HIDDEN MARKOV MODELS COMPARED TO THE WAVELET TRANSFORM FOR P-WAVE SEGMENTATION IN EGC SIGNALS

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ABSTRACT

The aim of this study is to detect P-wave onset and end of electrocardiograms (ECG). This wave is important for detecting people prone to atrial fibrillation, one of the most frequent heart diseases, but the wave is very difficult to segment accurately because of its small amplitude and the very different shapes it can take. Two different methods are tested for the segmentation : the first one is based on Hidden Markov Models. Though results are good, some particular cases are not well segmented. However a second method based on the Continuous Wavelet Transform can solve those problems.

1 Introduction

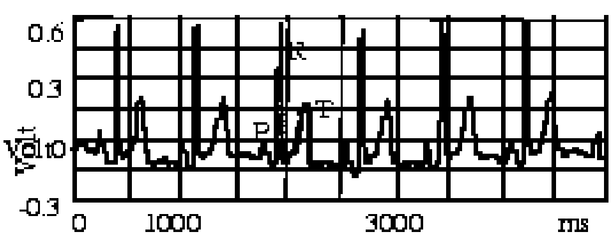

Figure 1: an electrocardiogram

P-wave detection is an important issue for many diagnosies, but is rather difficult because of its low amplitude compared to those of QRS complexes and T-waves, and its variable shape. Many approaches have been tested :

- adaptive methods which suppress R and T waves in order to better detect the P-waves [1],
- methods based on time-frequency transforms [2]
- syntactic methods using an alphabet to represent the different possible aspects of the signal [3]
- statistical methods, like Hidden Markov chains, based on the probability density of some parameters describing the signal [4].

The first approache, sometimes efficient, is difficult to adapt to a new database or to new configurations due to the use of empirical thresholds. Time-frequency methods and syntactic methods try to be more general. The advantage of statistical methods is that they can be used for any sort of configuration if the learning base is adapted. However there is no parameter which perfectly differentiates each state of an ECG. The Hidden Markov Model allows the evolution of the signal to be taken into account. The segmentation will consist in recognizing every state and the points of changes of state.

In collaboration with the Brest University Hospital, a database of 179 patients was built. Lead II of a standard twelve lead ECG was studied in relaxed conditions. The signal was sampled at 1 kHz and bandpass filtered between 0.01 Hz and 40 Hz. The recordings lasted one minute.

2 Segmentation based on a Hidden Markov Model

2.1 The model

First, the QRS complexes are detected. Many efficient methods exist for this step and the mistakes that they cause are rare, so the methods will not be detailed here. Then, a Markov Model [5] was defined representing a single beat. The observed parameter is the local slope of the ECG. An amplitude measurement alone or associated with the slope was also tried, but it caused a reproducibility problem: the amplitudes of the waves are very different from one signal to another and the baseline fluctuations modified the results a lot. However

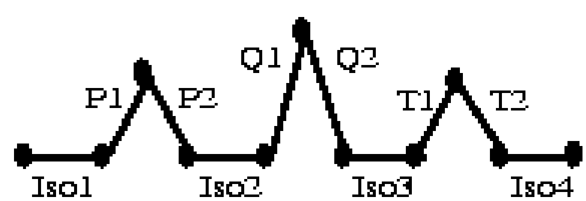

Figure 2: the different states of the Hidden Markov Model

their influence on the slope is limited and this parameter does not vary so much from one patient to another.

A beat is decomposed into ten states : four isoelectric segments and two states per wave (figure 2).

Each state can be associated with a phase of the heart activation. This model can be used for any lead but the states would then not necessarily correspond to the same activation phases.

Hidden Markov Models allow the temporal evolution of the observation. to be taken into account The ECG represents the electrical activation of the heart which takes place in a logical order : first the atria are polarised (P-wave), then the ventricles are polarized (QRS complex) and finally depolarized (T-wave). Pathologies can modify this evolution and must be included in the learning base in order to be recognized. n order to rep-

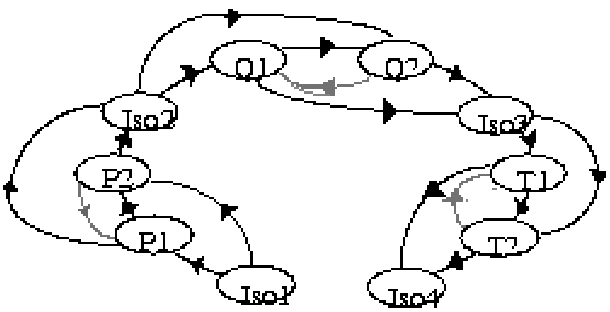

Figure 3: the possible transitions of the hidden Markov model for the ECG.

resent this evolution, our model is based on a left-right (or Bakis) model: the state index increases with time. But such a model is not sufficient. We have added more jumps to allow the model to go back in certain conditions and to jump some states. So a left-right model was defined with (figure 3) :

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

Although the defined states are sufficient for any situation encountered the transitions allowed are not. For example a premature ventricular beat (a QRS complex appearing without a P-wave before it) cannot be detected. Such a detection would be possible if a transition from state 1 (Iso 1) to state 5 or 6 (Q1 or Q2) existed. We did not consider such situations because they were not frequent enough in our database. But a simple modification would allow such a recognition.

