Detection of Myocardial Ischemia with Hidden Semi-Markovian models

J Dumont[1,2], G Carrault [1,2], P Gomis[3], GS Wagner[4], AI Hernández[1,2]

[1] Université de Rennes 1, LTSI, Rennes, F-35000, France
[2] INSERM, U642, Rennes, F-35000, France
[3] Universitat Politècnica de Catalunya (UPC), ESAII, Barcelona, Espagne
[4] Duke University Medical Center, Durham NC, USA

Abstract

A new method for myocardial ischemia detection is proposed in this communication. The originality of this method relies on the analysis of the dynamics of times series extracted from the ECG, whereas traditional methods are based on static decision rules. After the extraction of a feature vector, from ECG signals from the STAFF3 database, the dynamics are characterised with an Hidden Semi-Markovian Model (HSMM). The ischemic detector uses a reference HSMM and an ischemic HSMM and then compare the log-likelihood of the time series. Results obtained with percutaneous transluminal coronary angioplasty (PTCA) records of the STAFF3 database show an improved detection rate (96% of sensibility and 80% of specificity) with respect to other methods applied on the same database.

1. Introduction

The detection of myocardial ischemia is still a problem of public health medicine with two main objectives. The first one, in case of acute ischemia, is to reduce the delay between the appearance of ischemia and the application of an adapted reperfusion procedure [1]. The second objective is the reliable detection of transient ischemic episodes, because their frequency of apparition is an indicator for risk stratification of future infarcts [2]. Although ST-segment remains the most common electrocardiographic method used in monitoring systems [3], it is admitted that to overcome its low specificity, other indicators have to be analysed in a joint fashion [4]. The STAFF3 database aims to study new indicators on ischemic episodes induced by balloon inflation (PTCA) and accurately annotated. Studies published in the literature on this subject [5–9] reveal some modifications occurring during ischemia, such as changes in the QRS high frequencies, duration of the QRS or changes in T-wave shape. However these changes are based on the application of a threshold on the instantaneous values of these series to detect the ischemia, without taking into consideration their dynamics. In this case, noise spikes can, for example, provide false alarms. The correlation between the indicators is also underexploited. To improve this detection, it appears then important to take into consideration the temporal evolution of these indicators and if possible their joint evolution. This work focuses on the application of Hidden Semi-Markovian models on such kind of indicators, to improve the detection of ischemic events. The next section describes the methods employed, with the extraction of the indicators from ECGs, the learning of HSMM to characterize normal and ischemic dynamics, and finally the conception of an ischemia detector. Section III evaluates this detector on the STAFF3 database and reveal the most sensible and specific indicators derived from the proposed HSMM approach.

2. Methods

Ischemic data are analysed in 3 steps: step A) feature extraction from the ECG signal, step B) modelling of the time series and C), the step of ischemia detection.

2.1. Feature extraction from ECG signals

This step aims to reduce the data size to provide to the detector and also to retain information which can be easily interpreted by cardiologist. In this perspective, standard ECG indicators are preferred rather than, for example, KLT coefficients describing the ST-T segment or discrete wavelet coefficients representing the QRS. These standard ECG indicators are obtained from the segmentation of ECG beats, applied in 5 steps :

1. Suppressing power line interferences with an adaptive filtering.
2. Beat detection in every ECG leads with the Pan & Tompkins algorithm.
3. Application of a principal component analysis on every beats detected in step 2. This step aims to project the beats in an orthogonal featuring space and thus to reduce

the number of leads (from 12 to 2 in our case).
4. Beats are realigned to the first one by a rotation in the new featuring space. This minimizes ECG morphology variations due to respiration.
5. Beats are segmented with an algorithm based on a wavelet decomposition [10]. It allows estimating the position of the beginning and the end of the QRS, the T wave end, and the position of the extrema of the Q, R, S and T waves. The magnitude of the extremum and the ST level [11] are also conserved.

After the application of this signal processing chain, the following indicators (table 1) are extracted and re-sampled to 1Hz. Two examples of the time series analysed afterwards are presented figure 1.

Table 1. Extracted indicators.

Magnitudes	waves Q, R, S and T, ST level
Intervals	RR, QRSd (duration of the QRS complex), QT and RT

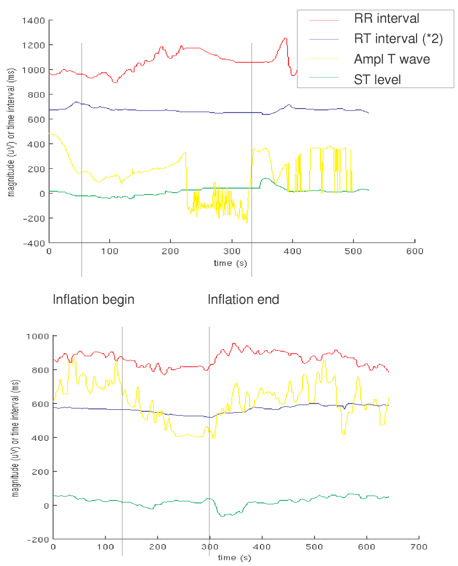

Figure 1. Two examples of time series, obtained from ECG from the STAFF3 database and with annotations concerning the inflation periods.

