DISCRIMINATION BETWEEN ISCHEMIC AND HEART-RATE RELATED ST-EPISODES
Non-linear Classification for an Online Capable Approach

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Abstract: Transient ST-episodes recognized in the ECG are regarded as marker of myocardial ischemia. As disturbed ST-sections may appear as ST-episodes a differentiated analysis is necessary to avoid misinterpretations. The presented study aims for the discrimination of ischemic and heart-rate related ST-episodes. Our approach includes the morphologic description of the ventricular repolarization by means of the Karhunen-Loève-Transformation and the non-linear classification using an artificial neural network. The proposed selection of used ECG segments guarantees that the classification procedure indicating ischemic attacks can be done before the complete episode is acquired. This online-capable approach gains accuracies up to 94.2 % for the discrimination of ischemic and heart-rate related ST-episodes.

1 INTRODUCTION

The reliable detection of transient myocardial ischemia by automated ECG processing still remains a challenging task. A wide variety of non-ischemic factors affect the correct detection of ischemic events (Moody and Jager, 2003). Typically, that ECG signal segment is analysed to detect ischemia which contains the ventricular repolarization (VR) or a part of the VR. Basically, three methods have been pointed out:

- ST-level: At a single point within the ST-segment the difference between the given amplitude and the isoelectric level of the considered beat is measured (Smrdel and Jager, 2004; Studler et al., 2001; Taddei et al., 1995)
- Several discrete features typically including the ST-deviation, ST-Slope and the T-wave peak are combined to classify ECG segments as ischemic ones (Exarchos et al., 2006; Papaloukas et al., 2002)
- Complete morphology: Sections of the signal (or transformed sections of the signal constituting a more efficient data representation) are considered as a whole to detect ischemia (Jager et al., 1998; Minchol et al., 2005; Papadimitriou et al., 2001)

The ST-level carries highly relevant information regarding ischemic events. The computational simplicity and the interpretability account for the wide usage of the ST-level as criterion. However, limitations of the automated processing arise from non-ischemic factors causing modifications of the VR. Thus, further characterizations of the ST-episodes are required to exclude non-ischemic factors. (Smrdel and Jager, 2008)

The correct classification of occurring alterations of the VR may be hindered by non-specific distortions (e.g. baseline wander, muscle noise, atrial fibrillation). Furthermore, there exist factors that specifically alter the VR. The most challenging factors include sudden or slow shifts in the electrical axis of the heart, changes in the ventricular conduction and heart-rate (HR) related modifications (Jager et al., 2003).

Promising approaches have been presented to detect the shifts in the electrical axis of the heart and the
changes in the ventricular conduction (Dranca et al., 2006; Smrdel and Jager, 2004). Typically, those approaches are based on the assessment of modifications of ventricular depolarization and are referred to as reference tracking (Smrdel and Jager, 2004). The HR related modifications are hardly separable from ischemic modifications. Some approaches have demonstrated their general capability. But still existing limitations claim for further investigations of physiological and methodical aspects. Thus, our study intends to distinguish HR related ST-episodes from ischemic ones. Thereby, our investigations focus on morphologic modifications of the entire VR, precisely the ST-T-interval, during transient ST-episodes.

The paper is organized as follows: Section 2 gives a comprehensive overview of the approaches dedicated to the discrimination of ischemic episodes from HR related ones. Section 3 contains information on methodology, data material and the procedure of signal processing. Section 4 shows numerical results. The discussion of the results and some conclusions as well as perspectives are given in section 5 and section 6, respectively.

2 STATE OF THE ART

2.1 Former Studies

The Computers in Cardiology Challenge entitled "Distinguishing ischemic from non-ischemic ST changes" faced the outlined problem in 2003 (Moody and Jager, 2003). Finally, there were only two participating groups submitting an approach. However some more publications dealing with this subject have been published afterwards. The preparation of the complete Long-Term ST-Database (LTSTDB) was the precondition for comparable investigations into this topic.

