A Real Time QRS Complex Classification Method using Mahalanobis Distance

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Abstract

An unsupervised method to recognize and classify QRS complexes was developed in order to create an automatic cardiac beat classifier in real time. After exhaustive analysis, four features extracted from the QRS complex in the time domain were selected as the ones presenting the best results: width, total sum of the areas under the positive and negative curves, total sum of the absolute values of sample variations and total amplitude. Preliminary studies indicated these features follow a normal distribution, allowing the use of the Mahalanobis distance as their classification criterion. After an initial learning period, the algorithm extracts the four features from every new QRS complex and calculates the Mahalanobis distance between its feature set and the centroids of all existing classes to determine the class in which the new QRS belongs to. If a predefined distance is surpassed, a new class is created. Using 44 records from the MIT-BIH we have obtained 90,74% of sensitivity, 96,55% of positive predictivity and 0.242% of false positives.

1. Introduction

Critical care patient monitoring has been a constant challenge to Biomedical Engineering, especially for those studying the cardio-respiratory system. With the advancement of micro-processed systems, it has become possible to implement reliable automatic cardiac arrhythmia analyzers in cardiac monitors.

The classification of beats, one of the steps of this analysis, intends to identify alterations in the cardiac beat pattern through the analysis of the characteristics or features of the QRS complexes.

There are three main obstacles to overcome in order to be implemented in cardiac monitors: real time operation, low processing cost and independence from the selected leads.

This study developed an unsupervised algorithm to recognize and classify QRS complexes in order to overcome those obstacles.

2. Methodology

The database of the Massachusetts Institute of Technology and Beth Israel Hospital (MIT/BIH) was used for development and analysis of the algorithm, since it is one of the databases indicated for performance evaluation of ventricular arrhythmia detection systems by the Association for the Advancement of Medical Instrumentation, AAMI/EC57 [1]. This database has 48 records, each 30 minutes long, in two ECG channels. In compliance with the recommendation, the records with "paced beats" were excluded, since this algorithm does not possess a pacemaker detector.

The records were adapted to meet the requirements of the monitor employed in the study (Dixtal DX2010), using the software *xform*, available in the MIT-BIH database CD-ROM. Sampling frequency was altered from 360Hz to 250Hz, signal gain from 200 adu/mV (analog to digital unit /mV) to 160adu/mV, signal resolution from 11 bits to 12 bits and baseline from 1024 to 2048.

Afterwards the most adequate features of the QRS complex were searched to be used in classifying beats in real time. Quality of classification features is a key factor in determining performance of an automatic cardiac beat classifier, discriminating different morphologies and allowing the creation of different arrhythmia classes. With this purpose in mind, the time domain extraction of QRS features [2] was chosen because of its low processing cost, which allows easy implementation in real time.

From a set of nine features extracted from the QRS complex, Costa and Moraes [3] concluded, with a reduced database, that the use of only four features offers the best compromise in terms of processing cost and time domain extraction performance. Those features which could be extracted independently from the chosen lead were then selected. The following features were concluded to be the best set for the creation of an automatic cardiac beat classifier in real time:

1. width W of the QRS complexes, represented by the number of samples which contain the QRS complex;

2. total sum of the areas under the positive and negative curves, calculated by the expression:

$$AM = \sum_{i=0}^{N-1} \left| x_i - x_0 \right| \tag{1}$$

where N is the total number of samples in the QRS complex, i is the position of the sample in relation to the beginning of the complex, x_0 is the first sample and x_i is the sample;

3. total sum of the absolute values of sample variations in the QRS complexes:

$$SV = \sum_{i=0}^{N-2} |x_{i+1} - x_i| \quad (2)$$

4. total amplitude of the QRS complexes:

$$A = \max(x_i - x_0) - \min(x_i - x_0),\ 0 \le i \le N-1 \quad (3)$$

The extraction of the features of the QRS complex was made from records generated by a QRS delineator software. The ECG signals in these records had a bandwidth (0.7-17Hz at –3dB) limited by a band pass filter proposed by Ligtenberg and Kunt [4], in order to reduce noise and EMG, as well as baseline wandering. Thus, the features were obtained through the samples of the QRS complex and the notations generated by the delineator software.

For the following step the features chosen to form feature clouds were used in a 4-dimension space, each cloud representing a feature class.

