Mathematical morphology based ECG feature extraction for the purpose of heartbeat classification

Pawel Tadejko, Waldemar Rakowski
Technical University of Bialystok
Faculty of Computer Science
15-351 Bialystok, Wiejska 45A, Poland
{ptad@ii, W.Rakowski}@pb.bialystok.pl

Abstract

The paper presents the classification performance of an automatic classifier of the electrocardiogram (ECG) for the detection abnormal beats with new concept of feature extraction stage. Feature sets were based on ECG morphology and RR-intervals. Configuration adopted a Kohonen self-organizing maps (SOM) for analysis of signal features and clustering. In this study, a classifier was developed with SOM and Learning Vector Quantization (LVQ) algorithms using the data from the records recommended by ANSI/AAMI EC57 standard. This paper compares two strategies for classification of annotated QRS complexes: based on orginal ECG morphology features and proposed new approach - based on preprocessed ECG morphology features. The mathematical morphology filtering is used for the preprocessing of ECG signal. The problem of choosing an appropriate structuring element of mathematical morphology filtering for ECG signal processing was studied. The performance of the algorithm is evaluated on the MIT-BIH Arrhythmia Database following the AAMI recommendations. Using this method the results of recognition beats either as normal or arrhythmias was improved.

Index-terms

ECG, preprocesing, mathematical morphology, ECG filtering, feature extraction, heartbeat classification

1. Introduction

The analysis of heart beat cycles in ECG signal is very important for long-term monitoring of heart patients. However, it is very costly for the medical expert to analyze the ECG recording beat by beat since the ECG records may last for hours. Therefore, it is justified to develop a computer-assisted technique to examine and annotate the ECG recording to facilitate review by medical experts. This computer annotation will assist doctors to select only the abnormal beats for further analysis.

1.1. Arrhythmias classification

Automatic classification of cardiac rhythms still remains a vital problem in clinical cardiology, especially when it is performed in real time. Several researchers have addressed the problem of automatic classification of cardiac arrhythmias [2, 3, 4, 5, 16, 19, 22]. Annotation of ECG recording requires the detection of various types of heartbeats. This is a pattern recognition task. Very often, a classifier is to be trained to recognize different types of beats. The training set of the classifier is usually a large database, which consists of the ECG beats from a large pool of patients. However, these classifiers suffer from the problem of poor generalization because there are usually some variations in the “normal” range among human beings. Even doctors may experience difficulty in assessing abnormal ECG beats if only considering the reference values based on the general patient population.

1.2. Heartbeat classifier

There are two general approaches to the training process: building general heartbeat classifier [2, 5, 16, 19, 22] and patient-adapting classifier [3, 4].

However, most of the approaches proposed in the literature deal with a limited number of arrhythmic types and process the entire ECG signal extracting several features from it, such as the P wave, which is an extremely time-consuming process and sometimes difficult due to the presence of noise. Other researches suggested that there is a
need to incorporate local information of a specific patient to improve the recognition of abnormal ECG beats and thus help to improve the generalization.

This work proposes a method for the normalization of variations in ECG beats, based on mathematical morphology and resampling model, which can be easily applied to the ECG signal.

2. Mathematical morphology

By “morphological signal processing” we mean a broad and coherent collection of theoretical concepts, mathematical tools for signal analysis [18]. Originally MM was applied to analyzing images from geological or biological specimens. However, its rich theoretical framework, algorithmic efficiency, easy implementability on special hardware, and suitability for many shape-oriented problems have propelled its widespread diffusion and adoption by many academic and industry groups in many countries as one among the dominant image analysis methodologies [1, 11, 12, 13].

As a result, MM nowadays offers many theoretical and algorithmic tools to and inspires new directions in many research areas from the fields of signal processing, image processing and machine vision, and pattern recognition.

2.1. Mathematical morphology transformations

Morphological filters are nonlinear signal transformations that locally modify geometric features of signals. They stem from the basic operations of a set-theoretical method for signal analysis, called mathematical morphology, which was introduced by Serra [18].

In morphological filtering [1, 11, 12, 13], each signal is viewed as a set, and its geometrical features are modified by morphologically convolving the signal with a structuring element (SE), which is another set of simple shape and size. By varying the structuring element we can extract different types of information from the signal.

A structuring element is characterized by its shape, width, and height. The values of the structuring element determine the shape of the output waveform.