Usually the classification process of ST-episodes as ischemic or HR related ones is characterized as follows: 1. Selection of features → 2. Selection of signal intervals → 3. Calculation of the selected features in the selected time intervals corresponding with an episode → 4. Episode classification → 5. Repeat step 3-4 for all episodes.

The classification is typically based on a set of features \( \mathcal{F} = \{F_1, F_2, \ldots, F_N\} \). The features are extracted from certain signal intervals \( I \) positioned in relation to the ST-episode (see Figure 1). Examined features include the ST-deviation, HR related features, features based on the heart rate variability (HRV) as well as different morphological features (for a more comprehensive list see table 1). The feature selection process, if carried out, and the classification process is usually accomplished by linear methods (Faganeli and Jager, 2008; Minchole et al., 2007; Xing et al., 2007).

Table 2 gives the results yielded in different studies distinguishing between ischemic episodes and HR related ones. Note, that the used test data and some boundary conditions vary between the studies. This leads to a lack of comparability.

2.2 Problem Specification

In our opinion two aspects should be investigated.

Non-linear Separability. As a linear separability of the features in the feature space is not proven, the usage of a non-linear classifier is examined.

Online Classification. For the future we aim to use the classification within ambulatory monitoring devices. The approaches proposed in the literature require the ST-episode to be terminated, thus not allowing an online application. Our idea is to carry
Table 2: Results obtained in different studies distinguishing ischemic and heart-rate related ST-episodes (details on the measures used to describe the performance are given in section 4).

<table>
<thead>
<tr>
<th>Study</th>
<th>Se</th>
<th>Sp</th>
<th>P−</th>
<th>P+</th>
<th>Acc</th>
</tr>
</thead>
<tbody>
<tr>
<td>(Faganeli and Jager, 2008)</td>
<td>77.9</td>
<td>73.9</td>
<td>(93.5)</td>
<td>(40.9)</td>
<td>(77.2)</td>
</tr>
<tr>
<td>(Langley et al., 2003)</td>
<td>98.3</td>
<td>-</td>
<td>82.8</td>
<td>-</td>
<td>-</td>
</tr>
<tr>
<td>(Minchole et al., 2007)</td>
<td>82.2</td>
<td>88.4</td>
<td>87.6</td>
<td>83.2</td>
<td>83.1</td>
</tr>
<tr>
<td>(Xing et al., 2007)</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>86.2</td>
</tr>
<tr>
<td>(Zimmerman et al., 2003)</td>
<td>63.8</td>
<td>-</td>
<td>48.2</td>
<td>-</td>
<td>-</td>
</tr>
</tbody>
</table>

- As basis for the definition of ST-episodes the single-channel annotations are used
- Values are calculated using the numbers given in the contribution
- Results obtained with the CinC challenge ST-episodes (including many events not constituting relevant ST-episodes as defined by annotation protocol B)
- 623 ischemic and 112 heart-rate related episodes are used for classification, the remaining episodes were excluded manually from the classification due to problems in the feature extraction phase
- Selected episodes (61 ischemic and 26 heart-rate related episodes from 21 patients) are used

Figure 1: Intervals used to extract features. Although exact timing and number of the intervals may vary, the outlined timing (just before and after the annotated starting point ($I_1$ and $I_2$, respectively) and around the maximum ST-deviation ($I_3$) of the transient ST-episode) is common.

Figure 2: Annotation of relevant transient ST-episodes. In accordance with annotation protocol B of the LTSTDB, an episode is annotated if the minimum threshold $thres_1$ of 100 $\mu$V is exceeded for a minimum time $T_{min}$ of at least 30 s. To find the boundaries of the episode, the ST-deviation must stay under the delineation threshold $thres_2$ of 50 $\mu$V for at least 30 s.

