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ECG Beat Classification by a Fuzzy Logic

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Abstract: A Fuzzy logic architecture that can be used to classify ECG is presented . It uses a feature extractor to characterize the heart electrical axis before being classified by a Fuzzy Logic Network. Obtained results indicate that Fuzzy logic may accurately classify most of the ECG beats, therefore can be used as a diagnostic tool for heart disease.

Key Words: ECG Beat, Electrical Axis, Classification, Fuzzy Logic

Introduction

Very valuable diagnostic information can be obtained from the ECG signal. Extraction of features from the ECG waveform is very necessary in order to develop a highly accurate diagnostic tool. Some features such as QRS - complex, T - wave and P - wave amplitudes, width's and R- intervals are very important in determining the state of the heart (Josephson, 1989; Laiken *et al.*, 1988 and Laister and Riggs, 1984). Intensive research on ECG signals has been carried out by many researchers in various areas, such as ECG compressing implementation techniques, ECG heart beat classifications, heart rate variability analysis and measurement, QRS- complex detection, etc.(Johnson, 1994; Sapoznikov,1993 and Nygards,1983). For each ECG waveform it is possible to extract certain features from the heart electrical axis, which permits classification of the ECG waveform. This classification has been done in traditional analysis way. (Engelse and Zeelenberg,1979; Schamrotha,1989 and Saunders,1991) In this paper another technique is presented which uses a fuzzy logic to classify the ECG beat after Zadeh's work on fuzzy sets(Zadeh,1965) many theories in fuzzy logic were developed in Japan, Europe, United States, and elsewhere. Since the 1970s Japanese researchers have been advancing the practical implementation of the fuzzy logic theory. They have been commercializing this technology and currently, there are over 2000 patents in the area from fuzzy air conditioner, to fuzzy washing machine. The U.S. Space Administration has been involved in the use of fuzzy logic in space control decision making. Energy consumption could be analyzed using fuzzy set(Oder *et al.*,1993) . Also systems could be controlled using fuzzy rules(Mamlook *et al.*,1998) . Fuzzy rules based models are easy comprehended because it uses linguist terms and the structure of IF-THEN rules. Fuzzy decision is a new and exciting method. The idea behind fuzzy decision is to develop a control mechanism for a system that would otherwise not be controllable because of an inability to model the system, non-linearity of the system, and/or non-stability of the system. A Fuzzy decision-maker can be applied to uncertain systems in which a priori information about the system is incomplete; it uses fuzzy IF-THEN rules, which are expressed not by equations but by linguistic synthesis. And it is easy to be adjusted by changing the fuzzy rules to match the changed system.

The essential steps in designing the Fuzzy decision-maker for a system are as follows:

- Specify the fuzzy variables of the system.
- Specify the membership function for each fuzzy variable.
- Search the effective fuzzy decision rules or put expert knowledge into rule-based fuzzy Decision-maker.
- Defuzzify the decision action by using the centroid method.
- Implement the computer simulation.

In the past several years, a large number of papers focus on fuzzy algorithms (Sugeno,1985; Kawaji,1991 ; Hayashi, 1992;Nguyen *et al.*,1992 ; Palm,1992; Hellendoorn,1993 and Zhang *et al.*, 1997) (Hayashi, 1992 and Zhang *et al.*,1997). A fuzzy decision maker system has the advantages of being robust to the variations in system dynamics(Karayiannis and Pai, 1996), model-free without any a priori information required, successfully utilized in the complex ill-defined processes(Lee,1990). One of the important problems involved with the design of fuzzy logic decision-maker is the development of fuzzy IF-THEN rules for fuzzy system. The number of fuzzy IF-THEN rules increases exponentially as the number of variable increases, and the complexity of fuzzy decision-maker increases as the number of fuzzy IF-THEN rules increases. In order to reduce the complexity of a fuzzy decision-maker, a methodology for analysis and reconstruction of a robust decision-maker using fuzzy IF-THEN rules is developed in (Mamlook *et al.*,1998). Simulation results in (Mamlook *et al.*,1998) indicate that the reconstructed decision-maker is more efficient and performs as well as the original fuzzy controller.

Architecture: The proposed architecture is shown in Fig. 1. It consists mainly of three parts: 1st part will produce real time ECG signal waveform the second part is the feature extractor which will produce a cretin set of features and the third part is the decision-maker part which will produce the results and classify the state of the QRS-Complex.