The value of r in the equation

$$r^2 = (x-m_x)`\, \boldsymbol{C_x}^{-1}(x-m_x) \quad (4)$$

is called the **Mahalanobis distance** from the feature vector x to the mean vector m_x, where C_x is the covariance matrix of x; it can be demonstrated that surfaces in which r is constant are ellipsoidal with center in m_x. The Mahalanobis distance can be used in a minimum distance classifier as following (Figure 1): be m_1, m_2, ..., m_n the centroids of the n classes, and be C_1, C_2,..., C_n the corresponding covariance matrixes. An feature vector x is classified by measuring the Mahalanobis distance from x to each of the centroids, and by attributing x to the class in which the Mahalanobis distance is minimum [5].

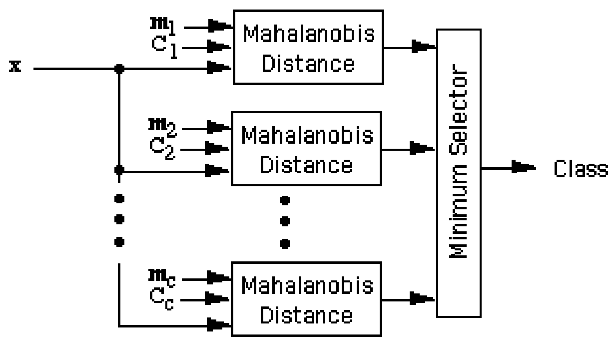

Figure 1. Mahalanobis distance in a minimum distance classifier.

It can also be proved that (4) is the matrix generalization of the scalar expression:

$$R^2 = (x-m)*(x-m)/s^2 = [(x-m)/s]^2 \quad (5)$$

In order to use the Mahalanobis distance as a minimum distance classifier the involved features must have a normal distribution. A study was therefore made to define the distribution of probabilities of the chosen QRS complex features. Some database records were selected for this evaluation; the database records were extracted and used to generate histograms with *MatLab*.

The algorithm delineates in real time each new QRS complex detected and extracts the four features. The next step is to calculate the Mahalanobis distance in relation to the centroids of the pre-existing classes. The new beat is included in the class for which the Mahalanobis distance between the centroid features and the beat features is smallest. A new class is created every time the features of a new beat are at a larger distance in relation to all existing classes than a pre-determined limit. Therefore, the Mahalanobis distance indicates which class each beat belongs to or if there is need to create a new class.

A very important characteristic of the algorithm is that the centroids are self-adjustable, allowing an interactive dislocation of the feature clouds. For each new beat that is incorporated in a class a re-calculation of the class centroid features is performed, taking into consideration its previous values and the feature values of this new beat. Moreover, the algorithm also allows the exclusion of classes that contain few beats and/or remain without new occurrences for a long time. These are excluded in order to minimize processing costs.

An initial learning period of forty seconds was determined as a way to enhance the sensitivity of the algorithm. During this time, the maximum distance determined for the creation of a new class is reduced so that more classes are created and the number of false positives is reduced.

It is important to notice that the whole procedure described before is performed only in one channel and does not depend on the chosen lead.

All tests were performed following the recommendation of the AAMI/EC57 [1]. Therefore, new notation files were created during the test period, containing beat notations generated by the proposed algorithm. A beat-by-beat comparison for each of the 44 records in the database was made using the software *bxb* from the MIT-BIH database CD-ROM; the original notation files from the database were confronted with the ones generated by the algorithm. The metrics employed, related to the VEBs (Ventricular Ectopic Beats), were: sensitivity, positive predictivity and false positive index. Another important information is that the branch block beat types were considered normal for test purposes. The fusion beats, however, were considered normal or ventricular at times, according to the class they were placed. Moreover, only the detected and delineated beats were considered, since the purpose of the tests was to evaluate classifier performance.

3. Results

In all cases (records 116, 119, 201, 208, 213 and 233) the features, both for normal beats and Multiform Premature Ventricular Contraction (PVC), had a distribution similar to normal (Figures 2 and 3). Therefore, the Mahalanobis distance could be used in the form (5) as a classification criterion.

It is important to notice that the feature Width, in Figures 2 and 3, did not present a well characterized distribution because its discretization in a few points did not allow for good characterization. Even with the use of records with a larger number of beats the result is not expected to be better, since distribution would remain in the range presented.