3 MATERIALS AND METHODS

3.1 The Long-term ST-Database

In our study, the Long-Term ST-Database (LTSTDB) (Jager et al., 2003) which is freely available on Physionet (Goldberger et al., 2000) is used.

The LTSTDB consists of 86 Holter ECG recordings of 21 up to 24 hours length. Each record contains two or three ECG channels sampled at 250 samples per second. Based on the ARISTOTLE algorithm (Moody and Marc, 1982), the annotation of the fiducial points $q_i$ of all QRS-complexes is provided.

Medical information created by experts is also included for every record: a measure of the ST-segment variations compared to the isoelectric level (named ST-level function) is provided. Furthermore, a function accounting for non-ischemic factors like axis-shift and conduction changes is prepared (named ST-reference function). A third function is named ST-deviation function. It is the combination of ST-level function and ST-reference function and serves as the basis extracting significant transient ST-episodes.

ECG segments are considered as ST-episodes if the ST-deviation function exceeds a minimum threshold $thres_1$ for a minimum time $T_{min}$ (see figure 2).
Using the annotation protocol B of the LTSTDB, the settings are $T_{\text{min}} = 30 \text{ s}$ and $\text{thres}_1 = 100 \mu\text{V}$. To confirm the beginning and end of an episode, the recording must run at least $30 \text{ s}$ below threshold $\text{thres}_2$ of $50 \mu\text{V}$. Each lead is annotated separately. The final annotation of transient ST-episodes for each of the 86 records is derived by the disjunction of all single-lead based annotations. Further on, the time and absolute value of maximum ST-deviation of each channel indicating the ST-episode is part of the annotation. (Jager et al., 2003)

Each of the annotated ST-episodes is classified as ischemic or HR related by experts. This ST-episodes are the input to our classification process. The expert classification of the episodes determines the gold standard. Following annotation protocol B of the LTSTDB, overall 912 transient ST-episodes (743 ischemic and 169 HR related episodes) are found. There is one constraint forcing us to exclude 10 episodes from the evaluation (9 episodes from record s30661, 1 episode from record s20621). Due to persistent ventricular arrhythmic events in these episodes it was not possible to extract a representative normal beat for at least one of the intervals required in the classification process. Therefore, 10 episodes were discarded resulting in 902 ST-episodes to classify.

Within a typical processing, one signal interval (e.g. $I_2$ in figure 1) for the feature extraction is used whose timing depends on the maximum ST-deviation of the considered episode ("maximum based approach"). To find out the global extremum the whole episode must be known, thus, forcing the classification to be carried out after the end of the episode. This is a serious disadvantage to the processing as an episode may last some minutes. From the medical point of view it is desirable to carry out the classification before the attack is finished. Therefore we developed an approach using a different position of the time interval $I_3$. We use the instant $t_e$ - the earliest instant at which the ST-episode is confirmed (according to annotation protocol B this applies when $\text{thres}_1$ is exceeded for $30 \text{ s}$). The time interval $I_3$ is situated directly before $t_e$ ("online capable approach": see figure 3). We compare the developed approach with a typically used maximum based approach. For both approaches the intervals $I_1$ and $I_2$ are placed directly before and after the onset of the ST-Episode. The duration of all intervals is equally set to $20 \text{ s}$.

### 3.3 Morphologic ECG description

#### 3.3.1 KLT based signal description

The Karhunen-Loève-Transformation (KLT) is a signal dependent linear transform. The KLT ensures the minimization of the resulting square error between an original signal $x$, also called pattern vector, of length $N$ and its reconstruction $x_{\text{rec}}$ calculated from a feature vector consisting of $n$ KLT coefficients $k_1 \ldots k_n$ with $n < N$. Due to its advantageous properties the KLT is a widely used concept in different fields of automatic ECG processing (Castells et al., 2007).

