ECG SEGMENTATION AND P-WAVE FEATURE EXTRACTION: APPLICATION TO PATIENTS PRONE TO ATRIAL FIBRILLATION

Ronan Lepage[1], Jean-Marc Boucher [1],Jean-Jacques Blanc [2], Jean-Christophe Cornilly [2]

[1] ENSTB, d partement SC, BP832, 29285 Brest Cedex, France

[2] CHU de la Cavale Blanche, d partement de Cardiologie, Brest, France

Abstract- **This paper presents an automatic analysis method of the P-wave, based on lead II of a 12 lead standard ECG, which will be applied to the detection of patients prone to atrial fibrillation (AF), one of the most frequent arrhythmias. It focuses first on the segmentation of the electrocardiogram P-wave, which is performed in two steps: first, detection of the QRS complexes, then association of a wavelet analysis method and a hidden Markov model to represent one beat of the signal. After segmentation, the P-wave is isolated and a set of parameters, which have the ability to detect patients prone to AF, is calculated from it. The detection efficiency is validated on an ECG database of 145 patients including a control group and a study group with documented AF. A discriminant analysis is applied and the results obtained show a specificity and a sensitivity between 65% and 70%.**

Keywords *:* atrial fibrillation, ECG segmentation, P-wave, hidden Markov model, wavelets, ECG database

I. INTRODUCTION

Atrial fibrillation (AF) is a very frequent arrhythmia, which affects mainly elderly people: 2% to 5% of people over 60 years old and 10% over 70 years old. It results in partial disorganisation of the atrial electric activity, due to two electrophysiological conditions: slowed conduction velocity in various atrial areas and heterogeneity of the cell refractory period. Although it is not a lethal disease, it can lead to very disabling complications such as cardiac failure and atrial thrombosis, with the subsequent risk of a stroke.

The aim of this study is to try to automatically detect patients prone to atrial fibrillation (AF) during a routine electrocardiogram (ECG) in a cardiology department.

II. DATABASE

We recorded a 12 lead ECG in resting conditions but we only worked on lead II, where the P-wave is the most visible. International ECG databases are available (CSE base, MIT-BIH base) but they are not devoted to AF, with few records on this subject and very little information on the patients. So we decided to create our own database in collaboration with the Brest University Hospital. The signal is sampled at 1 kHz and bandpass filtered between 0.01 Hz and 40 Hz. The records last 1 minute (about 60 beats)

In order to detect patients prone to AF, we considered 145 patients divided into two groups. For each patient, an echocardiogram was recorded to analyze cardiac chamber dimension.

- The control group includes 63 patients (38.4 years old – 14.0, 48 men and 15 women) without any history of atrial tachycardia and with normal echocardiographic atria. In spite of the young age of the patients, this group might include some patients prone to AF. However the mean age of the group, lower than that of the study group, justifies the fact that this group is reliable. An age-matched group has to be built to confirm the results but we need to be sure the people included will not have an AF accident in the years following the recording.
- The study group includes 82 patients (61.4 years old – 13.8, 48 men and 34 women) with documented AF. We included patients who had sinus rhythm restored a few hours or days before analysis. These patients have a similar ECG as they had before their fibrillation. But the results will have to be confirmed via a long-term study.

III. AUTOMATIC SEGMENTATION

In order to obtain an automatic measurement of the P-wave parameters used in the detection procedure, we need to perform an ECG segmentation to accurately isolate the P-wave. The association of wavelet analysis and hidden Markov models (HMM) gives a robust segmentation taking advantages of the ability of signal rupture detection by the wavelet transform and of the statistical description in states by HMM [4]. The ECG is segmented in three steps:

- a redundant multiresolution analysis scheme using a Haar transform with 4-levels of resolution is applied to the ECG signal.
- the QRS complexes are detected by thresholding the wavelet coefficients, which leads to a segmentation of the ECG signal into beats.
- each beat is segmented into waves by applying a HMM to each resolution level , and then by fusing the informations.

