.103 ( Algorithm label ) | | | | |
|---|---|---|---|---|---|---|
| | | NORM | LBBB | RBBB | VPC | APC |
| NORM | (Total：2083 beats) | 2062 | 0 | 0 | 6 | 15 |
| LBBB | (Total：0 beat) | 0 | 0 | 0 | 0 | 0 |
| RBBB | (Total：0 beat) | 0 | 0 | 0 | 0 | 0 |
| VPC | (Total：0 beat) | 0 | 0 | 0 | 0 | 0 |
| APC | (Total：2 beats) | 0 | 0 | 0 | 0 | 2 |

(b)

| ( Reference label ) | | Summary results ( Algorithm label ) | | | | |
|---|---|---|---|---|---|---|
| | | NORM | LBBB | RBBB | VPC | APC |
| NORM | (Total：19843 beats) | 18863 | 185 | 221 | 285 | 289 |
| LBBB | (Total：4125 beats) | 181 | 3755 | 85 | 89 | 15 |
| RBBB | (Total：3403 beats) | 85 | 89 | 3080 | 56 | 93 |
| VPC | (Total：2334 beats) | 87 | 39 | 31 | 2162 | 15 |
| APC | (Total：1782 beats) | 73 | 15 | 7 | 16 | 1671 |

(c)

| | Summary results | | | |
|---|---|---|---|---|
| Class | TP | FN | FP | TN |
| NORM | 18863 | 980 | 426 | 11218 |
| LBBB | 3755 | 370 | 328 | 27034 |
| RBBB | 3080 | 323 | 344 | 27740 |
| VPC | 2162 | 172 | 446 | 28707 |
| APC | 1671 | 111 | 412 | 29293 |

Fig.8. The final decision results of the second experiment (according to Table 2) (a) Performance measures using Tape No. 103 as an example; (b) Summary results of beat-by-beat, record-by-record testing results;(c) Performance measures used in this study.

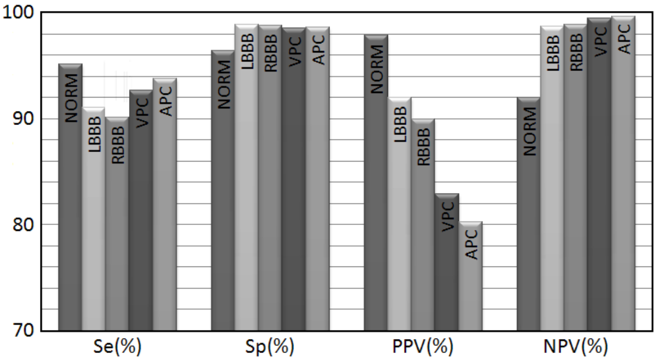


Fig. 9. Summary results of beat-by-beat, record-by-record performance of the second experiment.

### *4.3. Performance comparison*

The total classification accuracy (TCA) of heartbeat case classification depends on the following three basic factors: (i) the used heartbeat qualitative feature set, (ii) the applied classification method, and (iii) the organization of the training strategy. The organization of the training strategy is the most important factor. For comparing performance of FLM, three studies concerning about the training strategy which contains five types of QRS complexes collected from all patients in the MIT-BIH database are selected and compared with our proposed method. Jekova et al. [24] presented the Kth nearest neighbor rule (knn) and Neural networks (NN) for heartbeat classification. Dokur and Olmez [13] developed heartbeat classification using a hybrid neural network and investigated three neural networks for heartbeat classification, namely restricted Coulomb energy (RCE), intersecting spheres (InS) and multi-layer perceptron (MLP), respectively. Each neural network adopts two feature extraction methods, discrete Fourier transforms (DFT) and discrete wavelet transform (DWT). In paper [13], one knows that decision making is performed with three stages: normalization process; feature extraction; and artificial neural network. The feature extraction employs divergence analysis to determine the best features. However, the process to compute divergence analysis takes too much time due to the required complex mathematic computations such as class scatter matrix. Moreover, the learning algorithm of Ins Network is also time consuming. It takes about 13 minutes long for the illustrated example in this paper. Christov et al. [2] proposed heartbeat classification using Morphological descriptors (MD) and time-frequency descriptors (TFD). The MD method for calculating a large collection of morphological descriptors was applied to all QRS complexes annotated as NORM, LBBB, RBBB or VPC in the MIT-BIH arrhythmia database. The TFD method requires the extracted heartbeats with fixed length. Because previous studies [2, 13, 24] adopted records of ECG signals of length

