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Automated Methods for Ischemia Detection in Long Duration ECGs

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Abstract: Myocardial ischemia diagnosis using long duration electrocardiographic recordings is a simple and non-invasive method that can be used in the every day medical practice. Several techniques that automate ischemia detection have been proposed during the last decade. They are based on different methodological approaches which include digital signal analysis, rule-based techniques, fuzzy logic methods and artificial neural networks, with each one of them exhibiting its own advantages and disadvantages. Most recent systems employ artificial neural networks to utilize the classification stage since they have demonstrated great consistency in producing accurate results. The performance of the developed detection systems is very promising but they need further evaluation.

1. Introduction

Myocardial ischemia is the most common cause of death in the industrialized countries and as a consequence its early diagnosis and treatment is of great importance.[1–3] In the electrocardiographic (ECG) signal ischemia is expressed as slow dynamic changes of the ST segment and/or the T wave.[4,5] Long duration electrocardiography (e.g Holter recordings, continuous ECG monitoring in the coronary care unit), is a simple and non-invasive method which observes such alterations. The development of suitable automated analysis techniques can make this method very effective in supporting the physician's diagnosis and guide clinical management.

The commercial systems used for ischemia detection in long duration ECGs do not support automated diagnosis. They can only detect the ST segment and possibly the T wave changes and measure certain characteristics (average values of ST segment deviation, ST slope or the T wave amplitude for a time window of 30 s to 2 min). Changes on those characteristics define potential ischemic episodes, which the medical expert has to evaluate visually in order to confirm the diagnosis. All the reported clinical trials, in which systems of continuous ECG monitoring have been used for ischemia diagnosis, refer to post-processing where the outputs of such systems (the measurements of the ECG features) are summoned up, grouped and assessed and the diagnosis is based upon manual interpretation by the physicians. The usage of such procedures is limited because it is highly time consuming. Current research points towards systems which will automate the diagnosis of ischemia.

The automated detection of ischemic episodes is divided into four stages. In the first stage the ECG signal is preprocessed and noisy patterns like the baseline wandering, the A/C interference and the electromyographic contamination are removed. In the second stage all the necessary ECG features (J point, isoelectric line and T wave peak) are extracted and measured. Based on the evaluation of the above features, in the third stage each cardiac beat is classified as normal or ischemic. In the final stage all the ischemic beats are grouped properly and the ischemic episodes can be identified.

Following the above, different types of systems have been proposed in the literature for the automated detection of ischemia. These mainly vary in the technique they utilize in the last two stages. According to the utilized technique each system can be categorized into one of the following: a) digital signal analysis,[6–12] b) rule-based,[13–17] c) fuzzy logic[18] and d) artificial neural network (ANN).[1,19–26] Each system exhibits its own strong characteristics that will be discussed in the sequel. Furthermore, the current tendency is towards using more complicated and sophisticated methods aiming at developing systems of improved performance.

2. Description of the different systems

The systems that will be presented refer to the detection of myocardial ischemia. Some of them are designed to detect the ischemic episodes related to ST segment deviation only and not to T wave alterations.

2.1. Digital Signal Analysis Systems

Ischemia detection using digital signal analysis techniques is based on the transformation of the original recorded signal and the extraction of new indexes capable to diagnose myocardial ischemia. These techniques analyze the ECG signal in the time or/and the frequency domain, utilize parametric models and transform it applying signal analysis methods (wavelets or Principal Component Analysis – PCA).

Badilini et al. constructed a system to diagnose myocardial ischemia using the frequency characteristics of the ST segment.[6] They observed that the frequency distribution of the ST segment for the whole ECG is wider and contains smaller frequency values in the ischemic beats than in the normal ones. After the characterization of each one cardiac beat as ischemic or not an ischemic episode is defined as the ECG interval that lasts ≥ 20 s and contains $\geq 2/3$ of ischemic beats. This system has been tested on a dataset of 20 normal and 24 ischemic Holter ECGs and achieved sensitivity and specificity of 95.8 % and 90 %, respectively.

Vila et al. analyzed the heart rate variability in the time-frequency domain.[7] After an adaptive optimal kernel technique has been applied, the generated spectrum was divided into three frequency bands: very low, low and high. Using the minimum and maximum values of these bands as well as their energies the ischemic episodes due to ST segment changes could be identified. The system was evaluated using 14 out of 90 recordings of the European Society of

Cardiology (ESC) ST-T database,[27] which is widely used as the standard annotated database for ischemia detection, but not quantitative results were reported.

Pitas et al. applied an autoregressive method for the detection of the ischemic beats.[8] A second order parametric model was used for the representation of each cardiac cycle. The two parameters of this model utilized to identify the ischemic beats. The system was evaluated in a rather small dataset of 8 ischemic and 8 normal beats and accuracy of 87.5 % was reported.