2.2. Elementary mathematical morphology operators

In the sequel we use definitions of grey-level morphology basic operators in the same form as in [18]. Let us recall that erosion $\ominus$ of a function $f : R \rightarrow R$ by a structuring element $b : R \rightarrow R$ can be defined as

$$ (f \ominus b)(s) = \min_x \{f(s+x) - b(x) : s+x \in D_f \land x \in D_b \} $$

where $D_f \sup f$, $D_b \sup b$. In a similar way, dilation $\oplus$ is an operator given by

$$ (f \oplus b)(s) = \max_x \{f(s-x) + b(x) : s-x \in D_f \land x \in D_b \} $$

Two other operators: closing $\bullet$ and opening $\circ$ are defined with help of (2) and (3), i.e.

$$ f \bullet b = (f \oplus b) \ominus b, \quad f \circ b = (f \ominus b) \oplus b $$

3. Self-Organization Map and Learning Vector Quantization

The Self-organizing Map (SOM) is an artificial neural network architecture based on unsupervised, competitive learning [8]. It provides a topology preserving smooth mapping from a high-dimensional input space to the map units usually arranged as a two-dimensional lattice of neurons (nodes). Thus, the SOM can serve as a tool for cluster analysis of complex, high-dimensional data.

A parametric reference vector $m$, is associated with every node. A data vector $x$ is compared to all reference vectors in any metric and the best matching node is defined, e.g., by the smallest Euclidean distance between the data vector and any of the reference vectors. During learning, those nodes that are topographically close in the array up to a certain distance will activate each other to learn from the same input:

$$ m_j(t + 1) = m_j(t) + h_{c_j}(t)[x(t) - m_j(t)] $$

where $t$ is an integer representing time, and $h_{c_j}$ is the so-called neighbourhood kernel describing the neighbourhood that is updated around the best-matching node in response to the present feature vector $x(t)$. Initially, the neighborhood is large. The size reduces as clustering converges, until no neighboring neurons will get updated. Several suitable kernels can be used, e.g. a so-called bubble kernel or a gaussian kernel, relating to different ways of determining the activating cells. The kernel also includes the learning rate parameter $\alpha(t)$.

With time, the size of the neighbourhood and the learning rate are diminished. The described learning process leads to a smoothing effect on the weight vectors in the neighbourhood and by continued learning to global ordering of the nodes [8, 9].

Learning Vector Quantization (LVQ) [8, 10] is a supervised, clustering-based classification technique which classifies a feature vector $x(t)$ according to the label of the cluster prototype (code word) into which $x(t)$ is clustered. Classification error occurs when the feature vectors within the same cluster (hence, assigned to the same class label) are actually drawn from different classes. To minimize classification error, the LVQ algorithm fine tunes the clustering boundary between clusters of different class labels by
modifying the position of the clustering center (prototype or code word). This method is called “learning vector quantization” because this clustering based classification method is similar to the “vector quantization” method used for signal compression in the areas of communication and signal processing.

4. Evaluation Method

The proposed method consists of three steps (Figure 1): (a) preprocessing (feature extraction), (b) feature vector preparation (feature selection), (c) arrhythmic episode classification. The MIT-BIH arrhythmia database [15] is used for evaluation of the method.

We evaluate various combinations of morphological filters and conduct experiments for different structuring elements [17, 20]. It turns out that results are strong depends on shape and size of structuring element. Since the opening and closing operations are intended to remove impulses, the structuring element must be designed so that the waves in the ECG signal are not removed by the process.

4.1. Datasets

To evaluate the performance of our approaches, we used the 48 tapes of the MIT/BIH arrhythmia database, which comes along with a very detailed annotation for each beat. The Association for the Advancement of Medical Instrumentation (AAMI) has summarized those detailed classes to four classes of clinical relevance, as shown in Table 1 [14]. Four records (102, 104, 107, and 217), including paced beats, are excluded from the study in compliance with the standards recommended for reporting performance results of cardiac rhythms by the AAMI.

The original signals in the MIT/BIH arrhythmia database are two-leads, sampled at 360 Hz. The ECG signal of Lead 1 is used in this study.

4.2. Denoising and baseline wander elimination

The electrocardiogram (ECG) signal is the electrical interpretation of the heart activity; it is a set of of, well defined, successive waves denoted: P, Q, R, S, and T waves [7]. However, as the major part of real signals; the real picked-up ECG signal is corrupted by several sources of noise: EMG (electromyogram) signal (a high frequency signal related to muscle activity), the BLW (the baseline wandering: a low frequency signal caused mainly by the breathing action), the electrode motion (usually represented by a sharp variation of the baseline).

Background normalization is performed by estimating the drift in the background and subtracting it from the incoming data. Processing the data through a sequence of opening and closing operations performs impulsive noise suppression.

Let us take two possibly different structuring elements \( b_1 \) (for opening) and \( b_2 \) (for closing) of the type considered so far. In this way we obtain as follows:

\[
\text{bgn}(f) = f - 1/2[(f \circ b_1) \bullet b_2 + (f \bullet b_2) \circ b_1]
\]

(5)

The ECG signal, as well as any baseline drift, is estimated by processing the data using an opening operation followed by a closing operation. Processing the data using a closing operation followed by an opening operation forms a second estimate of the signal. The result from this step is the average of the two estimates. For opening operation structuring element \( b_1 \) has size of \( L \) and for closing \( b_2 \) size of \( 2L \). The size of the first SE \( L \) should be longer than QRS interval.