Hidden Markov models are based on the hypothesis that at a given instant, the state of the system only depends on the previous state. In addition, the hidden process (the electrophysiological process) is observed through a set of stochastic processes producing the observation. Here, the observations are the wavelet coefficients, whose probability densities are estimated by a non-parametric model.

The ECG represents the electric activation of the heart which takes place in a logical order: first the atria are

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Abstract

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depolarized (P-wave), then the ventricles (QRS complex) and finally the ventricles are repolarized (T-wave). Each state can be associated with a heart activation time [3]. An experimental analysis on the database with various ECG shapes led us to model a beat by ten states: four isoelectric segments and two states per wave (figure 1):

A. state iso1: isoelectric line
B. state P_1: first part of atrial activation
C. state P_2: second part of atrial activation
D. state iso2: isoelectric line
E. state Q_1: first part of the ventricular activation
F. state Q_2: second part of ventricular activation
G. state iso_3: isoelectric line
H. state T_1: first part of the ventricular repolarization
I. state T_2: second part of the ventricular repolarization
J. state iso_4: isoelectric line

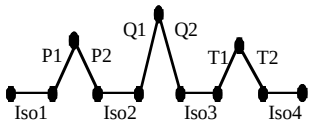

Figure 1: the different states of the hidden Markov model.

From the study of our database, we defined a left-right model (figure 2) with:

- at most the possibility of jumping one state except after P2, Q2 and T2 (if the model does not go back, it necessarily goes to the following state),
- three back transitions allowed: P2-P1, Q2-Q1 and T2-T1.

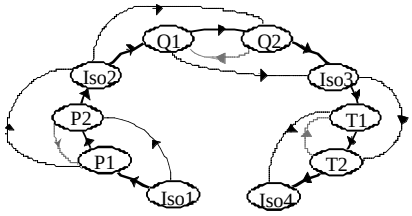

Figure 2: the possible transitions of the hidden Markov model for the ECG.

To estimate the probability densities of the wavelet coefficients in each state we used a gaussian kernel estimator [8]. The kernel density estimation is an attractive non-parametric estimator and a diffeomorphism suppresses border convergence difficulties by using an appropriate regular change of variable.

This method is applied to each resolution level, which produces four segmentations for one ECG signal (figure 3). The problem is how to select the resolutions giving the best results. Some of them are excluded on medical grounds: for instance, it is known that a P-wave has a duration between 60 and 190 ms, and we can suppress those which are outside these limits. For the others, the values are averaged.

The choice of the learning base is essential. All the cases that might be encountered have to be included. However the learning phase can be repeated when a new configuration appears so that the model can be adapted. We tried to include most of the configurations we encountered, especially the different P-wave shapes [1]. We selected 24 patients and 10 beats for each of them in the segmentation learning procedure. We compared the results between manual and automatic segmentations by taking the duration of the mean of the P-wave as a parameter. Two different cardiologists (cardiologist 1, cardiologist 2) performed two manual segmentations.

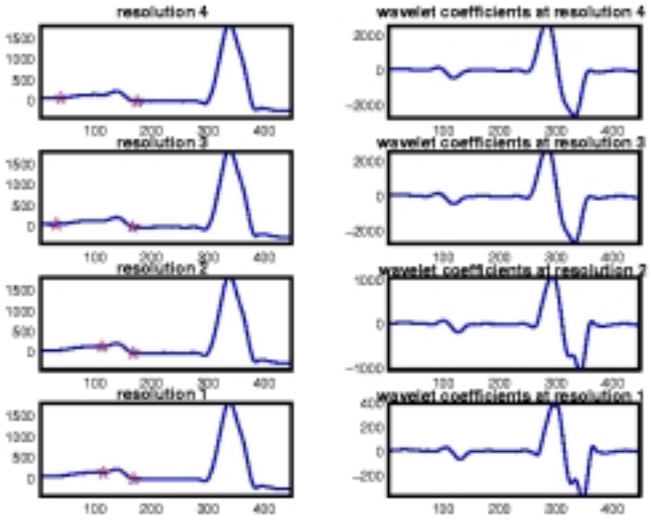

Figure 3: P-wave segmentation at each resolution level (indicated by *)

