Adaptive Time-frequency ECG Analysis

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Abstract

Non-stationary analysis of ECG using Choi-Williams (CW) distribution is presented. Analysis was applied on subjects with AMI who have undergone thrombolysis, in V1 Holder recordings. Two groups of patients were regarded: successfully and non-successfully thrombolysed patients. The time-frequency map generated by CW transform was divided in nine areas, relevant to ECG features. Characteristic parameters were extracted from each area and linear discriminant analysis was applied on these parameters, leading to a prediction index. Applying the method to ECGs at the sixth hour after lysis, the successfully thrombolysed patients were distinct from the non-successfully thrombolysed ones.

1. Introduction

The current study addresses the problem of ECG analysis using features based on Choi-Williams transform (a modification of Wigner-Ville transform). Definition of area s of interest for the specific problem and selection of appropriate features that ensure efficient classification are the main issues discussed. The task of feature selection, not a trivial task in general, is approached in a heuristic manner, rather than using a typical statistical test.

As an example, the classification of thrombolysis success was examined. Previous studies have also applied Time-Frequency analysis in order to explore occlusion-reperfusion phenomenon as well as the effect of angioplasty on ECG. In the present work, a quantitative approach is proposed, leading to the classification of cases.

Analysis was applied on ECG data from MI patients who had undergone thrombolysis. Two groups of patients were regarded, successfully and non-successfully thrombolysed. The Time-Frequency plane was divided in areas and parameters (max value and energy) were calculated in each area. These parameters were used for classification, using linear regression. Bootstrapping was applied for the calculation of regression coefficients, thus leading to a robust classification even with a small dataset.

Adaptivity was introduced in two ways: by selection of the most appropriate features from a pool of calculated parameters and by adjustment of the most interesting time-frequency areas for the calculation of parameters. Selection of features may be initiated by use of a statistical independence test, like t-test. Other classification criteria are introduced and further used in the iterative feature selection procedure, like maximization of inter-class distance and minimization of intra-class distance, for class compactness. A feature from the pool of parameters that meets the predefined criteria is added to the feature vector and the iterative procedure is repeated until convergence. Another heuristic method is used for fine-tuning of the time-frequency areas of interest. Initial setups are used and the classification procedure iterates adjusting the time-frequency areas in order to succeed maximization of the classification criteria.

2. Methods

The general procedure proposed in the current work comprises of the steps displayed in Figure 1. The initial signal undergoes a time-frequency transformation, so that signal components are revealed. Features are extracted from the time-frequency plane. A linear function of the selected features is assumed to be capable of discriminating the two groups of successfully and non-successfully thrombolysed patients. The weights of the linear function are thus calculated and various aspects of classification are discussed. Finally the linear classification function is considered as system model function and its behavior at different stages of thrombolysis is explored.

2.1. Data used

ECG data were acquired from AHEPA Cardiological Clinic of Thessaloniki. Twenty onepatients were examined, all of which had undergone thrombolysis after MI. Thrombolysis was successful for twelve of them. All patients had 2 channel magnetic tape Holter recordings for

48hrs following onset of thrombolysis and for 24 hrs prior to discharge (7^{th} or 10^{th} day). Patients with bundle brunch block were excluded. Holter data (V_1 type lead) were digitized at 800 Hz.

Time-series of 512 samples were processed, corresponding to one ECG-beat or 640 msec. QRS complex was detected all signals were aligned according to QRS complex. Noise reduction filters were applied where necessary.

In order to reassure a more robust statistic and override the problems related to single beat processing, three consecutive beats are stored and analyzed for each patient and each time (0-12hrs). For each subject, the average of the three beats was used in the analysis, thus reducing small statistical differences due to additive noise.

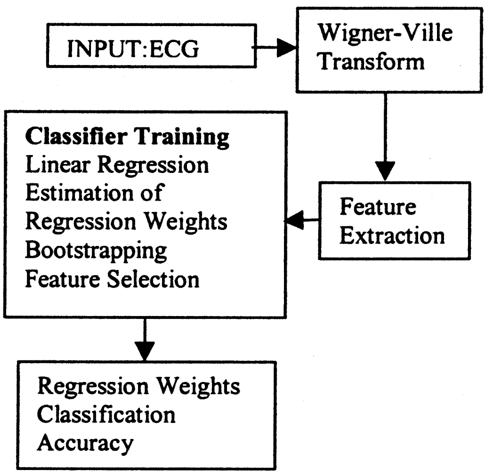

Figure 1. General view of the Methodology followed

2.2. Time-frequency analysis

The Wigner-Ville Distribution (WVD) is a time-frequency representation with excellent time and frequency resolution, appropriate for signal analysis [1]. Let x(t) be a complex continuous time analytic signal. The WVD distribution is defined in the time domain as:

$$W_x(t,f) = \int_{-\infty}^{\infty} x(t+\tau/2)x^*(t-\tau/2)e^{-j2\pi f\tau}d\tau \quad (1)$$

(1)

The discrete time equivalent of (1) is:

$$W_x(nT,f) = 2T\sum_{l=-L}^{L} x(n+l)x^*(n-l)w(l)w^*(-l)e^{-j4\pi fl} \quad (2)$$

where T is the sampling period and w is a sliding symmetrical, finite-length analysis window, w(lT)=0 for abs(l) > L. The above relation gives the Discrete Wigner Ville Distribution (DWVD) at the time origin. The DWVD at any point in time can be evaluated by shifting signal x(t) so that time t is mapped to the time origin.