30-minute in the MIT-BIH arrhythmia database, their heartbeat classification abilities were compared by using Se and PPV. Table 7 lists the performance comparison between the proposed method and some existing methods, the Knn and NN method [24], the hybrid neural network method [13] and MD-TFD [2]. Table 7 shows that the proposed method has the same detection ability as existing methods [2, 13, 24], but the proposed method is more simple and faster than the other existing methods. Utilizing the proposed method, the average time required for processing 30-minute long of ECG data is less than 1- minute.

Table 7. Comparisons of the proposed method with other existing methods.

| | | | NORM | LBBB | RBBB | VPC | APC | |
|---|---|---|---|---|---|---|---|---|
| FLM | | Se (%) | 95.06 | 91.03 | 90.50 | 92.63 | 93.97 | |
| | | PPV (%) | 97.79 | 91.96 | 89.95 | 82.89 | 80.22 | |
| | | TCA (%) | | | | | | 93.78 |
| Knn-NN [24] | Knn | Se (%) | 94.80 | 58.10 | 88.50 | 88.80 | 74.50 | |
| | | PPV (%) | 98.09 | 74.36 | 78.86 | 54.79 | 78.49 | |
| | | TCA (%) | | | | | | -- |
| | NN | Se (%) | 86.54 | 64.94 | 58.59 | 85.98 | 62.82 | |
| | | PPV (%) | 95.57 | 54.32 | 57.32 | 48.30 | 64.84 | |
| | | TCA (%) | | | | | | -- |
| RCE Network [13] | DWT | Se (%) | 93.2 | 39.1 | 78.4 | 86.5 | 63.0 | |
| | | PPV (%) | 86.0 | 72.2 | 73.9 | 54.5 | 96.3 | |
| | | TCA (%) | | | | | | 60.0 |
| | DFT | Se (%) | 86.3 | 60.8 | 47.0 | 77.6 | 85.0 | |
| | | PPV (%) | 73.1 | 38.0 | 73.6 | 60.6 | 92.2 | |
| | | TCA (%) | | | | | | 50.1 |
| InS Network [13] | DWT | Se (%) | 100 | 94.6 | 98.6 | 91.3 | 100 | |
| | | PPV (%) | 96.7 | 91.0 | 94.2 | 93.5 | 98.0 | |
| | | TCA (%) | | | | | | 95.7 |
| | DFT | Se (%) | 77.3 | 78.0 | 82.0 | 66.6 | 94.6 | |
| | | PPV (%) | 74.3 | 70.4 | 70.2 | 75.7 | 83.5 | |
| | | TCA (%) | | | | | | 78.2 |
| MLP Network [13] | DWT | Se (%) | 100 | 48.0 | 74.6 | 98.6 | 99.3 | |
| | | PPV (%) | 92.6 | 96.0 | 99.1 | 81.3 | 78.8 | |
| | | TCA (%) | | | | | | 87.6 |
| | DFT | Se (%) | 89.3 | 81.3 | 88.6 | 92.0 | 96.0 | |
| | | PPV (%) | 93.7 | 77.2 | 73.4 | 76.2 | 91.3 | |
| | | TCA (%) | | | | | | 84.7 |
| MD - TFD [2] | MD | Se (%) | 96.60 | 93.80 | 96.45 | 92.10 | 99.00 | |
| | | PPV (%) | 99.20 | 95.83 | 92.20 | 75.80 | 97.00 | |
| | | TCA (%) | | | | | | -- |
| | TFD | Se (%) | 96.90 | 95.70 | 94.40 | 90.80 | 97.15 | |
| | | PPV (%) | 98.40 | 99.20 | 99.25 | 73.50 | 99.20 | |
| | | TCA (%) | | | | | | -- |

## 5. Conclusion

This study proposes a FLM to analyze ECG signals for determining the heartbeat case. The proposed method is easily performed and requires no complex mathematical calculations (such as cross-correlation and Fourier transformation). The average time required for processing 30-minute long of ECG data is less than 1 minute, and the maximum memory requirement is only about 2 MB. The records of ECG in the MIT-BIH arrhythmia database are experimented to illustrate the effectiveness of the proposed method. In the experiments, the sensitivities were 95.06%, 91.03%, 90.50%, 92.63% and 93.77% for NORM, LBBB, RBBB, VPC and APC, respectively. The total classification accuracy (TCA) was approximately 93.78%. The proposed algorithm indeed provides an efficient, simple and fast method for determining the heartbeat case from the ECG signals.