The coefficient of correlation between these two manual segmentations was 79% and the associated standard deviation: 11. We remark that there exist some differences between the two cardiologists, but in fact these differences are relatively unimportant (low standard deviation) and in fact insignificant. The higher differences were noticed when the beginning and the end of the P-wave were difficult to choose in the presence of a lot of noise. The exact moment of the beginning or end of the atrial depolarization can be hard to find on some ECGs (the rise of the slope can be very slow), but these exact moments are poor in information, so a difference of 20 ms or more on a P-wave segmentation can be acceptable for our study. Assuming that cardiologists did not make mistakes in their segmentations, we considered that both were correct and took them as references for the rest of the study. In order to compare these with automatic segmentation, we plotted the mean (cardiologist 1,cardiologist 2) versus automatic segmentation (figure 4). We found a correlation coefficient of 77% and a standard deviation of 13.

After the isolation of a P-wave by segmentation, parameters are measured on it in order to proceed to a classification. The lengthening of the P-wave duration is a classical parameter used by physicians for the detection of patients who have suffered from atrial fibrillation. The P-wave high frequency part seems to contain information on the atrial conduction defect. The ratio of spectral power contained in the 20-50 Hz band and in the 0-20 Hz is known to be greater for patients with AF [5] and the ratio of the power contained in the 20-30 Hz and in the 0-30 Hz to be smaller [6]. For the detection procedure, the first step is to measure such parameters on the P-wave, and the second step to apply a discriminant analysis by using these parameters.

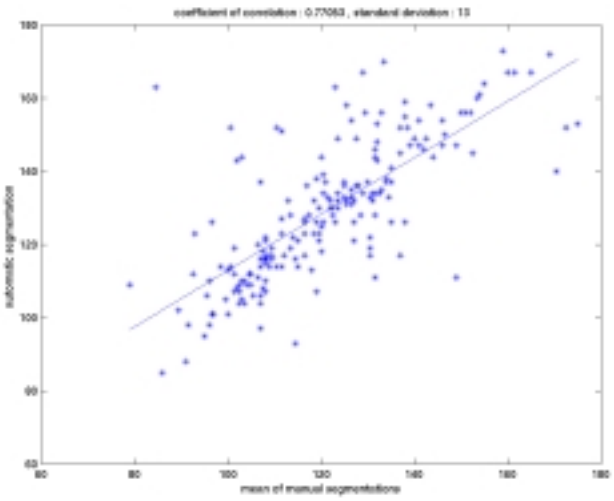

Figure 4: Comparison between manual and automatic segmentation on the P-wave duration mean

IV. DETECTION OF PEOPLE PRONE TO ATRIAL FIBRILLATION

We defined three types of parameters:

Time parameters: the P-wave duration which is easily computed from the segmentation.

Shape parameters : one of them is computed by the repartition function method [7]. If f (t) is the function describing a shape, the repartition function is defined by $F(X) = \frac{\int_{-\infty}^{X} f(t)dt}{\int_{-\infty}^{\infty} f(t)dt}$. In order to compare two shapes f (t) and f' (t), the area of the difference between F (X) and F'(X) is computed and is compared to a threshold, which is estimated from the learning base. The other parameters are the coefficients of a 4th order polynomial interpolation of the P-wave .

Spectral parameters: these are extracted from a Morlet continuous wavelet analysis [2] obtained on the segmented P-wave. The QRS complex is suppressed, which avoids having to take it into account (for low frequencies, the wavelet extends to the QRS complex, which has higher amplitude and disturbs the P-wave analysis). As we know the position of the P-wave, we replace the rest of the ECG with an isoelectric line. The following parameters were chosen: if D is the P-wave beginning and F its end (in ms), the parameters are the energy computed in the following temporal windows: D-32 to D+32, D to D+64, D to F, F-64 to F, F-32 to F+32 and in the following spectral bands: 0 to 15.625 Hz, 15.625 to 31.25 Hz, 31.25 to 46.875 Hz