In order to avoid aliasing (interference between the negative and positive regions of the spectrum), the equivalent analytic signal of the initial real signal has to be used, as defined by equation 3. It is obtained by adding to the real signal its Hilbert transform as the imaginary part.

$$z(n) = x(n) + jH[x(n)] \quad (3)$$

where H[] is the Hilbert transformer.

The mathematical properties of the Wigner distribution make it an attractive function for the time-frequency representation of a signal. However, the Wigner distribution often peaks in regions of the time-frequency plane that do not correspond to our intuitive notion of the time-frequency structure of the signal under analysis. These regions were identified as the cross terms. In case we have a multi-component signal, such as a seismic recording, the interference by the cross terms may seriously hamper the interpretation of the Wigner distribution as a time-frequency energy density function.

Cohen's general class of TFD's is defined by

$$W_C(t,f) = \iint \varphi(\vartheta,\tau)W_x(\vartheta,\tau)e^{j2\pi t\vartheta - j2\pi f\tau}d\tau d\vartheta \quad (4)$$

where the kernel $\varphi(\vartheta,\tau)$ specifies the particular distribution that is obtained.

Since the WS is a quadratic transform, the WS of the sum of two signals is not the sum of the individual WS's, but also has cross-terms. These cross-terms make it difficult to interpret the WS. These cross-terms may be suppressed by appropriate filtering, in the ambiguity function domain, that is, by appropriate choice of the kernel $\varphi(\vartheta,\tau)$.

In order to reduce the effects of the cross-terms, Choi and Williams [2] proposed using the kernel

$$\varphi(\vartheta,\tau) = \exp(-\vartheta^2\tau^2/\sigma^2) \quad (5)$$

where the parameter σ controls the suppression of cross-terms and the frequency resolution. The bigger σ gets, the more it resembles Wigner-Ville distribution. Unfortunately, increased suppression of cross-terms invariably leads to smearing or loss of resolution of the auto terms in the time-frequency plane. The value of σ applied in the current work was 0.025.

2.3. Definition of parameters

In order to proceed to classification, a quantitative approach has to be followed. In this direction, parameters have been defined that represent the characteristic features of the time-frequency distribution of the ECG in a reduced subspace, compared to the initial time-frequency data. These features will be used as input in the classification process.

$$Mean_i = \sqrt{\frac{\sum_{t=t_i}^{t_{i+1}}\sum_{f=f_j}^{f_{j+1}}|DCWD(t,f)|^2}{num}}$$

$$Max_i = \max\{DCWD_{abs}(t,f)\}, \quad t_i \le t < t_{i+1},\ f_i \le f < f_{i+1} \tag{6}$$

The Mean and Max stated in Eq. 6 correspond to the total energy and the maximum value of a time-frequency area. The Discrete Choi-Williams distribution is stated as *DCWD*.

Eighteen parameters are eventually extracted from each DCWD, which are simple and basic features of the time-frequency map. The parameters and the naming used are explained in Table 1.

For simplicity, a sequential index (1-18) will be assigned to each parameter, as follows

T1F1MN=1, T1F2MN=2, T1F3MN=3
T2F1MN=4, T2F2MN=5, T2F3MN=6
T3F1MN=7, T3F2MN=8, T3F3MN=9
T1F1MX=10, T1F2MX=11, etc

2.4. Classification - bootstrap method

In the present work, the available sample of patients is apriori classified in two groups, according to the success of thrombolysis, a distinction based on clinical evidence.

Our hypothesis is that a linear combination of the selected features (linear discriminant function) will classify cases in two classes reflecting the two groups of thrombolysis. The time-frequency features discussed in section 2.3 are used as variables in the linear expression of Eq 5 and the weights α_i of the discriminant function for each parameter i are estimated (the weights α_i in Eq 7). Finally, their contribution to the discrimination of the two groups is investigated.

$$f = \sum_i a_i \cdot parameter_i \qquad f = 10 \ \text{for group1} \qquad f = -10 \ \text{for group2} \tag{7}$$

Since the available amount of medical data was not really big, a Bootstrap technique through resampling of data was applied in order to produce robust statistics from a small sample of measurements [3]. The bootstrap is essentially a computer-based method to repeat experiments, with slightly different datasets produced by reassignments of observations. These assignments and recomputations are done thousands of times and treated as repeated experiments. In the present work, implementation of bootstrapping involves the repetition of the regression algorithm (Eq 7), each time with a different dataset generated via permutation of the initial dataset. After a large number of such repetitions, a statistic is produced for each estimated weight (α_i) and the mean value for each weight is depicted from the statistic, while confidence intervals are also calculated for each estimate.