Table 1: QRS-Electrical Axis Angles and Fuzzy Decision

No.	I-II	I-III	II-III	Max./ Min Value	Fuzzy Decision
1	92.94724	93.6022	83.30255	93.6022	Normal
2	90.28910	90.3317	83.72287	90.3317	Normal
3	77.33917	76.00632	72.041	77.33917	Normal
4	91.50706	91.68926	85.95472	91.68926	Normal
5	93.64988	94.45383	84.22383	94.45383	Normal
6	77.67251	75.28871	68.3903	77.67251	Normal
7	-5.44674	2.9815	-1.14012	2.9815	Normal
8	72.06539	73.18514	75.74872	75.74872	Normal
9	69.91133	67.4867	63.54751	69.91133	Normal
10	67.70311	61.95574	55.44101	67.70311	Normal
11	72.39445	70.10055	65.72582	72.39445	Normal
12	30.02936	72.83945	71.2488	72.83945	Normal
13	0.568490	49.32819	89.96116	89.96116	Normal
14	61.72565	64.06671	67.02732	67.02732	Normal
15	-88.4373	-88.1955	-95.6768	-95.6768-88.1955/	Abnormal
16	74.26168	74.34123	74.68833	74.68833	Normal
17	18.92708	46.9921	62.51811	62.51811	Normal
18	87.1980	87.45725	92.10084	92.10084	Normal
19	53.46261	60.52138	67.72978	67.72978	Normal
20	109.9571	112.95	104.5611	112.95	Abnormal
21	4.659844	43.91612	65.85564	65.85564	Normal
22	92.51232	92.90296	85.51574	92.90296	Normal
23	30.64617	50.32323	62.44697	62.44697	Normal
24	29.91642	38.95608	40.94892	40.94892	Normal
25	23.87404	-1.88419	8.259766	23.87404 / -1.88419	Normal
26	69.28957	69.89524	71.03419	71.03419	Normal
27	74.40224	73.1825	70.29411	74.40224	Normal
28	72.06816	72.4777	73.38373	73.38373	Normal
29	36.42547	34.72676	34.4552	36.42547	Normal
30	-27.2676	-38.8627	-27.8085	-27.2676 / -38.8627	N/U - Abnormal
31	96.63324	98.65761	84.35499	98.65761	Normal
32	89.77218	89.7174	79.26706	89.77218	Normal
33	114.770	-172.566	45.79144	114.77 / -172.566	Abnormal
34	84.64339	84.04756	79.21007	84.64339	Normal
35	79.91239	78.00334	70.7636	79.91239	Normal
36	78.98059	79.05458	79.33904	79.33904	Normal

Real ECG Data Collection: A cardiologist to detect the ECG signal from subjects under clinical examination uses an ECG detector. The clinical findings are recorded by a cardiologist for further investigation. The ECG signals amplified by Gould Universal Signal Conditioner with isolated pre-amplifier and adjustable frequency DC-10KHz (-6dB) and a measurement range (full-scale) 25uV-250 mV. The low pass filter with 150 Hz cutoff frequency is used to reduce any possible noise due to the measurement system wiring. Also it prevents aliasing effect induced by digitization. A sixteen channel twelve bits Metrabyte signal data acquisition board is used to digitize the detected ECG signal. The sampling frequency of the data should be carefully selected, choosing a low sampling frequency means loss of information. Therefore, using a high sampling rate is better. It is recommended to use a sampling rate at least twice as high as the Nyquist rate. Abnormal cases have higher frequency than normal cases. Thus it is better to make abnormal case determinants for the sampling frequency. A 300 Hz sampling rate is used to digitize the ECG signal. A Dadisp digital signal processing software on a Pentium compatible AT computer is used along with the data acquisition board. Real time data of ECG signals are saved and stored for further analysis, processing and investigation . Fig.1 shows the hardware block diagram.