Senhadji et al.[9] studied three different families of wavelets (Daubechies, cubic spline and Morlet). The obtained features were used for beat classification as normal, ischemic due to ST segment deviation or premature ventricular contraction. The system was evaluated in a small dataset containing 20 ischemic and 20 normal beats and they achieved sensitivity and specificity of 95 % and 100 %, respectively.

Jager et al. developed a system based on the principal component analysis of the ECG signal.[10, 11] The first five components for the QRS complex and the first five of the ST segment were computed. They defined also thresholds studying ECG recordings to be used for ischemic episode detection. Their system was evaluated using the ESC ST-T database and the obtained sensitivity and positive predictive accuracy is 85.2 % and 86.2 %, respectively.

Laguna et al. studied the whole ST-T interval using principal component analysis.[12] They used the variations of the principal components during ventricular repolarization, instead of using the common ST characteristics (deviation or slope). The method was evaluated using the ESC ST-T database but not quantitative results were reported.

2.2. Rule-Based Systems

Rule-based systems employ sets of rules that are derived from medical knowledge in order to evaluate the extracted ECG features and detect the ischemic episodes.

Shook et al.[13] estimated the average of the ST absolute deviation (maximum ST segment depression from the isoelectric line), the average of the ST deviation (ST segment depression at the point J80, which is the point that lies 80 ms after J) and the average of the ST slope (slope between the points J and J80) in every 30 s of the ECG signal. They used certain rules (1mm for the absolute deviation, 0.75mm for the deviation and zero for the slope) in order to classify the ischemic episodes. They also used a second set of rules (1mm for the absolute deviation, 1mm for the deviation and zero for the slope) to classify each ischemic episode as "definite" or "probable" depending on which set of rules is triggered. The final system's output is the margins of the "definite" and "probable" ischemic episodes. The system was evaluated using 18 24-hour ambulatory ECGs and they achieved sensitivity and positive predictive accuracy of 90 % and 96 %, respectively. It is noted that the system employs rules that refer to ST segment depression only.

Taddei et al. designed a rule-based system for two lead ECG recordings which employs a geometric algorithm that calculates a 2D loop for the ST segment.[14] For each cardiac beat the ST segment deviations are estimated in the two leads and then each pair of values is graphically represented sequentially in time. The graphical representation contains also two circles with center the origin of the axes (the radius of the first and the second circle is 60μV and 100μV, respectively). Each ischemic episode is defined as the path which is for at least 30 s between the two circles and for at least 20 s out of the wider circle. The system was tested using the ESC ST-T database and the achieved sensitivity and positive predictive accuracy is 82 % and 81 %, respectively. It should be noted that the system uses information only from the ST segment and assumes that an ischemic episode contains only ischemic beats.

We have developed a four stage system based on two leads ECGs.[15, 16] In the first stage the signal is preprocessed for noise reduction and feature extraction (J point, isoelectric line, T wave peak).[28] In the second stage each beat was classified as normal, ischemic or artifact using a set of three rules (ST segment elevation, ST depression and T wave inversion or flattening). In the third stage each 30 s ECG window was classified as ischemic or not depending on the percentage of the ischemic beats contained in that window (≥75%). In the fourth stage the start and end points of each ischemic episode were identified merging the results for each of the two leads. The system was evaluated on the ESC ST-T database and the sensitivity and positive predictive accuracy 93.75 % and 78.50 %, respectively. Advtantages of the system are its ability to perform well in ECGs with substantial amount of noise and to characterise the type of the ischemic episode (ST segment deviation vs. T wave changes).[17]

2.3. Fuzzy Logic Systems

The rules employed in the rule – based systems correspond to inflexible thresholds; this being the main disadvantage of these systems. Near the threshold value the classification is realized without taking into account the noise distortion or the subjectivity of each patient. Fuzzy expert systems are more or less an extension of the rule-based systems as they also employ sets of rules but their logic is not two-valued (yes or no) but fuzzy. This simulates better the procedure followed by the physicians.

Vila et al. developed a system which fuzzyfies the rules used by the ESC to define the episodes in the ESC ST-T database.[18] The fuzzyfied rules are used to characterize each cardiac beat as ischemic with a certain possibility (from zero to one) and to define the ischemic episodes with a degree of certainty as well. The ESC ST-T database was used for the evaluation of the system. 30 out of the 90 recordings were used for training in order to determine the optimum threshold value for the certainty degree associated with the detection of an ischemic episode. The sensitivity and positive predictive accuracy obtained is 81 % and 68 %, respectively.

