IDENTIFICATION AND DELINEATION OF QRS COMPLEXES IN ELECTROCARDIOGRAM USING FUZZY C-MEANS ALGORITHM

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ABSTRACT

Over the past few years, there has been an increased trend toward processing of the electrocardiogram (ECG) using microcomputer. The system based on microcomputer can perform the needed medical services in extremely efficient manner. In fact, many systems have already been implemented to perform signal processing task such as 12-lead ECG analysis. All these applications require an accurate detection of QRS complex of ECG. Thus QRS complex detection is an important part of many ECG signal processing system. This paper presents application of Fuzzy C-Means algorithm (FCM) for detection of QRS complex in ECG signal. The performance of the algorithm is validated using original 12-lead ECG recording from the standard ECG data base. Significant detection rate is achieved. The onset and offset of the QRS complexes are found to be within tolerance limit given by CSE library.

Keywords: ECG, QRS complex, FCM, Delineation

1. INTRODUCTION

Correct detection of QRS-complexes forms the basis of most of the algorithms used in automated processing and analysis of ECG. The other waves like T and P waves are detected by identifying their position relative to QRS complex.

The ECG recording may contain various challenging problems such as segment with high noise content, sudden change in QRS amplitude and morphology, or muscle and electrode artifact which are not often detected correctly. Hence reliable and correct detection of QRS complexes, under various backgrounds, is very important in any algorithm used for ECG analysis. The correct performance of these systems depends on several important factors such as quality of ECG signal, the applied detection rule, the learning and testing dataset used.

Fig.1 displays typical ECG cycle. To facilitate the analysis, the horizontal segment of this waveform preceding the P wave is designated as baseline or isopotential line. The P wave represents depolarization of atria musculature. The QRS complex is mainly due to depolarization of the ventricle. The T wave is the wave of ventricular repolarization. The U wave if present is generally believed to be the result of after potential in ventricular muscle.

Various methods, for QRS detection are found in the literature, method based on digital filter [6, 22], mathematical transformation [2, 4, 11, 19, 20], pattern recognition [9, 28, 24,], artificial neural networks [31, 13, 25], genetic algorithm [14, 15], heuristic method [7, 23,] and statistical methods [16, 17, 18]. This paper presents an application of Fuzzy C-Means algorithm (FCM) [29] for the detection of QRS complexes, using the entropy criteria for the generation of the feature signal. This method is suitable for the detection of all kind of morphologies of QRS complexes. It not only detects the QRS complex but also locates their
onset and offset accurately, within the tolerance limits specified by the physicians in CSE library.

2. OVERVIEW OF FUZZY C-MEANS

Pattern recognition techniques can be classified into two broad categories: unsupervised techniques and supervised techniques. These two types of techniques are complementary. For example unsupervised clustering can be used to produce classification information needed by the supervised pattern recognition technique. The Fuzzy C-Means algorithm is an unsupervised fuzzy clustering algorithm [29]. Conventional clustering algorithm finds “hard partition” of a given dataset based on certain criteria that evaluate the goodness of partition. By “hard partition” we mean that each datum belong to exactly one cluster of the partition. While the soft clustering algorithm finds “soft partition” of a given dataset. In “soft partition” datum can partially belong to multiple clusters. A soft partition is not necessarily a fuzzy partition, since the input space can be larger than the dataset. However, most soft clustering algorithms do generate a soft partition that also forms fuzzy partition.

A type of soft clustering of special interest is one that ensures membership degree of point x in all clusters adding up to one, i.e.,

$$\sum_{j} \mu_{c_j}(x_i) = 1 \quad \forall x_i \in X$$

(1)

A soft partition that satisfies this additional condition is called a constrained soft partition. The Fuzzy C-Means algorithm, which is best known fuzzy clustering algorithm, produces constrained soft partition. In order to produce constrained soft partition, the objective function $J_1$ of hard c-means has been extended in two ways:

(1) The fuzzy membership degree in cluster has been incorporated in the formula.

(2) An additional parameter $m$ has been introduced as a weight exponent in fuzzy membership.