2.2. Analysis of the dynamics

The aim of this work is to characterize the difference of evolution of the time series between an ischemic episode and standard conditions. A model based approached has been chosen: in a learning step the dynamics will be embedded into the models and in a second step, it will be possible to test the membership of new time series to the available models. Hidden semi-Markovian models are a specialisation of markovian models to represent multivariate time series with continuous observations. The states that compose the models in this work have the following properties :

- Each state represents a subspace of the observed distributions. To reduce the computation time, these distributions (multidimensionnal in our case) are represented by gaussian laws.
- Each state represents the time spent in itself with a gaussian law, truncated in zero. In the case of continuous time series, when the time spent in the state can be long, the gaussian law seems indeed more adapted than the geometrical law initially present in standard HMM (figure 2).

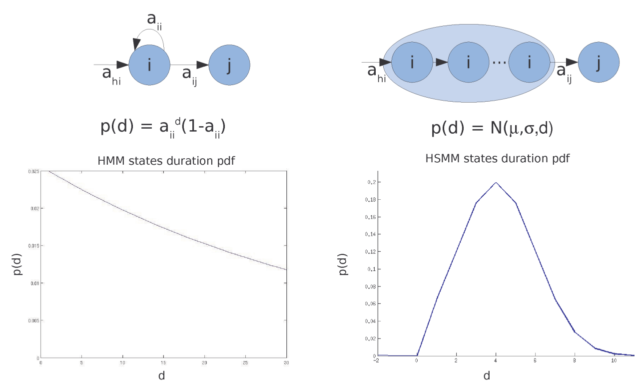

Figure 2. Structure of the models and states duration probability function for an HMM and an HSMM. Whereas in HMM the state duration is characterized by a probability to loop on itself, thus generating a geometric law, in HSMM, a normal law truncated in zero is learned.

For each patient and each variable, a reference value (computed as the median on the 20 first seconds) is systematically removed. These variations, compared to their corresponding reference value, represent the input series to our models. Then, to analyse the different variables with the same weight, the time series are normalized according to the standard deviation measured on reference records. Parameters from the models are firstly initialized with an HMM and secondly the Viterbi algorithm [12], adapted to the HSMM, is applied. Two models are learned on a subset of the STAFF3 database. Mod_{PTCA}, that characterizes the ischemia is learned first. Mod_{Ref}, that characterizes normal variations, inherits from the states of Mod_{PTCA}, but conserves its own transition matrix and probability laws for the state durations. This particularity for the learning aims to differentiate the time series in priority with their dynamics and not their magnitudes.

2.3. Ischemia detector

With a sliding window, which is observing a part of the multivariate time series (O_i), it is possible to compute the log-likelihood with respect to the two models, and to put them into competition. However, rather than applying the maximum of likelihood (eq. 1),

$$classe = \underset{\{Ref,PTCA\}}{\text{argmax}} \{LogP(O_i, \{Mod_{Ref}, Mod_{PTCA}\})\} \quad (1)$$

a threshold S is used to perform the detection, as proposed in algorithm 1.

Algorithm 1: Decision algorithm based on loglikelihood comparisons

if $LogP(O_i, Mod_{Ref}) - LogP(O_i, Mod_{PTCA}) > S$ **then**
  no ischemia
else
  ischemia

Using this threshold is justified by the fact that in ”normal” periods, the Mod_{PTCA} log-likelihood is sometimes slightly higher than Mod_{Ref} whereas in ischemic periods, the difference in favour of Mod_{PTCA} is usually very clear (cf section 3.2). This threshold is thus optimized on the training data, by minimizing the total number of detection errors.

3. Results

Experiments are lead on the STAFF3 database. This database contains records from 108 patients. For this study, only 68 patients without previous myocardial infarcts history are considered and 4 records had to be removed because of lead disconnections. Concerning the records, there is at least, for each patient:

- one 12-leads ECG recorded during the PTCA, with accurate annotation on the beginning and end of the inflation,
- one 12-leads ECG recorded before the operation.

3.1. Learning Mod_{Ref} and Mod_{PTCA} from the STAFF3 database

The reference model (Mod_{Ref}) and the PTCA model (Mod_{PTCA}) are learned through the procedure represented in figure 3. Two learning data sets (a reference one and an ischemic one) are extracted from the STAFF3 database to create these 2 models, from half of the patients, randomly selected. For Mod_{Ref}, we are using in priority the pre-inflation period. If the record doesn't contain pre-inflation data, the pre-operation ECG is used instead. For Mod_{PTCA}, we are exploiting the data between the beginning and the end of the inflation procedure.