Feature Extractor; The ECG waveform is composed of four waves: P, QRS-complex, T and U waves as shown in Fig. 2."In this study the QRS-complex electrical axis feature is considered based on Einthoven 's Triangle method "

Examination of QRS-Complex Electrical Axis Angles: As shown in Fig. 3. The angle value produces valuable information about heart disease as follows : Angles which lies between -30 clockwise and +110 (A and C zones) are considered normal , while angles which

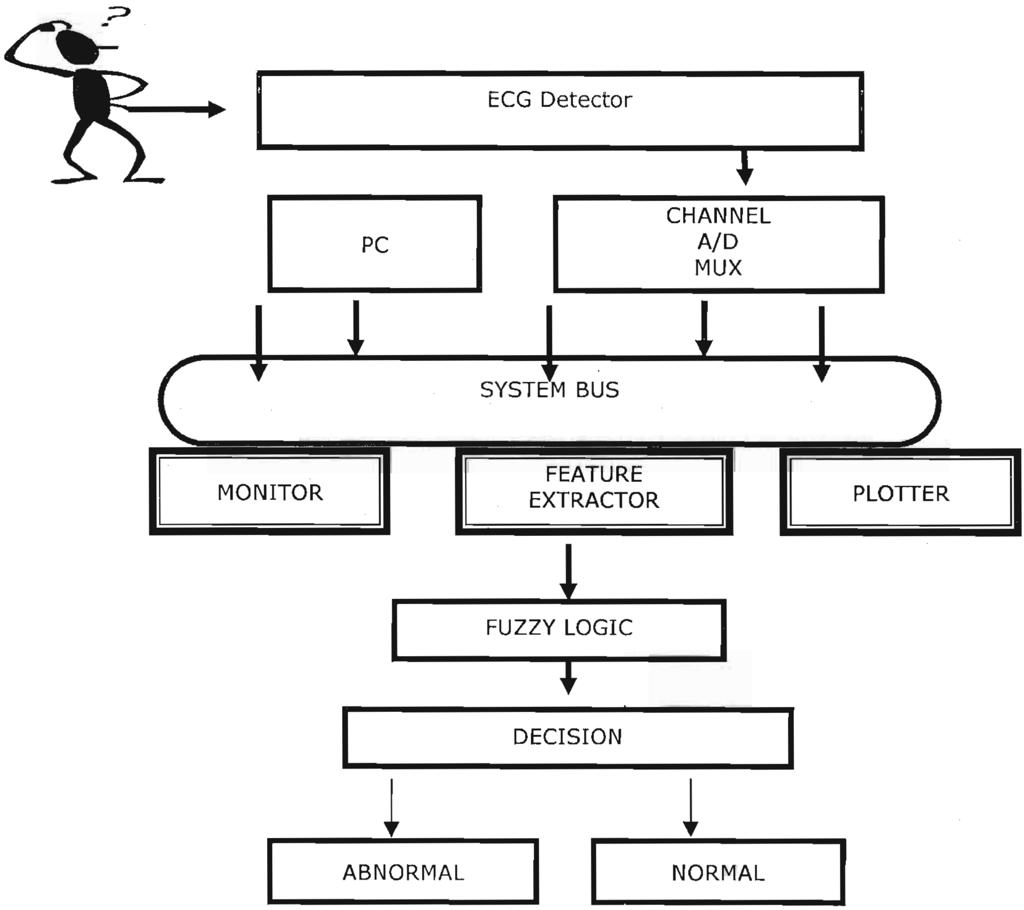

Fig. 1: Proposed Architecture Block Diagram

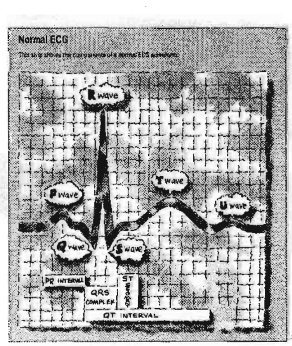

Fig. 2: Normal ECG Waveform

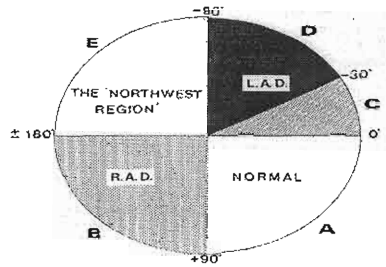

Fig. 3: QRS-complex Electrical Axis Angles

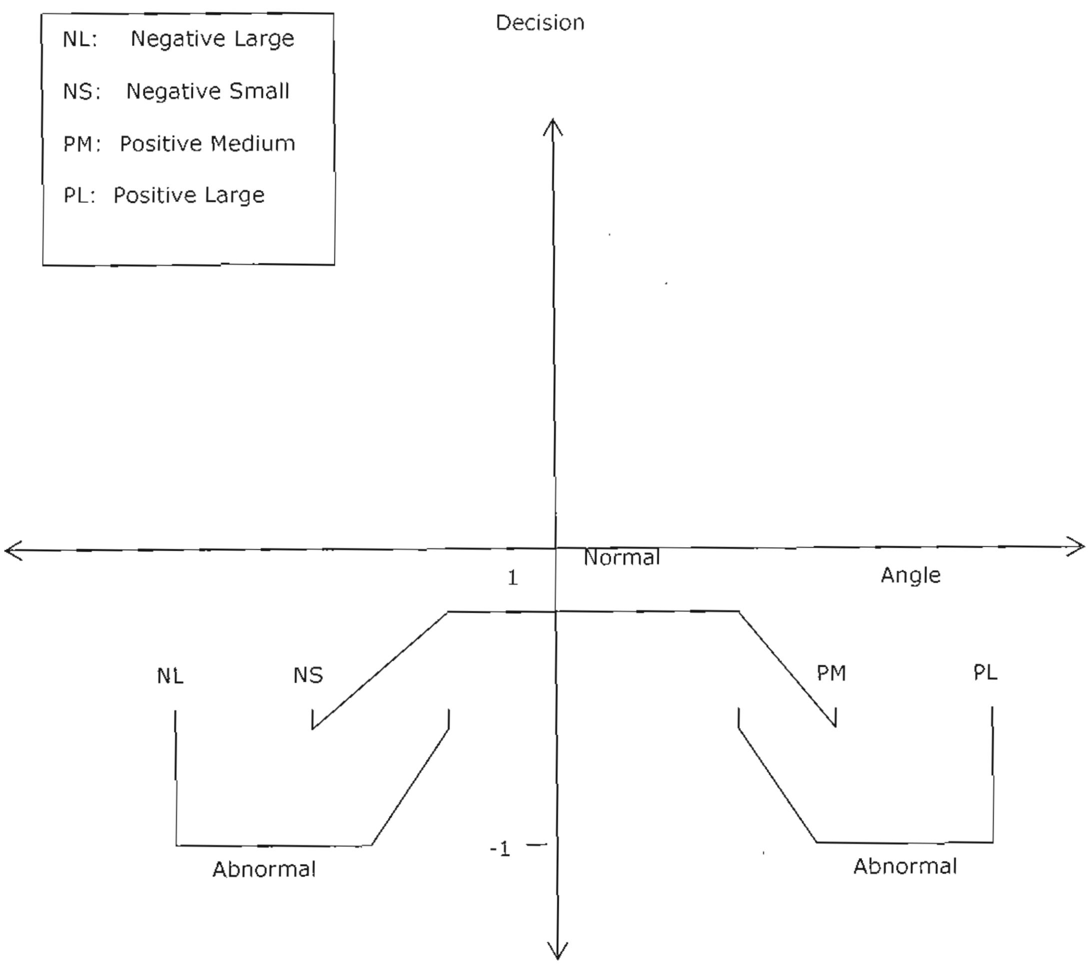

Fig. 4: Fuzzy IF-THEN Rules

lies between -30 and -90 Abnormal angles . Any angle lies between -90 and -180 counter clockwise (zone D) are considered rare and represents uncommon clinical findings.

Results and Discussion

In the cardiac cycle the QRS-complex wave that is the major part of the ECG waveform is very important and full of diagnostic information. In this paper the QRS-complex electrical axis angles will be used as the main feature input to the proposed Fuzzy logic decision maker .Fuzzy Logic decision maker starts by taken the Maximum/Minimum value of the Angles (MANG) in table 1 then it uses fuzzy IF - THEN RULES: IF MANG angle is between NS and PM as shown in fig.4 then the decision is normal, otherwise the decision is abnormal. Table 1 shows the QRS Electrical axis Angles and the results of the fuzzy decision maker. It can be shown that three subjects are considered Abnormal, while one subject has a critical angle, and the other 32 subjects are normal.

Conclusion

Suitable Computer-aided ECG signal analysis and classification system can be used to distinguish between normal and abnormal QRS complex. The use of a conventional Fuzzy logic network together with a feature detector is shown to be capable of classifying the QRS event in the ECG signal as normal or abnormal one of the advantages of the Fuzzy Logic Decision Maker (FLDM) method presented here is that it uses fuzzy sets that enabled us to condense large amount of data into smaller set of variable rules. Also FLDM method used minimum and maximum operations and fuzzy if-then rules, which are easier and faster than other methods. The Fuzzy logic technique can shed some insights on the above results (Table 1), since it is a kind of statistical reasoning. Using fuzzy set rules (Fig. 4) enabled us to condense large amount of the data collected Table 1 into small set of variable rules.

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