4.3. Feature vector

Here we investigate the use of raw amplitude of the time domain ECG signals after noise suppression and baseline drift removal as feature vectors to represent the ECG beats. After the R-peak is located, the ECG signal in a window of 550 ms is taken as an ECG beat. The lengths of the signal before and after the R-peak in each beat are 140 ms and 410 ms, respectively, such that the window covers most of the characterization of the ECG beat. The signal in each window is then resampled to form a feature vector of 20-dimensions. The R-R interval (the interval between two consecutive R-peaks) is also used in this study by appending it to the 20-dimensional feature vector.

4.4. Additional preprocessing

It has been proven that as belonging to nonlinear filtering techniques - morphological dilation and erosion satisfy the causality and the additive semigroup property required by multiscale analysis for signals of any dimension with local maxima and local minima as singular points [1, 12, 13].

Many experiments have been done to test the performance of morphological filters used in ECG signal preprocessing [17, 20]. The experiments show that non-standard filter block construction, especially combination of elementary morphology operators (as sequence operations), has very big impact for characteristic of output signal.

We propose a feature-preserved transformation for signal processing of ECG data, based on mathematical morphology filtering. For extraction and normalization of the ECG features, the length of the SE should be less than QRS interval.

Therefore, we chose 10, 20, 30 points as the length \( L \) of the SE. Here, we take the flat structuring element (SEXXF), triangle SE (SEXXT, \( y = -\text{abs}(x) + L \)), line SE (SEXXL,
Figure 1. Block diagram of the proposed hybrid method

<table>
<thead>
<tr>
<th>MIT-BIH heartbeat types</th>
<th>AAMI heartbeat class</th>
<th>Notation used in this work</th>
</tr>
</thead>
<tbody>
<tr>
<td>normal beat (NOR)</td>
<td>NORMAL (N)</td>
<td>NL</td>
</tr>
<tr>
<td>left bundle branch block beat (LBBB)</td>
<td></td>
<td>LB</td>
</tr>
<tr>
<td>right bundle branch block beat (RBBB)</td>
<td></td>
<td>RB</td>
</tr>
<tr>
<td>atrial escape beats (AE)</td>
<td>Any heartbeat not in the other classes</td>
<td>AE</td>
</tr>
<tr>
<td>nodal (junctional) escape beat (NE)</td>
<td></td>
<td>NE</td>
</tr>
<tr>
<td>atrial premature beat (AP)</td>
<td>SVEB (S)</td>
<td>AP</td>
</tr>
<tr>
<td>aberrated atrial premature beat (aAP)</td>
<td>Supraventricular ectopic beat</td>
<td>AA</td>
</tr>
<tr>
<td>nodal (junctional) premature beat (NP)</td>
<td></td>
<td>NP</td>
</tr>
<tr>
<td>supraventricular premature beat (SP)</td>
<td></td>
<td>SP</td>
</tr>
<tr>
<td>premature ventricular contraction (PVC)</td>
<td>VEB (V)</td>
<td>PV</td>
</tr>
<tr>
<td>ventricular escape beat (VE)</td>
<td>Ventricular ectopic beat</td>
<td>VE</td>
</tr>
<tr>
<td>fusion of ventricular and normal beat (fVN)</td>
<td>FUSION (F)</td>
<td>FS</td>
</tr>
<tr>
<td>paced beat (P)</td>
<td>NOTQRS (Q)</td>
<td>PB</td>
</tr>
<tr>
<td>fusion of paced and normal beat (fPN)</td>
<td>Ununknown beat</td>
<td>PF</td>
</tr>
<tr>
<td>unclassified beat (U)</td>
<td></td>
<td>NQ</td>
</tr>
</tbody>
</table>

Table 1. Beat classes according to MIT/BIH arrhythmia database and AAMI recommended practice
\[ y = \frac{(x + L)}{2} \] and scaling function of symlet wavelet (SESXX, name "sym10") to illustrate preprocessing effect. All function was centered on the origins and XX means 10, 20 and 30 points length.

4.5. SOM clustering and LVQ training

The issue of SOM quality is a complicated one [6]. Typically two evaluation criterias are used: resolution and topology preservation. There are many ways to measure them. The ones used here were chosen for their simplicity:

- \( qe \) (quantization error) - Average distance between each data vector and its BMUs (best matching units). Measures map resolution,
- \( te \) (topographic error) - the proportion of all data vectors for which first and second BMUs are not adjacent units. Measures topology preservation.

The average quantization error and the topographic error are measures used for this purpose. In order to study the behaviour of these factors we chose hexagonal topology map with automatic determination of map size.