A feature selection procedure using a Fisher's discriminant analysis led to a hierarchical choice of the parameters. For the evaluation of the classification , we will consider two cases :

.l=3 with three main features, which are
the repartition function value,
the energies in the band 3.9 and 7.8 Hz for D to F, 31.2 and 62.4 Hz for D to F,

. l=10 with ten features :
two polynomial coefficients,
the repartition function value,
the energies in the band 31,2 to 62,4 Hz for D to D+64,0,9 to 1,9 Hz for F-64 to F,15,6 to 31,2 Hz for F-64 to F,31,2 to 62,4 Hz for F-64 to F,0,9 to 1,9 Hz for D to F, 3,9 to 7,8 Hz for D to F,31,2 to 62,4 Hz for D to F

From this study, it can be concluded that the P wave duration is not the most pertinent feature to be used for the classification of patients prone to AF.

IV. RESULTS OF THE CLASSIFICATION

The whole database (145 patients) is composed of 82 documented AF patients and 63 normal patients. The system evaluation must take the low size of the database into account. On one hand, the resubstitution method ¤, which uses the same set for training and testing, is known to be a biased estimate of the error probability and to give an optimistic value. On the other hand, the holdout method (H), which consists in splitting the whole database in two, one part for training, the other part for testing, gives an unbiased estimate of the error probability, but overestimates it. A good compromise is to compute the mean (M) of these estimators to have a more realistic value of the true error probability. The learning and test bases contain N samples, divided in two sets of N_1 samples of AF patients and N_2 normal patients. The number l of selected parameters must stay low, because the ratio N/l must be large enough to preserve generalization properties of the classification system. A classic linear discriminant analysis is used for the detection. A 10 times trial is made where we randomly choose the two bases among the

145 patients and we estimate the specificity and sensitivity of the test in function of the number of selected parameters.

Table I shows these values for N=64, N_1= N_2=32, l=3 or 10.

l	3	10
R	Sp=0,69 (0,12) Se=0,70 (0,08)	Sp=0,76 (0,08) Se=0,7 (0,07)
H	Sp=0,696 (0,14) Se=0,63 (0,14)	Sp=0,55 (0,135) Se=0,67 (0,09)
M	Sp=0,65 Se=0,68	Sp=0,69 Se=0,67

Table I : Specificity and sensitivity of the discriminant analysis with l=3 or 10 for the resubstitution method, the holdout method and the mean. (in parenthesis, the associated standart deviation)

IV. DISCUSSION

A. Segmentation

One difficulty is to know whether segmentation is good or not. We compared the mean values of the P-wave duration resulting from automatic segmentation to those resulting from manual segmentation performed by specialists for each patient. Although the beats are amplified, specialists can make errors:

- the onset and end of the P-waves are difficult to define. If those instants have a well-defined electrophysiological meaning, they are not easily seen on the recording,
- the number of beats and the eye of the operator are also sources of inaccuracy.

The main errors were due to configurations too rare in our database and consequently not presented in the learning base. However, results are good and the advantages of the model are that it is quite simple and can evolve: it can be modified for new configurations if the learning base is adapted. Its robustness is good but can be increased:

- we may change the compromise between robustness to noise and detection of small artefacts,
- we may increase the learning base to be able to recognise as many configurations as possible,
- we may add new parameters to better describe each state, for example using more than one lead.

B. Classification

Results obtained are very promising and leads us to think that many people prone to AF could be detected. However, a long-term study has to be made to know wether the parameters are adapted to this purpose. Patients detected as risking an AF risk must periodically be tested; we also need to build reference groups including the different shapes of the P-waves .

V. CONCLUSION

This paper presents a P-wave segmentation method applied to an automatic classification of people prone to atrial fibrillation, one of the most frequent heart arrhythmia. The study is performed on lead II of a standard 12 lead electrocardiogram. The segmentation procedure, based on hidden Markov models and wavelets, takes into account some statistical properties of the signal but also some electrophysiological properties. However, it is simple, evolutional and robust. The classification results presented are good and show that this method could be of great help for medical diagnosis.

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