3.2. Application of the ischemic detector

The HSMM ischemic detector is applied on pre-operation records (to evaluate specificity) and inflation records (to evaluate sensibility) of the second half of the STAFF3 database patients. The time series of the records to test are extracted and the log-likelihoods for the two models are computed. For this specific application on the STAFF3 database, a sliding window of 140s has been set. This value has been chosen so that it is large enough to observe the changes due to ischemia and small enough to don't overlap on post-inflation periods. In each records, the lowest values of $LogP(O_i, Mod_{Ref}) - LogP(O_i, Mod_{PTCA})$ is conserved and the record is classified as having an ischemic event or staying ”normal” according to algorithm 1. In pre-operation records, the log-likelihood difference should never decrease under S, whereas it should drop below S at least once during inflation records. Figure 4 presents an example of the evolution of the log-likelihoods for a multivariate observation O_i made of the ST level and intervals RR and RT.

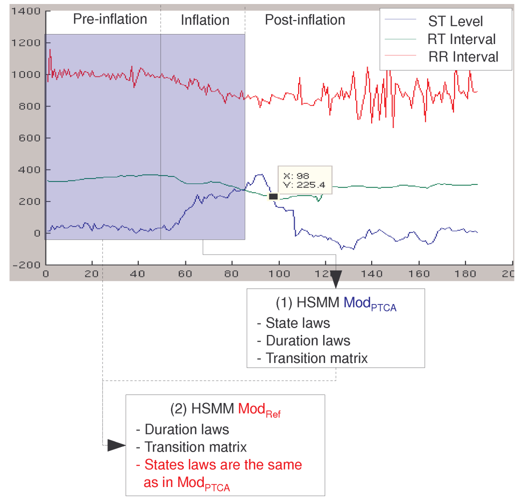

Figure 3. Learning an ischemic and a reference model. As explained in section 2.2, the models are learned in order to differentiate the dynamics, in this example from time series constituted of the RR and RT intervals and ST level.

3.3. Evaluation of the detector

To be sure to obtain results independent to the affectation of the records, 10 training/testing sets have been created. False positives correspond to ischemic detections obtained in preoperational records and false negatives to non detection in records with inflation. These events are accumulated over the 10 different tests. Sensibilities, specificities and error rates are computed with the following relations :

$$Se = 1 - \frac{\text{Nb Fn}}{\text{Nb PTCA}}; \; Sp = 1 - \frac{\text{Nb Fp}}{\text{Nb Ref}};$$

$$\text{Tx Err} = \frac{\text{Nb Fp + Nb Fn}}{\text{Nb PTCA + Nb Ref}}$$

Finally, different evaluations are performed (table 2), according to the indicators taken into consideration.

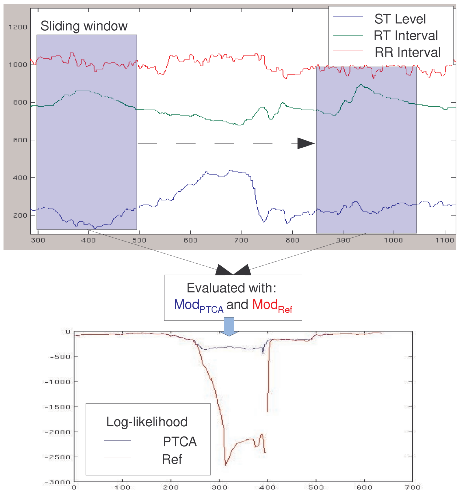

Figure 4. Learning an ischemic and a reference model. As explained in section 2.2, the models are learned in order to differentiate the dynamics, in this example from time series constituted of the RR and RT intervals and ST level.

Table 2. Results obtained on the STAFF3 database , Fn = false negatives, Fp = false positives, Se = sensibility, Sp = specificity.

Indicators	Nb Fn	Nb Fp	Se	Sp	Err rate
RT	13	64	96.0%	80.0%	12.0%
R magn.	40	68	87.5%	78.7%	16.9%
RT and R magn.	17	90	94.7%	71.9%	16.7%
RT and T magn.	10	110	96.9%	65.6%	18.8%

It appears that the indicators RT interval and R wave magnitude provide the most interesting results. The sensibility experimentally measured for the RT interval alone is 96% for a specificity of 80%. This specificity, obtained on the pre-operation records of the STAFF3 database, would correspond to a false alarm frequency rate of 3 false detections per hour of ECG recording.

4. Discussion and conclusions

An ischemic detector, based on HSMM and exploiting multivariate dynamics is proposed. HSMM are applied to learn the difference of dynamics, between an ischemic event and normal conditions, of various indicators extracted from the ECG. An EM algorithm, itself based on the Viterbi algorithm, has been extended to the HSMM to learn its various parameters. With this approach, the dynamics could be efficiently represented by the parameters of the models, with limited computation time and hyperparameters to tune. To test new time series, the two models are put in competition and a threshold is used to provide a decision, according to the likelihoods obtained. Results obtained from the STAFF3 database show the interest of this approach: a sensibility of 96% and a specificity of 80% are obtained. The RT interval appeared to be the most discriminant indicator. An extension of this work could consist in integrating also some more specific indicators about the T wave, like the coefficients of the KLT applied on the T wave [9]. The second indicator that seems to be relevant is the magnitude of the R wave. This result could be related to the observation of changes of the QRS slopes [5].

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Address for correspondence:

Jérôme Dumont
LTSI, Université de Rennes 1
Bat. 22, Campus de Beaulieu
35 042 Rennes Cedex