According to Kohonen, there are three different LVQ algorithms, called LVQ1, LVQ2, and LVQ3 developed at subsequent stages to handle classification problems with different natures. In this study, the learning-rate LVQ1 algorithm was used for the training and fine-tuning of the code book respectively. This stage is based on applying the training and accuracy classification using the MATLAB SOM Toolbox [21] and LVQ_PAK [10].

5. Results

The method allocates manually detected heartbeats (using MIT/BIT database annotations) to one of the classes showed in Table 1 (MIT-BIH heartbeat types). The labels in the annotation files of MIT/BIH database made by cardiologists are used as the ground truth in evaluating the classifier.

Figure 2 shows the quantization error for all MIT/BIH datasets. Average distance between each data vector and its BMUs is smaller for almost all SE except SES10, SES20.

Classifier performance has been estimated using two destination classification types in this study on the dataset comprises data from recordings 100, 103, 105, 113, 117, 121, 123, 200, 202, 210, 212, 213, 214, 219, 221, 222, 228, 231, 232, 233, 234. In the first evaluation, we used four destination classes according to AAMI recommendations, in second one - MIT-BIH heartbeat types showed in Table 1. The signals from 21 records used as training data and then each of them was used as testing set.

To determine the clustering performance of our method, on next step each record was processed as testing data.

The better results were obtained for classification of MIT-BIH heartbeat types. Some interesting trends emerge from these results. The results show (Table 2) that the classification performance for PV (premature ventricular contraction, PVC) and FS (fusion of ventricular and normal beat) preprocessed by MM filter are notably higher than the same resulting without any preprocessing stage. Specifically, accurate detection of premature ventricular contractions (PVCs) is imperative to prepare for the possible onset of lifethreatening arrhythmias. According to AAMI recommendations classes, we see that also aggregate classification performance for normal beats (NL, LB, RB, AE, NE) from any others heartbeat may be improved with mathematical morphology preprocessing.

6. Conclusions

However, the parameters of morphological operators for the ECG signal preprocessing intended to extract feature where tested on a limited number of subjects. Preliminary results showed that the proposed algorithm leads to an improvement in the heartbeat classification using MIT/BIH database.

The future research will be oriented on the improvement of the performance of the presented algorithm.

7. Acknowledgement

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Table 2. Classification performance [%] of MIT-BIH heartbeat type each recording of dataset using the AAMI recommended performance measures: without preprocessing vs. preprocessing with MM filtering stage

<table>
<thead>
<tr>
<th></th>
<th>NL</th>
<th>AP</th>
<th>NQ</th>
<th>PV</th>
<th>PB</th>
<th>LB</th>
<th>AA</th>
<th>FS</th>
<th>VE</th>
<th>RB</th>
<th>AE</th>
<th>NE</th>
<th>NP</th>
</tr>
</thead>
<tbody>
<tr>
<td>total beats</td>
<td>9175</td>
<td>432</td>
<td>306</td>
<td>788</td>
<td>3</td>
<td>1021</td>
<td>8</td>
<td>106</td>
<td>1</td>
<td>881</td>
<td>35</td>
<td>43</td>
<td>12</td>
</tr>
<tr>
<td>w/o. preproc.</td>
<td>95.99</td>
<td>86.34</td>
<td>92.81</td>
<td>80.71</td>
<td>0.00</td>
<td>49.56</td>
<td>0.00</td>
<td>56.60</td>
<td>0.00</td>
<td>87.63</td>
<td>97.14</td>
<td>58.14</td>
<td>16.67</td>
</tr>
<tr>
<td>w. MM SE10F</td>
<td>95.79</td>
<td>86.34</td>
<td>92.81</td>
<td>81.09</td>
<td>0.00</td>
<td>51.22</td>
<td>0.00</td>
<td>65.09</td>
<td>0.00</td>
<td>87.29</td>
<td>97.14</td>
<td>41.86</td>
<td>0.00</td>
</tr>
<tr>
<td>w. MM SES10</td>
<td>93.65</td>
<td>82.87</td>
<td>90.85</td>
<td>81.47</td>
<td>0.00</td>
<td>51.32</td>
<td>0.00</td>
<td>70.75</td>
<td>0.00</td>
<td>94.10</td>
<td>97.14</td>
<td>39.53</td>
<td>0.00</td>
</tr>
<tr>
<td>w. MM SES20</td>
<td>94.19</td>
<td>84.26</td>
<td>93.14</td>
<td>87.56</td>
<td>0.00</td>
<td>51.22</td>
<td>0.00</td>
<td>68.87</td>
<td>0.00</td>
<td>86.83</td>
<td>97.14</td>
<td>46.51</td>
<td>0.00</td>
</tr>
</tbody>
</table>

References