2.4. Artificial Neural Network Systems

Artificial Neural Networks (ANNs), due to their architecture and learning capabilities, can overcome problems met when dealing with medical data (small amount of data, non-linearity, high dimensionality, noise, high computational effort and difficulty in quantification).[29]

Stamkopoulos et al. adopted a multilayer perceptron (MLP) ANN for the detection of myocardial ischemia using only one lead.[19] The input to the ANN were digitized points from the ST segment. This system was trained with the backpropagation algorithm in order to classify each beat as normal, ischemic with ST elevation, ischemic with ST depression and unclassifiable. This was followed by the identification of ischemic episodes. The system was evaluated using 60 out of 90 recordings of the ESC ST-T database and the reported sensitivity and positive predictive accuracy were 84.4% and 78.8 %, respectively.

For the classification of the cardiac beats as normal or abnormal the same research group used two approaches, one based on a combination of two ANNs [20,21] and another utilizing an ANN of bi-directional associative memories.[22]

Silipo et al. applied an MLP to two-channel recordings using information only from the ST segment (ST deviation and slope).[1] This system classified each beat as ischemic or not and then all the classified beats were examined in groups of 20 s. If a group contained only ischemic beats then it was considered as an ischemic episode. All the episodes that were closer than 5 s were merged and the margins of the overall ischemic episodes were defined. The system was evaluated using 47 out of 90 recordings of the ESC ST-T database and the reported sensitivity and positive predictive accuracy were 85 % and 88 %, respectively.

In another work Silipo and Taddei utilized three different ANN topologies (MLP with input from seven ST intervals accompanied by a Principal Component Analysis to reduce the input dimension, recurrent ANN with input from four ST intervals and a knowledge – learning network) for ischemia detection.[23]

Papadimitriou et al.[24] developed an ANN system named sNet-SOM consisted of two components: (a) the classification partition self-organizing map (CP-SOM), and (b) the supervised expert network. The sNet-SOM was trained to classify the cardiac beats as ischemic or non using information extracted from the ST-T interval (sequence of five beats). The input dimension is reduced using Principal Component Analysis and wavelet transform. An episode was defined as ischemic when for at least 15 s the beats were ischemic. All episodes being closer than 5 s were merged. The best performance of the system (sensitivity 82.8 % and positive predictive accuracy 82.4 %) was obtained when the system was tested on 27 out of 90 recordings of the ESC ST-T database.

In the four – stage system that we have developed we used ANN for beat classification instead of the rule-based technique.[25] We have tested several feed-forward neural network architectures and various algorithms for training. A task specific cardiac beat database was developed in order to perform network training and testing. This database contains excerpts from the European Society of Cardiology ST-T database, which were diagnosed beat-by-beat from three experienced cardiologists. Subsequently, the results were used in another work where a feed-forward ANN was employed for ischemic episode detection.[26] The use of the system resulted to 90 % specificity and 89 % positive predictive accuracy when applied in the ESC ST-T database.

3. Comparison of different systems

The results obtained from each system cannot be compared directly since they were not evaluated with the same dataset. Furthermore, some of the studies described above did not report any quantitative results but only qualitative by means of stating that in the experiments that were run the system could discriminate the normal case from the ischemic.[7,12] Also some of the systems detected only the ST segment deviation in ischemic episodes[1,10,11,13,14,18,19,23] and not the T wave episodes as well.[16,17,24,26] Finally, some others classified the ECG records[6] or only the cardiac beats as ischemic or not[8,22,25] and from those several classified only the beats that were ischemic due to ST segment deviation.[9,20,21] Table 1 summarizes all the systems presented above giving information concerning the type of the system, the employed technique, the output of the system (beat classification or ischemic episode detection) and the dataset used for the evaluation of the system. In Table 2 the performance of the different systems resulting in episode detection are summarized. Table 3 contains the performance of the remaining systems.

The various ischemia detection systems that have been proposed so far can be grouped in four categories with each category exhibiting certain advantages and disadvantages. The digital analysis techniques are the most common techniques used in medical signals. They are easy to implement and have real time performance in reaching a decision. The rule-based systems' are simple to be implemented and their decision process resembles to the one of the medical experts. Fuzzy systems operate in the same manner and try to overcome the strict application of thresholds imposed by the rule-based systems. Besides that, fuzzy logic seems to have great potential in ischemia diagnosis since fuzzy rules can sufficiently describe the dynamic process that characterizes the ischemic episodes. However, they still need further improvement in order to improve their performance. The ANNs, after proper training, can usually detect ischemia more reliably than the other systems. Their main disadvantage is that they cannot provide interpretation regarding the diagnosis been made.

It should be mentioned that when comparing the systems presented in section 2 it should be taken into account that not all of them were evaluated with a standard reference database. Also some of them detect ischemic episodes based on ST segment and T wave changes, some ischemic episodes based only on ST segment changes and other are only able to classify cardiac beats (ischemic or normal).