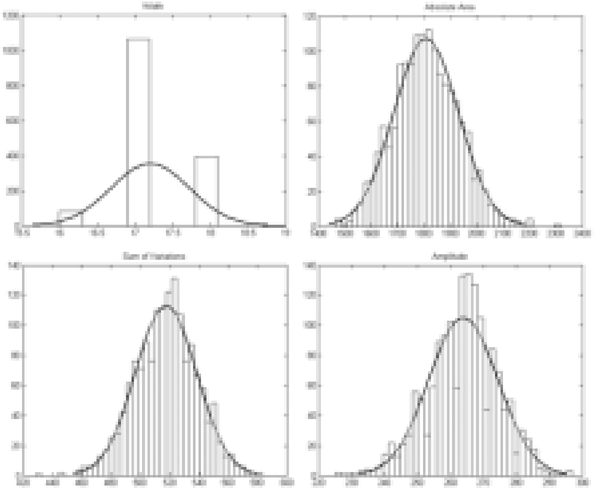

Figure 2. Distribution of the normal beat features for record 119. Clockwise from the upper left corner: W, AA, A and VS.

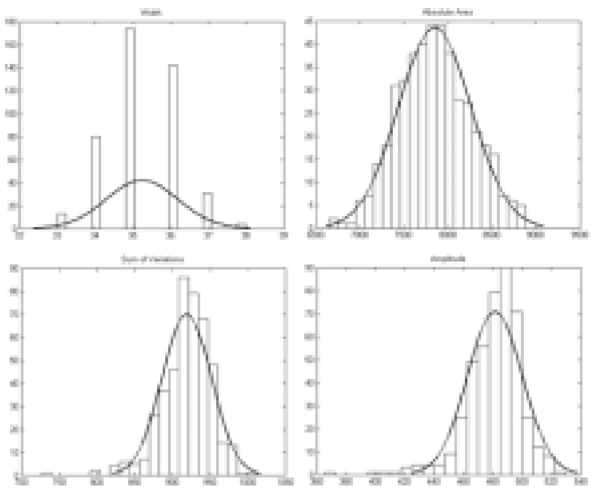

Figure 3. Distribution of the PVC features in record 119. Clockwise from the upper left corner: W, AA, A and VS.

Table 1 presents the test results for the algorithm in different amounts of the MIT-BIH database records.

Table 1. VEB Indexes of the classifier (%).

Number of records	Sensitivity	Positive Predictivity	False positives
44	90.74	96.55	0.242
43	92.42	96.60	0.242
43*	93.22	97.08	0.203
42	95.05	97.13	0.203

The first line presents the metrics for all 44 records in the database. With the exception of record 207 (second line in Table 1), a considerable increase in sensitivity can be seen, although the other metrics do not present significant changes. This result was expected, nonetheless, since record 207 contains sections of ventricular fibrillation, which directly impairs the sensitivity of the VEBs. Strictly following the recommendations of AAMI/EC57 [1], the record 207 wouldn't even be included in the tests.

In the third line of Table 1 the record 203 was excluded from the total 44 records, resulting in a significant increase in both sensitivity and positive predictivity, besides a marked decrease in the VEB false positive index. The exclusion of this record is due to the fact that its specific chosen features do not offer good performance for beat classification.

The estimated error [6] with the use of these four features in record 203 is 7.35%, too high when compared to the other records, around 4.00% at most. Figure 4 shows the output of the *bxb* software for record 203, where beat classification is shown (in lower case letters for the notations generated by the computer and in capital letters the notations from the original notation file). Sensitivity, positive predictivity and VEB false positive index are also shown.

At last, the fourth line of Table 1 shows the VEB indexes for 42 records of the database after the exclusion of the critical records 203 and 207. It shows, therefore, a large increase in VEB sensitivity and a small increase of the other indexes when the two mentioned records are excluded.

Figure 5 presents a two-dimensional graph generated by mapping [7] the four features extracted from the QRS complex for record 221 of the MIT/BIH database with the software *gnuplot*. Record 221 presents only two classes of beats: Multiform Premature Ventricular Contraction (PVC) and normal beats (NORMAL). Classification was performed with the proposed algorithm. Note that the data related to NORMAL and PVC formed well defined clusters, and only one PVC beat was grouped with NORMAL.

An adaptative method is used so the algorithm will not need to learn a pattern again after the initial learning period, so that the normal pattern (which will probably present variations in morphology after a long time of evaluation) continues to be classified correctly. Another advantage of the algorithm is that it does not establish a maximum number of patterns to be created, so that several classes of multiform ventricular beats can be created. Nonetheless, not more than 18 classes were generated using the MIT/BIH database (record 207), showing the algorithm is finding a reasonable number of patterns despite its malleability.