## Acknowledgments

This study has been supported by the National Science Council of Taiwan under Grant NSC 95-2221-E-008-069. The authors thank referee's valuable comments.

## References

[1] R. M. Rangayyan, Biomedical Signal Analysis: A Case-Study Approach, New York: Wiley, Inter-Science, 2001.

[2] I. Christov, G. Gómez-Herrero, V. Krasteva, I. Jekova, A. Gotchev and K. Egiazarian, "Comparative study of morphological and time-frequency ECG descriptors for heartbeat classification," *Med. Eng. Phys.*, vol. 28, pp. 876-887, 2006.

[3] P. Chazal, M. O'Dwyer, and R. B. Reilly, "Automatic classification of heart-beats using ECG morphology and heartbeat interval features," *IEEE Trans. on Biomed. Eng.*, vol. 51, pp. 1196-1206, 2004.

[4] R. D. Throne, J. M. Jenkins, and L. A. Dicarlo, "A comparison of four new time domain techniques for discriminating monomorphic ventricular tachycardia from sinus rhythm using ventricular waveform morphology," *IEEE Trans. on Biomed. Eng.*, vol. 38, pp. 561-570, 1991.

[5] F. Pannizzo and S. Furman, "Frequency spectra of ventricular tachycardia and sinus rhythm in human intracardiac electrograms: Application to tachycardia for cardiac pacemakers," *IEEE Trans. on Biomed. Eng.,* vol. 35, pp. 421-425, 1998.

[6] V. X. Afonso, W. J. Tomkins, T. Q. Nguyen, and S. Luo, "ECG beat detection using filter banks," *IEEE Trans. on Biomed. Eng.*, vol. 46, pp. 192-202, 1999.

[7] D. Benitez, P. A. Gaydecki, A. Zaidi, and A. P. Fitzpatrick, "The use of the Hilbert transform in ECG signal analysis," *Comput. Biol. Med.*, vol.31, pp. 399-406, 2001.

[8] A. Koski, “Modelling ECG signals with Hidden Markov Models,” *Artif. Intell. Med.*, vol. 8, pp. 453-471, 1996.

[9] M. Shahram and K. Nayebi, “ECG beat classification based on a Cross-Distance analysis,” *International Symposium on Signal Processing and its Applications*, ISSPA-2001, Malaysia, pp. 234-237.

[10] C. W. Li, C. X. Zheng, and C. F. Tai, “Detection of ECG characteristic points using wavelet transform,” *IEEE Trans. Biomed. Eng.*, vol. 42, pp. 21-28, 1995.

[11] 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, pp. 58-68, 1996.

[12] Z. Dokur, T. Olmez, E. Yazgan, and O. K. Ersoy, “Detection of ECG waveforms by neural networks,” *Med. Eng. Phys.*, vol. 19, pp. 738-741, 1997.

[13] Z. Dokur, and T. Olmez, “ECG beat classification by a novel hybrid neural network,” *Computer Methods and Programs in Biomedicine,* vol. 66, pp. 167-181, 2001.

[14] H. G. Hosseini, D. Luo, and K. J. Reynolds, “The comparison of different feed forward neural network architectures for ECG signal diagnosis,” *Med. Eng. Phys.*, vol. 28, pp. 372-378, 2006.

[15] Y. P. Meau, F. Ibrahim, S. A. L. Narainasamy, and R. Omar, “Intelligent classification of ECG signal using extended EKF based neural fuzzy system,” *Computer Methods and Programs in Biomedicine*, vol. 82, pp.157-168, 2006.

[16] M. Lagerholm, G. Peterson, G. Braccini, L. Edenbrandt, and L. Sornmo, “Clustering ECG complex using Hermite functions and self-organizing maps,” *IEEE Trans. Biomed Eng.*, vol. 47, pp. 838-848, 2000.

[17] L. A. Zadeh, Fuzzy sets as a basis for a theory of possibility, Fuzzy Sets and Systems 1, 1978.

