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CLASSIFICATION OF PVCS WITH A FUZZY LOGIC SYSTEM

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Abstract - **We propose a fuzzy logic system for the classification of premature ventricular beats (PVCs) in ECGs. The classifier uses novel features extracted from a time-frequency analysis performed by a filter bank in addition to measurements related to the timing of R-R intervals and morphology analysis. The performance of the algorithm is evaluated on *the MIT-BIH Arrhythmia Database* following the *AAMI* recommendations. The achieved sensitivity is 81.34% and the positive predictivity is 80.64%.**

I. INTRODUCTION

Classification of heartbeats from surface ECGs and internal electrograms is important for the automated analysis in medical devices used for example in intensive care, analysis of long term Holter recordings, and in implantable cardiac defibrillators.

The results of proposed algorithms leave room for improvement. They occasionally lack acceptance from cardiologists due to the inaccuracy and the implementation of classification rules which differ from the formulation of rules in a medical diagnosis.

Existing classifiers differ in the type of the features (e.g. heart rate, morphology, and template matching), the normalization process of the features, and the classification methods (e.g. thresholds, statistical classifier, and neural networks) [1,2,3].

Our goal was to develop a classifier for premature ventricular contractions (PVCs) with a small delay, low computational effort, which is implementable in an existing monitor system based on a filter bank approach [4], and is easy to understand in its function and rules by a cardiologist.

Classification with a fuzzy logic system [5] avoids hard thresholds, which seems to be an advantage when analyzing biological signals such as ECGs. The characteristics of the recordings may differ widely from patient to patient, for the same patient due to changes for example in position, activity level, or mental stress, and under the influence of noise. In addition, classifiers based on fuzzy logic support the implementation of rules based on the knowledge of a human expert and are implemented at low computational costs.

II. METHODS

Data and Feature Extraction

ECG data were obtained from the upper channel of the fully annotated *MIT-BIH Database* [6]. The recordings represent digitized data sampled with 360 Hz, which were obtained by analog Holter recordings. Each recording has a length of 30 minutes and the records for the database were chosen partially at random and partially to represent e.g. typical arrhythmias, signal distortions, and changes in ECGs.

Nine features served as parameters to distinguish between PVCs and other types of heart beats. Three features were extracted from the heart rate: (1) the ratio of the current to the previous R-R interval, (2) the ratio of the current to the average of the previous eight R-R intervals, and (3) the irregularity of the last 8 R-R intervals. Four features were chosen to represent the morphology of the heart beats: (1) amplitude, (2) direction of the maximum deflection, (3) width of the local maximum or minimum, and (4) peak-to-peak distance within the QRS complex. Another two features were derived using time-frequency information from a uniform filter bank [4,7]. The energy $E_{0,1}$ in the first two subbands of the filter bank represents the low frequency signal contents (< 11.25 Hz).

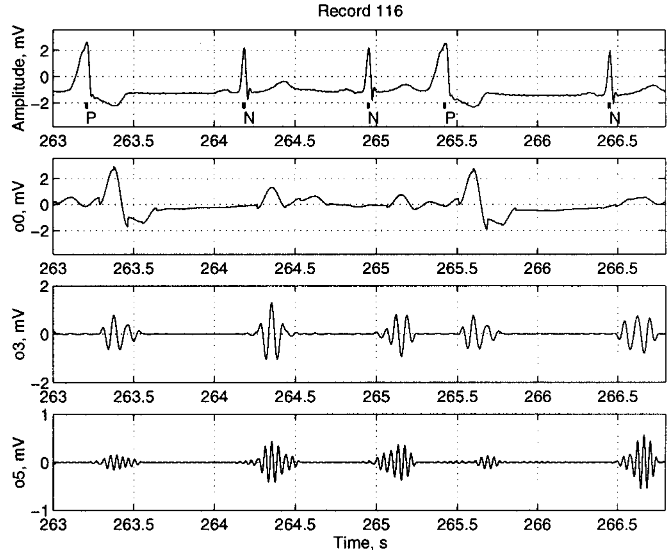

Fig. 1. Outputs from the filter bank for record 116. The original signal (top row) is split in subbands, representing the signal contents in different frequency ranges. The second row o_0 is the low-pass filtered portion of the original signal (0-5.625 Hz). Rows three and four show the outputs o_3 (16.825-22.5 Hz) and o_5 (27-33 Hz) of the filter bank. Wider QRS-complexes have higher amplitudes in low subbands and lower amplitudes in high subbands compared to steeper QRS-complexes. Beats labeled in the top row with 'P' are PVCs and beats labeled with 'N' are non-PVCs.