The extended objective function, denoted by $J_m$, is:

$$J_m(P, V) = \sum_{i=1}^{k} \sum_{x \in X} (\mu_{c_i}(x))^m \|x - v_i\|^2$$

(2)

where $P$ is fuzzy partition of dataset $X$ formed by $C_1, C_2, ..., C_k$ and $k$ is number of clusters. The parameter $m$ is weight that determines the degree to which partial members of cluster affect the clustering result. Like hard c-means, fuzzy c-means also tries to find good partition by searching for prototype $v_i$ that minimizes the objective function $J_m$. Unlike hard c-means, however, the fuzzy c-means algorithm also needs to search for membership function $\mu_{c_i}$ that minimizes $J_m$. A constrained fuzzy partition $\{C_1, C_2, ..., C_k\}$ can be local minimum of the objective function $J_m$ only if the following conditions are satisfied:

$$\mu_{c_i}(x) = \frac{1}{\sum_{j=1}^{k} \left( \|x - v_j\|^2 \right)^{m-1}}$$

$$1 \leq i \leq k, x \in X$$

(3)

$$v_i = \frac{\sum_{x \in X} (\mu_{c_i}(x))^m x}{\sum_{x \in X} (\mu_{c_i}(x))^m}$$

$$1 \leq i \leq k$$

(4)

Based on this theorem, FCM updates the prototypes and membership function iteratively using equation 3 and 4 until a convergence criterion is reached. Here it is worth mentioning few important points regarding the FCM algorithm: (1) It guarantees converge for $m > 1$. (2) It finds local minimum of the objective function $J_m$. (3) The result of applying FCM to a given dataset depends not only upon the choice of parameter $m$ and $c$, but also on the choice of initial prototype.
3. ALGORITHM FOR QRS DETECTION

In this section, it is described how the proposed algorithm can be applied for the detection of QRS complex. Fig.2 displays the result of each step of the proposed method when applied to single lead ECG recording to clearly demonstrate how the algorithm works and its effectiveness in the identification of QRS complexes. The algorithm is as follows.

Step 1: A raw digital ECG signal is acquired as shown in fig. 2(a).

Step 2: A raw ECG signal is often contaminated by disturbances such as power line interference and base line wander. The finite impulse response (FIR) notch filter proposed by Van Alste and Schilder [1] is used to remove base line wander. The adaptive filter used to remove base line wander is special case of notch filter, with notch at zero frequency (or dc). The bandwidth of the filter is \( \left( \mu / \pi \right) \times f_s \), where \( f_s \) is the sampling frequency of the signal and \( \mu \) is the convergence parameter. In this case, the sampling frequency is 500 Hz and the value of the convergence parameter works is 0.0025. Frequencies in the range 0-0.5 Hz are removed to reduce the base line drift. The filter proposed by Furno and Tompkinson [8] is used to remove 50 Hz power line interference. Fig. 2(b) displays the filtered ECG signal after removal of power line interference and baseline wander.

Step 3: The gradient at every sampling instant is calculated to enhance the signal in the region of QRS-complex. The various slopes obtained at different sampling instant are divided in to two classes namely QRS-class and non-QRS class. Now mean and standard deviation are calculated for each class and probability of each sample belonging to QRS and non-QRS class is calculated.

Step 4: The entropy is used as a suitable criterion in the design of optimum feature selection. Entropy is a statistical measure of uncertainty. Features that reduce the uncertainty of a given situation are considered more informative than those that have the opposite effect. After calculating probability, entropies for the QRS and non-QRS class are calculated using the equation:

\[
h_i(x) = -p_i(x) \log_e p_i(x);
\]

where \( n \) is the number of samples present in the ECG recording. Here \( n=5000 \) for CSE database ECG recordings of ten seconds duration sampled at 500 Hz. The entropies are then normalized. Fig. 2(c) and 2(d) display the entropies in the non-QRS and QRS region.

Step 5: The values of QRS entropy are used to form input vector \( A_1 \). Apply Fuzzy C-means algorithm to obtain two cluster centers \( C_1 \) and \( C_2 \). Calculate the average value of the two cluster centers \( C_{\text{average}} \). Cluster center whose value is greater than \( C_{\text{average}} \) is designated as \( C_1 \) and other \( C_2 \). Calculate the distance of first element of vector \( A_1 \) from both cluster center \( C_1 \) and \( C_2 \). If it is closer to cluster center \( C_1 \) then assign value 0 to sign vector \( Y_1 \), otherwise assign value 1. Repeat the above step for all elements of QRS entropy vector.