Four classification criteria were considered:

- Least Classification error
- Maximum Distance between means of classes (ideally=10-(-10) =20)
- Minimum Mahalanobis Distance within each group, meaning that the class is concentrated
- Maximum Mahalanobis Distance between the two groups, meaning that the classes are distincted

2.5. Interval fine-tuning

The parameters defined in 2.3 are calculated in predefined intervals. Intuitively, the initial intervals set correspond to QRS, ST, T waves, which are recognized areas and correspond to well defined cardiac functionality. However, fine-tuning of the intervals is needed in order to find the best intervals, and it is performed heuristically.

Starting with initial values, intervals are randomly modified within a range and best performance is seeked according to least error and a cost function which is a combination of the criteria set above.The initial values to start with were assumed:

T1=187msec, T2=300msec, T3=425msec, T4=525msec and F1=6.4Hz, F2=25.6Hz, F3=42.24 Hz, F4=102.4Hz

2.6. Best parameters selection

The selected features to be used in the classification process have a physical meaning. However, it has to be investigated, which are the most appropriate from a pool of available features. In our case "appropriate" features are the ones that lead to the smallest classification error. The simple method of selecting just the best individual features, based on a statistical test, may fail dramatically [4]. On the other hand an exhaustive search of all the possible combinations of the features leads to a very large number of computations. Intermediate techniques have been used in the present work for the selection of the optimal feature subset. The regression/classification process was repeated and the addition of a feature each time was evaluated based on predefined criteria. The monotonicity property of the criteria was considered as a clue for the necessity of each feature.

Specifically, in the iterative procedure proposed, the algorithm starts with the very best t-test features (3-4 features) and sequentially a feature is added to the feature vector, provided that it improves results, according to predefined criteria (see the last paragraph of 2.4). The algorithm iterates until there is no more improvement or all features are added.

3. Results

3.1. Best intervals

Table 1 summarizes the best intervals found, meaning the ones that lead to the least error and the optimized the criteria set, using the TiFiMN and TiFiMX parameters.

Table 1. Best Time and Frequency Intervals.

Freq.-Point	Mean±Std (Hz)	Time-Point	Mean±Std (msec)
F1	7.5±1.8	T1	230.8±21.25
F2	28.5±4.8	T2	330±18.3
F3	52±7.5	T3	430±29.8
F4	87±17.4	T4	548±31.6

In the current example, the proposed method succeeded in classifying all samples correctly, using the time and frequency bands described in Table 1. T1-T2 interval corresponds to the last part of QRS, T2-T3 corresponds to ST segment, maybe until T-peak and T3-T4 part corresponds to the last part of T wave. Frequency points F1-F4 exhibit smaller variation than time points T1-T4, which means that frequency definition is more crucial. Interval 20-40 Hz (close to F2-F3 interval) is also referred by others [5] as the most important frequency area that responds to the occlusion-reperfusion procedure. It is important that this area was validated by an unsupervised procedure.

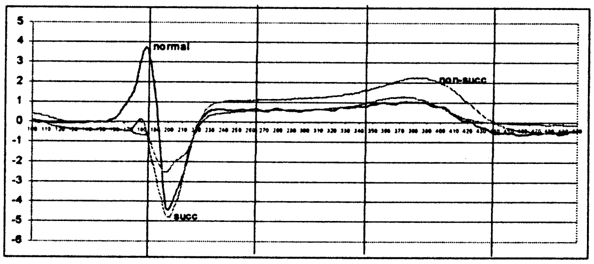

Figure 2. A figure that the best time intervals selected overlapped on an ECG.

3.2. Best features

Using the intervals set above, parameters are calculated (see Eq 4) and the contribution of each feature to classification is investigated. In Figure 3, one can see how the addition of the selected features improves classification, until there is no more improvement.

4. Conclusions

An initial work towards feature selection from a pool of features that best characterizes the problem under investigation and leads to optimized classification is presented.

A combination of techniques is proposed in order to add robustness to the classification method: use of Time-Frequency features that enhance signal characteristics, adaptation of features to data by heuristic search ,use of bootstrapping in order to deal with small dataset statistic, use of classification criteria which tend to optimizing the classes. Thus, the method could be applied in other problems where robust classification is required. The whole procedure could be improved by applying a more sophisticated and faster procedure for interval selection.

As far as the current problem is concerned, it has been evaluated that the intervals that mainly distinct thrombolysis success are: negative/last part of QRS (where late potentials might be present), ST segment and T wave. Ten out of eighteen features are selected during the second phase of the method, mainly the TiFiMN features.

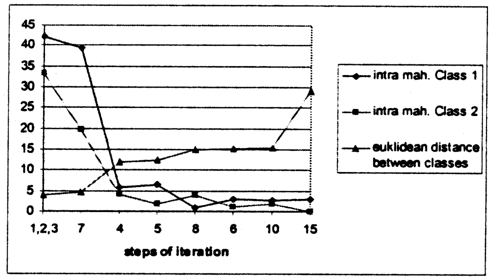

Figure 3. A figure that shows how each feature contributes to classification criteria, using feature enumeration set above (see 2.3).

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