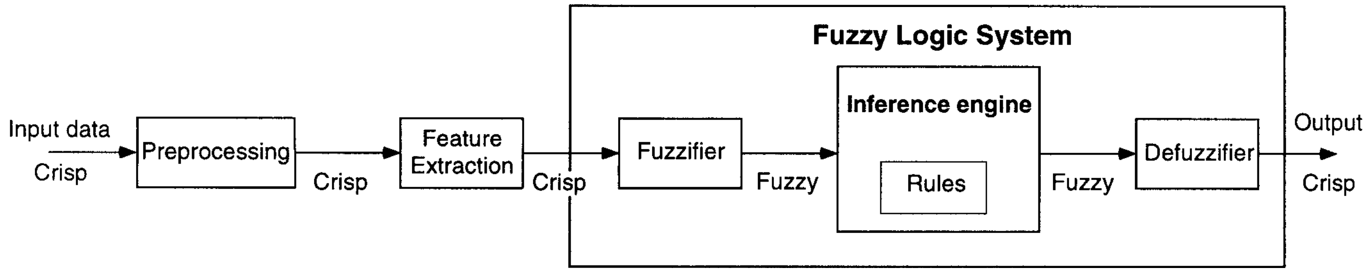

Fig 2. Block diagram for a Fuzzy Logic System for classification. Incoming data are preprocessed and features are extracted before the fuzzification. The inference engine combines the fuzzy sets and the implemented rules to a fuzzy output set. As a final result, the defuzzifier combines the rules and transforms the fuzzy output sets into crisp data (classes).

It was derived by squaring the amplitudes of the upsampled outputs (see Figure 1), integrating over a moving window with a length of 44 samples, and adding up the energy in subband 0 and subband 1. The (1) width of $E_{0,1}$ and (2) the ratio of the peaks of $E_{0,1}$ to the energy E_{07} in a frequency band including higher frequencies (< 45 Hz) was calculated to indicate the energy distribution over the frequency range. The dc component of the signal was subtracted previous to these calculations.

The normalization process selected to compensate for variations in the ECG is crucial for the calculation of the features. We compared a feature of an incoming beat to the average of the last eight features considered to be normal. The 'normal template' was reset, when the deviation of a feature for eight following beats was considered to lie within a physiological variance of ±15% .

Fuzzy Logic System

A Fuzzy Logic System consists of a fuzzifier, inference engine, and defuzzifier (see Figure 2).

The nine features described above were the input for the system. These data were assigned to fuzzy sets. Fuzzification can be seen as a form of quantization, in which the universe of discourse (the range of the input data) is assigned to degrees of membership in defined fuzzy sets. The shape of membership functions is variable (e.g. triangular, piecewise linear, Gaussian) and the degree of membership to fuzzy sets may vary from 0 to 1. Therefore, the degree of membership to a fuzzy set is a measurement of similarity to the particular set [8]. We used bell curve membership functions because of their smoothness and adaptability in width and steepness (see Figure 3). The sets were implemented as linguistic variables and their parameters were derived by existing definitions or the analysis of cluster plots (see Figure 4).

The inference engine maps fuzzy input sets into fuzzy output sets. Using linguistic variables for the sets allows for straight forward implementation of the rules, which were obtained by expert knowledge or cluster analysis again. They have the form of IF-THEN statements (e.g. IF *peakwidth* is wide AND *normalized R-R interval* is premature THEN *beat type* is PVC) and all of them are evaluated in parallel.
The results of all rules (which may be contradictory) are combined and a final result (class PVC or non-PVC) is derived by the defuzzifier.

Different implementations for the interpretation of logical operators in the rules and for the defuzzification method exist. We used the maximum operator for the union and the minimum operator for the intersection of fuzzy sets. The contribution of all rules was accounted for as the sum of each rule's output set. A total of 15 rules were implemented.

III. Results

The performance of the classifier was evaluated following the *AAMI* recommendations [9]. All records of the *MIT-BIH Database* were included except for four, which contain paced beats. Only the first five minutes of a record may be used to train the algorithm, because otherwise the training and testing would be performed on identical data instead of predicting rates on unseen data. Therefore, we used beats only from the first five minutes for our cluster plots. The test set includes 5,900 PVCs and 77,394 non-PVCs. The achieved sensitivity is 81.34% and the positive predictivity is 80.64%. Experiments using a fuzzy c-mean clustering algorithm [5] for adjusting the membership functions to the training set resulted in a worse performance.