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Beat-by-beat comparison results for record 203
Reference annotator: atr
     Test annotator: ann

                 Algorithm
         n     v     f     q     o     x
   _____________________________________
 N | 1971    34     0     0     0     0
 V |  163   158     0     0     0     0
 F |    1     0     0     0     0     0
 Q |    0     0     0     0     0     0
 O |    0     0     0     0
 X |    0     0     0     0

           VEB sensitivity:  49.22% (158/321)
 VEB positive predictivity:  82.29% (158/192)
   VEB false positive rate:  1.695% (34/2006)
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Figure 4. Output of the bxb software for record 203.

The use of the Mahalanobis distance allowed the software to use features with completely different metric values without differentiation. Although it brings benefits such as the use of one-dimensional threshold for the distinction of limits, this may bring consequences such as seen in record 203 where classification was done erroneously because distinct class features were placed in the same class in the general result.

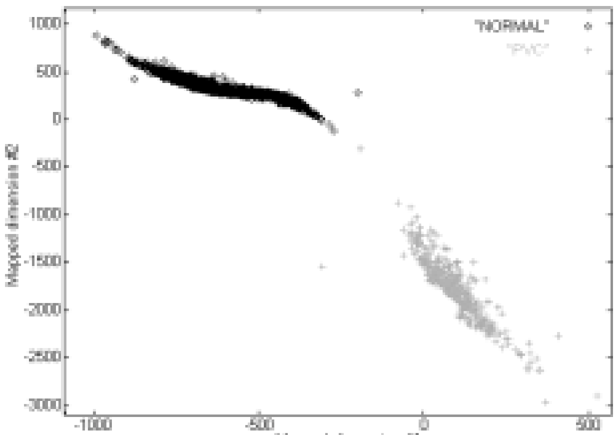

Figure 5. Graph generated by mapping the four features extracted from record 221 in a 2D space according to algorithm classification

4. Conclusion

An algorithm to classify QRS complexes in real time was presented in this study with the purpose of being implemented in cardiac monitors. For this purpose, it was necessary to search for a non-supervised classification method for cardiac beats with low processing cost, independence from the selected lead and self-adjustment features.

Another important factor to be noted is that its simple approach, when compared to more costly computing methods such as those using neural networks or fuzzy logic, makes implementation in real time more feasible.

All considered, the algorithm is effectively useful and can be implemented in commercial cardiac monitors with arrhythmia analysis characteristics, even fulfilling their requirements of real time processing.

A future project will be the development of a labeling algorithm so that, once classes are separated, they can in turn be classified themselves. Therefore the algorithm will not only identify several patterns existing in an ECG signal, but also be able to classify them.

Acknowledgments

We would like to thank Dixtal Biomedics for sponsoring this research, providing the equipment, database and knowledge which made the creation and development of this work possible.

References

[1] ANSI/AAMI EC57-1998: Testing and reporting performance results of cardiac rhythm and ST-segment measurement algorithms. In: AAMI - Association for the Advancement of Medical Instrumentation. – *CD-ROM AAMI standards and recommended practices*

[2] Enlghazzawi Z, Geheb F. A knowledge-base system for arrhythmia detection. Computers in Cardiology 1996. IEEE Computer Society Press, 1996:541-4.

[3] Costa EV, Moraes JCTB. QRS feature discrimination capability: quantitative and qualitative analysis. Computers in Cardiology 2000;27:399-402.

[4] Ligtenberg A, Kunt M. A robust digital QRS detection algorithm for arrhythmia monitoring. Computers in Biomedical Research. 1983;16:273-286.

[5] http://www.engr.sjsu.edu/~knapp/HCIRODPR/PR_Mahal/M_metric.htm. Pattern Recognition for HCI by Richard O. Duda. Department of Electrical Engineering, San Jose State University.

[6] Rauber TW, Barata MM, Steiger-Garção AS. A toolbox for analysis and visualization of sensor data in supervision. 93-International Conference on Fault Diagnosis. 1993, Toulouse, France. Obtainable from http://www.inf.ufes.br/~thomas/

[7] Sammon Jr JW. A nonlinear mapping for data structure analysis. IEEE Transactions on Computers, 1969;C-18;5:401-9.

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