Precondition for successful signal transformation using the KLT are adequate basis functions $\Phi$. The basis functions are the eigenvectors of the covariance matrix $C$ established by all training patterns

$$C = E \left\{ (X - M)(X - M)^T \right\}$$

where $X$ is a matrix containing all pattern vectors and $M$ is a matrix same-sized as $X$ containing copies of the mean $m$ of all pattern vectors. The eigenvector with the $i$-biggest eigenvalues $\lambda_i$ constitutes the $i^{\text{th}}$ basis function.

#### 3.3.2 Construction of Pattern Vectors

As described above, the KLT represents a pattern vector, here the VR, by a feature vector. The method used to create the pattern vectors in this work is derived from the one proposed by Laguna et al. (Laguna et al., 1999) (slight modifications are related to the preprocessing and the length of the resulting pattern vectors; details beneath).

For preprocessing purposes, a FIR bandpass filter (lower -3dB cut-off frequency at 0.5 Hz, upper -3dB
cut-off frequency at 17 Hz) is applied to the ECG. As no useful information regarding the global morphology of VR is expected (Blanchett et al., 1998; Laguna et al., 1999; Thakor et al., 1984), the filter can be used to reduce effectively baseline wander and high-frequency distortions.

As ECG segment $\mathbf{st}_i$ containing the VR of beat $i$ we regard the section of the signal starting at 85 ms after the fiducial point $q_i$ of QRS complex $i$ ending 240 ms prior to $q_{i+1}$. If the interval $rr_i$ between $q_i$ and $q_{i+1}$ falls below 720 ms the end of the VR is assumed to be at $q_i + \frac{2}{3}rr_i$. The extracted segment is aligned by the isoelectric level of the corresponding beat calculated using the algorithm proposed by Jager (Jager, 2006). Therewith, $\mathbf{st}_i$, is an isoelectric corrected ECG segment of variable length $l$.

The resulting vector of $\mathbf{st}_i$ is filled in the pattern vector $\mathbf{x}$, this is to say $x_i(k) = stt(k)$ for all $k < l$. The pattern vectors $\mathbf{x}$ are restricted to 120 samples in length (480 ms), for $k > l$ therefore $x_i(k) = 0$. All samples of $\mathbf{stt}(k)$ with $k > 120$ are discarded. In (Laguna et al., 1999) a resampling is applied to $\mathbf{stt}$, and a maximum length of 160 samples is used.

### 3.3.3 Construction of KLT Basis Function

To construct the basis functions of the KLT the complete LTSTDB is used. The pattern vectors for the construction of $\mathbf{X}$ are extracted following the method outlined in section 3.3.2. Signal sections marked as "noise" are excluded. Furthermore, premature contractions as well as beats adjacent to premature contractions are excluded. To account for the different energies contained in different morphologies, a normalization of beat energy to 1 is done. Figure 4 contains the first 4 resulting KLT basis functions.

The cumulated energy $CE_n$, calculated by

$$CE_n = \frac{\sum_{i=1}^n \lambda_i}{\sum_{i=1}^N \lambda_i}$$

(2)

describes the capability of the transform to represent data with a limited number of $n$ coefficients. Figure 5 contains the $CE$ for different $n$.

![Figure 4: First 4 KLT basis functions calculated using the scheme outlined in section 3.3.3.](image)

![Figure 5: Cumulated energy using different numbers of KLT coefficients.](image)

### 3.3.4 Calculation of Representative Feature Vectors

The calculation of morphology (feature vector) which is representative for the interval $I$ under consideration can be divided in two steps: transformation of the pattern vectors contained in that interval by means of the KLT and formation of a morphology representing the dominant morphology within the signal segment under consideration.

Step one includes the extraction of the set $X^I = \{x_1, x_2, \ldots, x_M\}$ containing all $M$ pattern vectors $x_i$ derived from the interval $I$ using the scheme described in section 3.3.2. Each of the pattern vectors is transformed separately into a feature vector $\mathbf{b}$ with $n$ coefficients.