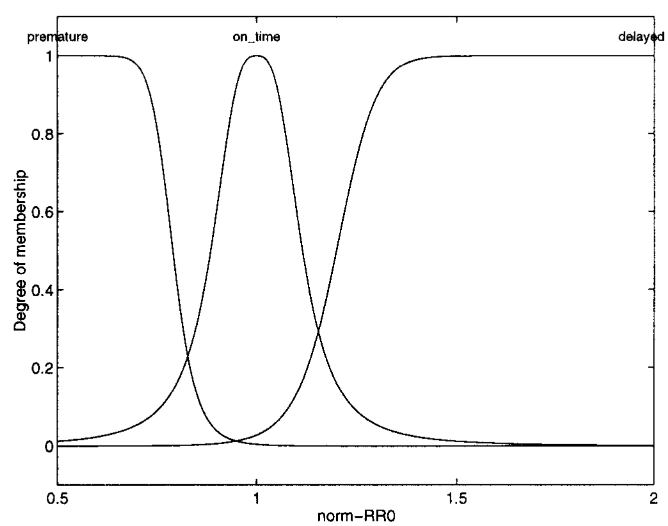

Fig 3. The bell curve membership functions premature, on time, and delayed for the feature normalized R-R interval (*norm-RR*$_0$). The feature could be described using fuzzy sets with linguistic variables. The degrees of membership to these fuzzy sets vary between zero and one.

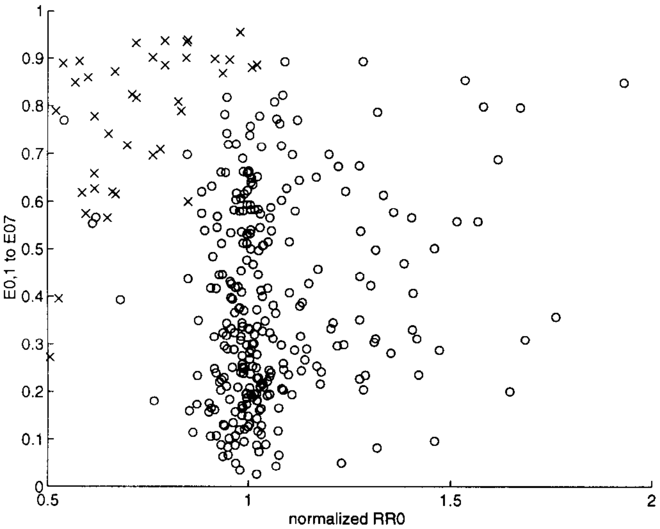

Fig. 4. Cluster plots of extracted features are used to determine some parameters of the membership functions. This plot shows the ratio of energies in the subbands ($E_{0,1}$ to E_{07}) vs. the normalized current R-R intervals (*normalized* RR_0). 200 non-PVCs (o) and 40 PVCs (x) were selected randomly from the training set.

IV. Discussion and Conclusions

The Fuzzy Logic System is a robust classifier which is efficiently implemented. Calculations with high computational efforts such as cross-correlations or Fourier transforms are avoided. The features extracted from the filter bank added information for the differentiation between PVCs and non-PVCs. Therefore, filter banks proved to be a useful approach not only for signal enhancement and beat detection in ECG analysis [4], but also for beat classification. Fine-tuning of the fuzzy classifier was difficult because the effects of changing membership functions and adding or removing rules were hard to predict in the nonlinear system.

Most false negative classifications were within segments of irregular rhythm due to atrial fibrillation or atrial premature beats. Some bundle branch blocks which reassemble the shape of PVCs also increased the number of misclassified beats. Some of the false positive classifications resulted from only small differences in shape and timing of normal and abnormal beats in the analyzed lead.

More features helping to distinguish these beats would potentially increase the performance of the algorithm. A simultaneous analysis of multiple leads could add information since changes in the shape of the waveform due to abnormal beats may not occur in each of the leads. In addition, problems arising from segments with contact problems of electrodes may decrease. Time-frequency analysis offers potential for the classification of other beat types as well. Afonso et al. classified paced beats with features extracted from the identical filter bank [10].

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