[18] Y. Zigel, A. Cohen, and A. Katz, “The weighted diagnostic distortion (WDD) measure for ECG signal compression,” *IEEE Trans. on Biomed. Eng.*, vol. 47, pp. 1422-1430, 2000.

[19] W. Y. Wang, I. H. Li, S. C. Li, M. S. Tsai, and S. F. Su, “A Dynamic Hierarchical Fuzzy Neural Network for A General Continuous Function,” *International Journal of Fuzzy Systems*, vol. 11, no. 2, pp. 130-136, 2009.

[20] W. Y. Wang, Y. H. Chien, Y. G. Leu, and T. T. Lee, “On-line adaptive T-S fuzzy-neural control for a class of general multi-link robot manipulators,” *International Journal of Fuzzy Systems*, vol. 10, no. 4, pp. 240-249, 2008.

[21] Y. C. Yeh, and W. J. Wang, “QRS complexes detection for ECG signal: The Difference Operation method,” *Computer Methods and Programs in Biomedicine,* vol. 91, pp. 245-254, 2008.

[22] MIT-BIH database distribution, Massachusetts Institute of Technology, 77 Massachusetts Avenue, Cambridge, MA 02139, 1998.

[23] R. A. Johnson, and D. W. Wichern, Applied Multivariate Statistical Analysis, New Jersey: Pearson Prentice Hall, 2007.

[24] I. Jekova, G. Bortolan, and I. Christov, “Assessment and comparison of different methods for heartbeat classification,” *Medical Engineering and Physics*, vol. 30, pp. 248-257, 2008.

**Yun-Chi Yeh** was born in Taiwan, R.O.C. He received B.S. degree in Electronic Engineering from the National Taiwan University of Science and Technology, Taipei, Taiwan, in 1981, and the M.S. degree in Electrical and Control Engineering from the National Chiao-Tung University, Taiwan, in 1986. He is currently working toward the Ph.D. degree in the Department of Electrical Engineering of the National Central University, and he is also a Lecturer of the Department of Electronic Engineering in Ching-Yun University, Chung-Li, Taiwan. His research interests include biomedical engineering and fuzzy logic.

**Wen-June Wang** received the B.S. degree in the Department of Control Engineering from National Chiao-Tung University, Taiwan in 1980; and M.S. degree in the Department of Electrical Engineering from Tatung University, Taiwan in 1984. Moreover, he received the Ph.D. degree in the Institute of Electronics from National Chiao-Tung University of Taiwan in 1987. Dr. Wang is presently a chair professor in the department of Electrical Engineering, National Central University, Taiwan. He was a visiting scholar for one year in Department of Mechanical Engineering, Georgia Institute of Technology, USA in 1994. Furthermore, he was the Dean of the College of Science and Technology, National Chi Nan University, Puli, Taiwan from 2005 to 2007 and served as the Dean of Research and Development Office, National Taipei University of Technology, Taiwan from 2007 to 2009. Until today, Dr. Wang has published more than 119 journal papers and 115 conference papers. He also received three times of Distinguished Research Award from the National Science Council of Taiwan. From 2003 to 2006, he is the convener of the Control Engineering Group of National Science Council in Taiwan.

Dr. Wang was elected as an IEEE Fellow of 2008. He serves as a member of editorial board of numerous journals including IEEE Trans. of Systems, Man, and Cybernetics Part-B, IEEE Trans. of Fuzzy Systems, and the International

Journal of Electrical Engineers *etc*. He is now the editor in chief of the International Journal of Fuzzy Systems, Furthermore, Dr. Wang served as the Chairman of Taipei Chapter, IEEE Control Systems Society, from 1999 to 2001, and serves as the Chairman of Taipei Chapter, IEEE Systems, Man, and Cybernetics from 2006 to 2008. His research interests include the areas of fuzzy systems, control control, neural networks, robotics, and pattern recognition. etc..

**Che Wun Chiou** received his B.S. degree in Electronic Engineering from Chung Yuan Christian University in 1982, the M.S. degree and the Ph.D. degree in Electrical Engineering from National Cheng Kung University in 1984 and 1989, respectively. From 1990 to 2000, he was with the Chung Shan Institute of Science and Technology in Taiwan. He joined the Department of Electronic Engineering, Ching Yun University in 2000. He is currently as Professor in Computer Science and Information Engineering at Ching Yun University. His current research interests include fault-tolerant computing, computer arithmetic, parallel processing, and cryptography.