Step two aims to sort out outliers and to construct a representative beat. Therefore, the median beat $\text{med}$ is obtained, using the medians of all coefficients. Around this median, a fixed radius $r$ is defined. All feature vectors $\mathbf{b}_i \in B^I$ within the predefined radius $r$ using the Euclidean distance $||.||$ are considered as member in the set of potentially representative beats $B_{rep} \subseteq B^I$. This is to say $B_{rep} = \{\mathbf{b}_i | ||\mathbf{b}_i - \text{med}|| < r | i \in \{1, 2, \ldots, M\}\}$. The representative feature vector is calculated as the average over all elements in $B_{rep}$.

### 3.4 Classification Procedure

#### 3.4.1 Classification by Means of Multilayer Perceptrons

Artificial neural networks (ANN) have the capability to solve highly complex and non-linear problems. Achieving high performance while maintaining relatively simplicity in their implementation render ANN very useful for classification tasks and account for
the today’s wide use of ANN in the field of ECG processing. (Maglaveras et al., 1998) Shortcomings of ANN are the lack of interpretability and the non-deterministic results due to random initialisation.

Probably, the multilayer perceptron is the most widespread neural network. It belongs to the class of supervised learning networks. We restricted ourselves to a kind of basic MLP characterized by feed-forward architecture, one hidden layer and fully connected adjacent layers. Our MLP showed a 24-36-1 architecture (24 input neurons, 36 hidden neurons, 1 output neuron). For the learning phase we used the backpropagation algorithm (Rumelhart et al., 1986).

### 3.4.2 Training and Evaluation Procedure

The validity of the results is limited by the number of episodes, the number of evaluation iterations and the non-deterministic network training. To cope with this problems we evaluate our method using a repeated non-deterministic network training. To cope with this method we used the backpropagation algorithm (Rumelhart et al., 1986).

The performance evaluation of the classification for the different test sets is based on the confusion matrix containing the events true positive (TP) (ischemia existent and classified), false positive (FP) (ischemia existent and HR related episode classified), true negative (TN) (HR related episode existent and classified) and false negative (FN) (HR related episode existent and ischemia classified). These events lead to the statistical values sensitivity $Se = \frac{TP}{TP+FN}$, specificity $Sp = \frac{TN}{TN+FP}$, positive predictivity $+P = \frac{TP}{TP+FP}$, negative predictivity $-P = \frac{TN}{TN+FN}$ and accuracy $Acc = \frac{TP+TN}{TN+FP+FN+TN}$.

Table 3 contains the results of the evaluation. Additionally to the mean classification performance the confidence intervals ($\alpha = 0.05$) are included.

### 5 DISCUSSION

#### Non-linear Classification

The usage of a non-linear classifier shows high performance. The obtained results ($Se = 96.8\%$, $+P = 97.1\%$; as $Se$ and $+P$ describe the handling of true ischemic episodes they are of major interest) outperform the results described in the literature, some of them by a considerable amount (compare table 2 and table 3).

#### Online Capability

The results using the online capable interval timing are very convincing (a drop in $Se$ and $+P$ of less than 1%). The used intervals do not necessarily consider the biggest morphological change within the ST-episode. But the comparison concerning the timing within different episodes is possible. This property could be an even more appropriate basis for the classification.

#### General Limitations

The results obtained by using standardized data are representative and reproducible. Thus, the LTSTDB and its annotations provide a good basis for our investigation. Nevertheless, the number of ischemic and HR related morphological alterations contained in the LTSTDB is limited. Further on, a part of the data is used for training purposes. Thus, it is only possible to generalize the results to a limited extent.

### 6 CONCLUSIONS

The obtained results render the KLT-based morphology description in combination with a non-linear clas-
classification scheme as very useful in the classification of ischemic and HR related transient ST-episodes. They indicate the possibility of a future online application which allows the usage of the method in monitoring devices.

REFERENCES