Step 6: Take the values of non-QRS entropy vector in vector \( A_2 \) and repeat the procedure as in step 4. Calculate the distance of first element of non-QRS entropy vector from both cluster center \( C_1 \) and \( C_2 \). If it is closer to cluster center \( C_1 \) assign value 1 to sign vector \( Y_2 \), otherwise assign 0 values to the sign vector. Repeat the above procedure for all elements of non-QRS entropy vector.

Step 7: The vector \( Y \) has value of 1 only where both the sign vector \( Y_1 \) and \( Y_2 \) has value of 1. It is displayed in Fig. 2(e). It is observed that continuous train of 1’s is observed in QRS regions and 0’s in non-QRS region.
Step 8: A continuous train of 1’s is picked and using their duration, average pulse duration of all the trains of 1’s is evaluated. The train of 1’s whose duration turns out to be more than average pulse duration is identified as QRS complex and other ones are discarded. This criterion is known as average pulse width criterion. The location of QRS complexes, after applying average pulse width criteria is shown in Fig. 2(f).

Step 9: The above steps are repeated for all the twelve leads.

4. PERFORMANCE EVALUATION AND DISCUSSION

The validation of the proposed algorithm for the QRS complex detection is done using 125 original, 12 lead ECG record of data set 3 of CSE ECG data base [30]. The data base 3 covers wide variety of the pathological case. Every record picked from CSE ECG data base is of 10 s duration sampled at 500 samples per second thus giving 5000 samples. Detection is said to be true positive (TP) if the algorithm correctly detects the QRS complex, it is said to be false positive (FP) if component other than our interest is detected and it is said to be false negative (FN) if the algorithm fails to detect the component of our interest. The result using the proposed FCM algorithm on CSE database for 12-lead is given in Table 1.

Fig. 3 displays performance of the algorithm for the record M01_47. Here, the lead aVL of the record has been selected to clearly demonstrate the effectiveness of the algorithm. As depicted in fig. 3(a), the preprocessor removes power line interference and base line wander. The QRS (non QRS) entropy is minimum (maximum) in the region where QRS complex (non-QRS) is present as shown in Fig. 3(b) and 3(c). The FCM algorithm correctly detects all the sixteen QRS complexes present in the record. Similarly, Fig. 4 shows lead aVR of record M01_117 where the algorithm has correctly identified nine QRS-complexes out of twelve. The amplitude and hence the slope of the third, seventh and eleventh QRS complexes is quite low in comparison with the other ones. Hence the algorithm has failed to detect these three QRS-complexes marked False Negatives (FN) in the figure.
5. DELINEATION

Delineation determines characteristic point (onset and offset) of QRS complexes in ECG signal. The procedure begins by applying single lead QRS detector to recognize beat activity in each lead, after that wave’s onset and offset are searched in each lead. The method performance has been evaluated with referee’s annotation and combine program median provided in CSE multilead measurement database.

The time difference of QRS onset and offset between automatic (proposed FCM algorithm) and referee cardiologist annotation/combine program median is calculated, which is known as error. The mean (m) is calculated as average of error. Standard deviation $S$ in ms is calculated. In order to assess the agreement between automatic (proposed FCM algorithm) and referee cardiologist annotation/combine program median for QRS onset and offset Bland-Altman analysis [3] is done.

Fig. 5-6 displays Bland-Altman plot of QRS onset and offset respectively, for comparing the performance of FCM with combine program median given by CSE. In case of QRS onset the standard deviation is $\pm 12.45$ ms and in case of QRS offset the standard deviation is $\pm 14.55$ ms, which is within the acceptable limits. Thus FCM based algorithm not only detects the QRS complexes of ECG, but also delineate them accurately.

6. CONCLUSION

This paper represents new method for the QRS complex detection in ECG signal using Fuzzy C-Means algorithm. The method has been comprehensively tested using the CSE ECG database covering wide variety of QRS complexes. A considerable detection rate is obtained. The delineation results show that the standard deviations of the error are within the tolerance limit.
Fig. 3 Detection of QRS complexes in lead aVL of record M01_47

Fig. 4 Detection of QRS complexes in lead aVR of record M01_117
Fig. 5 Bland-Altman plot for QRS onset

Fig. 6 Bland-Altman plot for QRS offset
REFERENCES


BIOGRAPHIES

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