All the described systems could be further improved, especially in the way that handle noisy recordings. The presence of noise in long duration ECG recordings is unavoidable so proper filtering must be utilized. Modern digital signal processing techniques like the wavelet transform can properly remove ECG noise.

4. Conclusions

The continuous development of sophisticated and up to date systems can make the automated ischemia detection on long duration ECG recordings a significant diagnostic tool. Computers can store large amount of clinical data and process them fast while at the same time can increase the objectivity of the decision making process. The systems being proposed have shown good results during their evaluation, but further testing is needed in the environment of the everyday medical practice.

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Table 1: Automated ischemia detection systems

Reference	Type	Employed technique	System Output	Evaluation Data
6	Digital Signal Analysis	ST segment displacement frequency distributions	Episode detection (ST changes only)	20 normal and 24 ischemic Holter ECGs
7		Time-frequency analysis	Episode detection (ST changes only)	ESC ST-T (14/90 records)
8		Autoregressive modeling	Beat classification	8 normal and 8 ischemic beats
9		Wavelet transform	Beat classification (ST changes only)	20 normal and 20 ischemic beats
10, 11		PCA	Episode detection (ST changes only)	ESC ST-T
12		PCA	ECG classification	ESC ST-T
13	Rule-based Systems	Thresholding of averaged ST features	Episode detection (ST depression only)	18 24-hour ambulatory ECGs (114 episodes)
14		Geometric method	Episode detection (ST changes only)	ESC ST-T (50/90 records)
15, 16		4-stage algorithm	Episode detection	ESC ST-T
17		4-stage algorithm	Episode detection (ST and T separately)	ESC ST-T
18	Fuzzy Logic	Linguistic filters and membership functions of trapezoidal possibility distributions	Episode detection (evaluated only on the ST changes)	ESC ST-T (60/90 records)
19	ANNs	MLP (20×10×2)	Episode detection (ST changes only)	ESC ST-T (60/90 records)
20, 21		Auto-associative nonlinear PCA with RBF	Beat classification (ST changes only)	ESC ST-T (34/90 records)
22		Bidirectional associative memories	Beat classification	ESC ST-T (9/90 records)
1		MLP (1×5×1)	Episode detection (ST changes only)	ESC ST-T (47/90 records)
23		MLP with PCA	Episode detection (ST changes only)	ESC ST-T
23		Recurrent	Episode detection (ST changes only)	ESC ST-T
23		Knowledge-learning	Episode detection (ST changes only)	ESC ST-T
24		CP-SOM	Beat classification	ESC ST-T (27/90 records)
24		CP-SOM with RBF	Beat classification	ESC ST-T (27/90 records)
24		CP-SOM with SVM	Beat classification	ESC ST-T (27/90 records)
24		CP-SOM	Episode detection	ESC ST-T
24		CP-SOM with RBF	Episode detection	ESC ST-T
24		CP-SOM with SVM	Episode detection	ESC ST-T
25		MLP (4×10×1)	Beat classification	ESC ST-T (10/90 records)
26		MLP (4×10×1) and Bayesian regularization	Episode detection	ESC ST-T

Table 2: Performance of the episode detection systems.

Reference	System Category	Se (%)[1]	PPA (%)[2]
10, 11	Digital Signal Analysis	85.2	86.2
13	Rule-based	90	96
14	Rule-based	82	81
16	Rule-based	93.75	78.50
17	Rule-based (ST episodes)	92.02	93.77
17	Rule-based (T episodes)	91.09	80.09
18	Fuzzy Logic	81	68
19	ANN	84.4	78.8
1	ANN	85	88
23	ANN (MLP & PCA)	77	86
23	ANN (Recurrent)	77	85
23	ANN (Knowledge-learning)	71	66
24	ANN (CP-SOM)	74.9	73.7
24	ANN (CP-SOM & RBF)	79.5	77.6
24	ANN (CP-SOM & SVM)	82.8	82.4
26	ANN	90	89

[1] Se: Sensitivity
[2] PPA: Positive Predictive Accuracy

Table 3: Performance of the beat classification systems.

Reference	System Category	Se (%)[1]	Sp (%)[2]	Acc (%)[3]
6[4]	Digital Signal Analysis	95.8	90	
8	Digital Signal Analysis			87.5
9	Digital Signal Analysis	95	100	
20, 21	ANN	79.32	75.19	
22	ANN			56.33
24	ANN (CP-SOM)			73.5
24	ANN (CP-SOM & RBF)			76.5
24	ANN (CP-SOM & SVM)			80.4
25	ANN	89.62	89.65	

[1] Se: Sensitivity
[2] Sp: Specificity
[3] Acc: Accuracy
[4] System for ECG classification