2.2 Estimation of densities

To estimate the probability densities of the slopes in each state a kernel-diffeomorphism estimator [6] with a gaussian kernel was used. The kernel density estimation is an attractive non parametric estimator and the diffeomorphism suppresses border convergence difficulties by using an appropriate regular change of variable. Using this estimator, the probability density function of the slope in each state was estimated:

2.3 Results

The choice of the learning base is essential. All the cases that can be encountered have to be included. However the learning phase can be repeated when new configurations appear so that the model can be adapted. We have included most of the configurations we encountered, especially the different P-wave shapes [7].

With 179 signals in our base, only 24 patients were included in the learning base and 10 beats for each of them. A larger learning base would probably give better results but keeping a small base will give more reliable results, not too dependent on our database.

One difficulty is to find a compromise between noise sensivity and the detection of small artefacts as shown on the first P-wave in figure 5. This is done during the learning process and has to be validated according to the quality of the ECG recordings.

RESULTS:	**119** segmentations with an error under 10 ms. **42** segmentations with an error between 10 ms and 20 ms. **18** segmentations with an error over 20 ms.

2.4 Comments

The results are good. The advantage of this model is that it is quite simple and evolutive: it can be modified to new configurations if the learning base is adapted. Its robustness can also be increased:

- we can change the compromise between robustness to noise and the detection of small artefacts,
- we can increase the learning base to be able to recognize as many configurations as possible,

It can also be easily adapted to other leads or other recording conditions. However, the main problem is a segment PQ with a slope different from zero followed by a small and negative Q-wave. The model does not detect the end of the P-wave. To solve this problem, we can use the capability of the wavelet transform to detect singularities [5].

3 Segmentation based on the continuous wavelet transform

A Morlet wavelet was used. The main problem is the size of the analysing wavelet at low frequency resolution, because it takes the QRS complex into account when it is centered on the P-wave (figure 7).

So, a hierarchical algorithm was implemented: we first detect the QRS complexes, then we suppress them and search for the P-waves.

To detect the QRS complexes, the wavelet transform of the signal is computed. It is a matrix with N lines (the number of decomposition levels) and M columns (the number of samples). The maximum of each column is detected, as well as the number of the line (the level), where it is obtained, which is called the index of the maxima (figure 6).

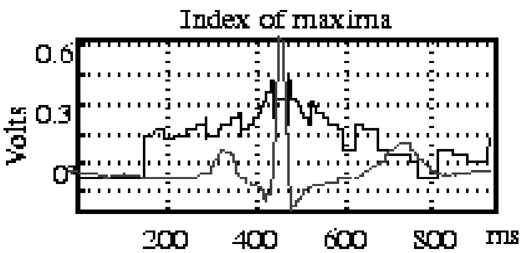

Figure 6: signal and maxima indexes.

We notice that important transitions are obtained for singularities. After detecting the biggest ones, their level gives the point where the segmentation of the QRS complexes must occur.

A derivation is then made followed by squaring this level.

To determine the QRS peaks, onsets and ends. It is interpolated by a third order polynomial in order to avoid important discontinuities (figure 8).

A new wavelet transform is then computed on the resulting signal and the same process is applied to detect the P-waves. But the P-wave frequency content is low so the result obtained is not accurate because the level considered has a bad time resolution. To improve accuracy the maxima chains are followed, level after level, on the wavelet transform in order to make the decision at a higher time resolution level (figure 9).

The configuration shown in this example is not well segmented using the hidden Markov model because of the negative slope of the PQ segment. The wavelet transform enables this problem to be solved. However, some thresholds are needed and their calculation make this algorithm difficult to generalize.

4 Conclusion

Two complementary methods of ECG segmentation have been presented. Hidden Markov Models can easily be applied to new signals by modifying the learning base. However the probability density functions are not clearly separated and, in certain cases, some mistakes between different states can be made. In these cases, the wavelet transform appears to be more accurate and can be an efficient solution to the problem.

