Cd-Hmm For Normal Sinus Rhythm

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ABSTRACT

To diagnose the cardiac abnormalities, it is important to detect and classify the cardiac arrhythmias. To achieve this we have to use the specialized program tools and visual demonstrations of new methods, as propagated by researcher from time to time. Our work is focused on classification of normal sinus rhythm and premature ventricular contractions of the human heart. We are using the wavelets for the feature selection and extraction (searching for a local maximum in the contour envelope successfully detects R-peaks) and Continuous Density Hidden Markov Models (CD-HMM) for the classification. The ECG data is taken from standard MIT-BIH arrhythmia database.

I. INTRODUCTION

The automatic processing systems are most frequently applied in medical domain as it is quite natural because modern medicine generates huge amounts of data, but at the same time there is often a lack of data analysis, classification and understanding. New methods can help in dealing with this problem; they can simplify and usually speed up the processing of large volumes of data. New algorithms work in time-frequency domain and combine some advantageous characteristics known from classical methods – mainly they allow frequency analysis with time information about analyzed features.

The automated detection and classification of cardiac arrhythmias is important for diagnosis of cardiac abnormalities. In practice, unsupervised methods may be required to detect arrhythmias in changing environment. Hidden Markov models are often used for such tasks in speech recognition but also in ECG processing. HMM can be combined with wavelet transform to obtain improved results [3].

Our work is focused upon the detection of premature ventricular contractions (PVC) among normal sinus rhythm (NSR). Premature ventricular contractions - these early depolarizations begin in the ventricle instead of the usual place, the sinus node. They are very
common, and are sometimes perceived as a palpitation. They often occur without the patient being aware of it at all. PVC's occure in bigeminy, trigeminy, quadrigeminy, ventricular tachycardia, ventricular fibrillation, etc.

An increased frequency of PVC's in patients with heart disease is statistically predictive of ventricular fibrillation and sudden death. In patients with some types of heart disease, PVC's or ventricular tachycardia do indicate an increased risk of serious arrhythmias. Therefore this work is focused on their detection.

II. METHODS

2.1 CONTINUOUS WAVELET TRANSFORM

In the proposed method, input data were transformed by continuous wavelet transform (CWT):

CWT(a,b) =

$$\frac{1}{\sqrt{a}}\int_{-\infty}^{\infty} \left(\frac{t-b}{a}\right) f(t)dt$$

where a is a scale and b is a time shift. Time-frequency spectrum enables to measure time-frequency changes in spectral components. Interpretation of a time-frequency resolution by CWT is as follows: CWT represents time-frequency decomposition realized by correlation of signal $f(t)$ with basic functions derived from the mother wave $\psi(t)$. Haar function was used as the mother wavelet for its simplicity:

$$\psi_H(t) = \begin{cases} 1 & 0 \le t < \frac{1}{2} \\ -1 & \frac{1}{2} \le t \le 1 \\ 0 & \text{others}, \end{cases} \qquad (2)$$

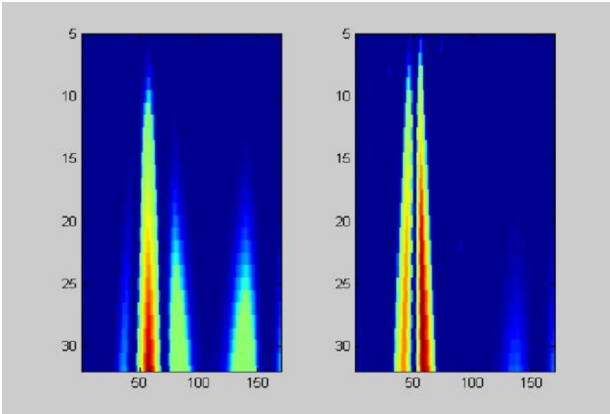

Fig. 1: *Continuous wavelet transform of the raw time data series (left panel – premature ventricular contraction, right panel – normal sinus rhythm).*

Scales were finally chosen from an interval of <1; 40>. The signals were extracted as periods of 250 samples (f_s=360 Hz) containing R-waves of each QRS complex. After transforming by CWT, the wavelet coefficients were squared and normalized.

2.2 Continuous Density Hidden Markov Model (Cd-Hmm)

The Hidden Markov model is a finite state machine having a set of states Q, each of which is associated with probability distribution, an output alphabet O, transition probabilities A, output probabilities B, and initial state probabilities **Π**. The current state is not observable. Instead, each state produces an output with a certain probability B. The CD-HMM stage is proceeded by the pre-processing step (CWT).

Continuous emission probability $B = \{b_j(O_t)\}$, where $O = O_1, O_2, \ldots, O_T$, the emission probability density function of each state is defined by a finite multivariate Gaussian mixture:

$$b_j(O_t) = \sum_{m=1}^{M} d_{jm} N(O_t, \mu_{jm}, C_{jm}), \qquad 1 \le j \le N \qquad (3)$$

where O_t is the feature vector of the sequence being modelled, d_{jm} is the mixture coefficient from the mth mixture in state j and N is a Gaussian probability with mean vector μ_{jm} and covariance matrix C_{jm} for the mth mixture component in state j. We will refer to these models as a continuous density HMM (CD-HMM).

The used CD-HMM had left-to-right topology. The number of states is possible to change. The first state is designated as the initial state and the last state as the output state.