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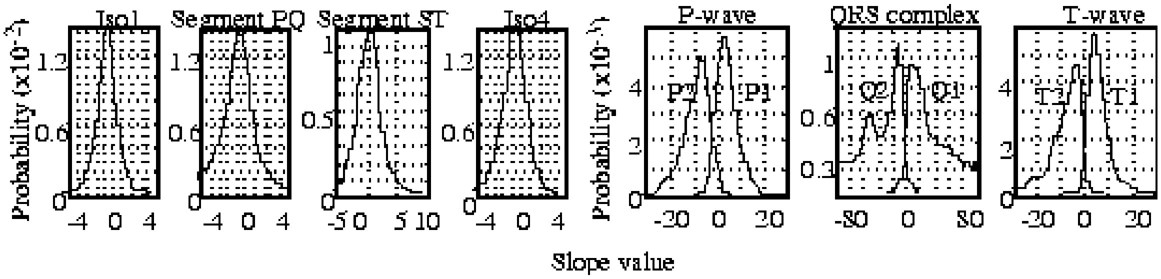

Figure 4: Probability density function of the slope in each state.

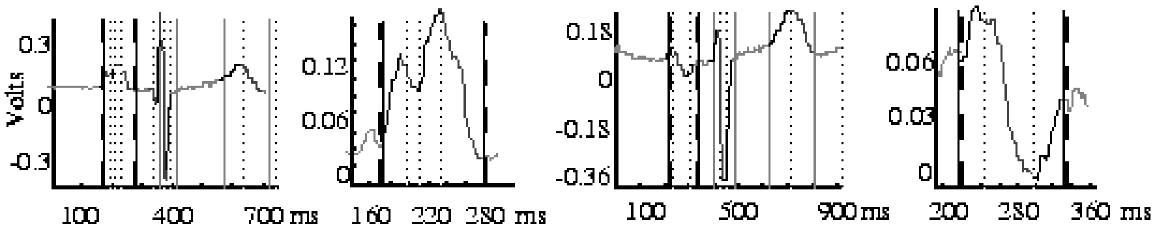

Figure 5: segmentation of two different beats; the results are accurate.

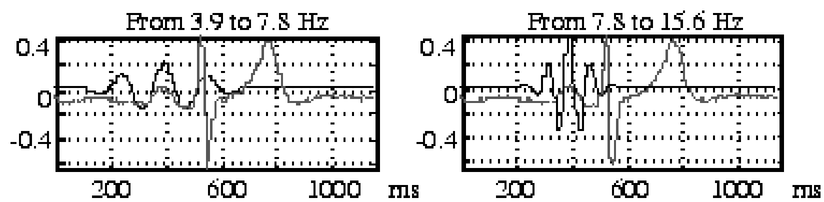

Figure 7: signal and analysing wavelet at low frequency resolution.

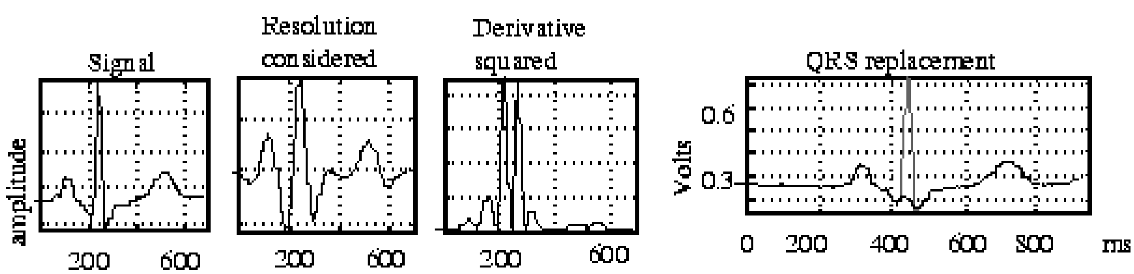

Figure 8: detection and replacement of a QRS complex.

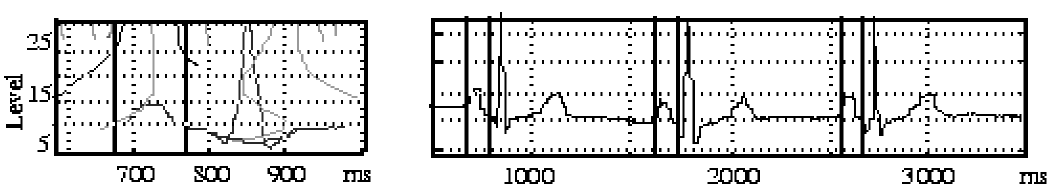

Figure 9: Detection of P-wave onset and offset using the maxima chains.