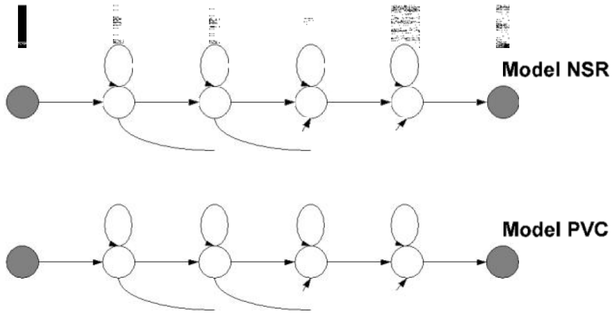

Fig. 2: *Structure of the used hidden Markov model.*

Initial transition probability A (for example for 10 state model) is:

$$A=\begin{bmatrix} 0100000000 \\ 00.330.330.33000000 \\ 00.330.330.3300000 \\ \ldots \\ 0000000000 \end{bmatrix}$$

Three problems are considered as fundamental in hidden Markov modelling applications:

1) Estimation of hidden Markov model parameters from a set of representative training data (parameters include state transition probabilities, output probabilities).

2) Efficient calculation of P (O|□)- the probability that a given observation sequence was generated by a particular hidden Markov model □ .

3) Determination of X*, the most likely underlying state sequence corresponding to a given observation sequence 0 such that P (0| X*,□) is maximum.

The importance of solving the first problem is obvious; model parameters must first be estimated before the models can be used for classification purposes.

Baum-Welch algorithm was used as a training method to find hidden Markov model parameters A, B with the maximum likelihood of generating the given symbol sequence in the observation vector.

The probability of state occupation must be calculated. This is done efficiently using the so-called Forward-Backward algorithm.

The solution to the second problem is often used as the basis for a classification system. By computing P (O|□) for each of*i* possible models and choosing the most likely model, classification can be inferred.

An alternative classification approach uses the solution of the third problem to find the single best state sequence which maximizes P (0| X*,□). Classification can then be inferred by choosing the model with the most likely best state sequence, which requires less computation than determining the most likely model.

The logarithmic Viterbi algorithm was used for the recognizing. It determines the most probable route to the next state, and remembers how to get there. This is done by considering all products of transition probabilities with the maximal probabilities already derived for the preceding step. The largest such is remembered, together with what provoked it.

Scaling the computation of Viterbi algorithm to avoid underflow is non-trivial. However, by simply computing of the logarithm it is possible to avoid any numerical problems.

III. RESULTS

The proposed method was used in an educational graphical program in Matlab environment. The program allows selection of a number of states and initial transition probabilities of the HMM model. After the reading of signals, students can visually follow whole classification process. They can also see results of the wavelet transform of the signal and the training process. They can compare results of the classification using transformed and raw ECG data.

The ECG data were taken from the standard MIT-BIH arrhythmia database automatically as a sequence of 250 samples (100 samples before R-waves and 150 after the R-waves. Graphical interface of the realized program is depicted on Fig.3.

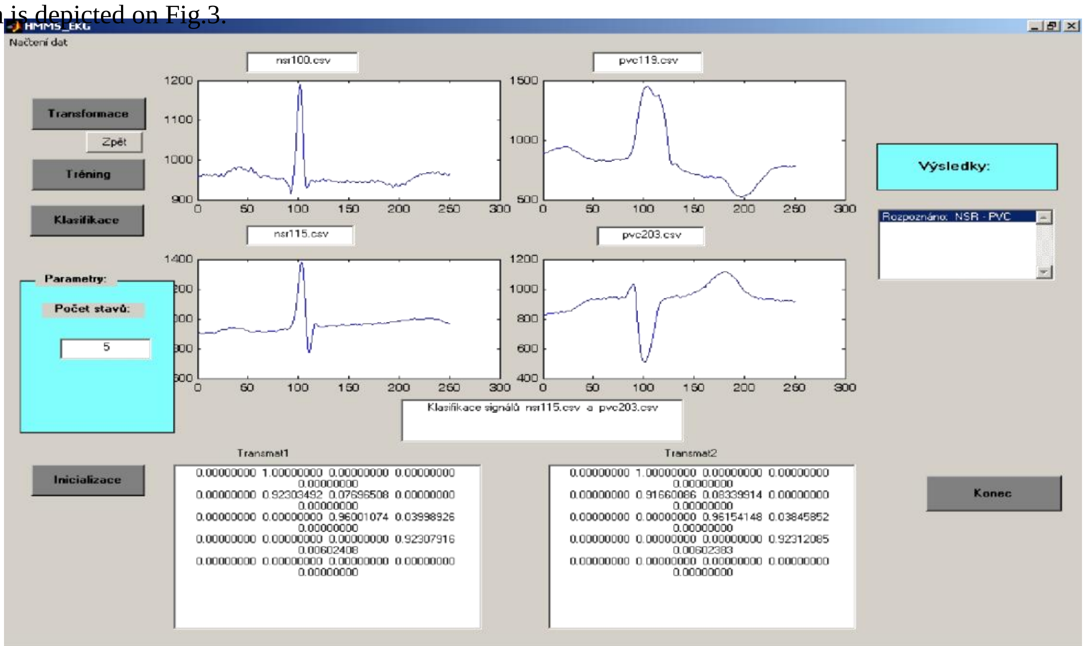

Fig. 3: *Custom-made program tool interface*

IV. CONCLUSION

An algorithm employs unsupervised way of the classification. Our work is focused on classification of normal sinus rhythm and premature ventricular contractions. It is demonstrated that wavelet methods can be used to generate an encoding of the ECG which is tuned to the unique spectral characteristics of the ECG waveform features. Left-to-right CD-HMM was used.

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