DISCRIMINATION BETWEEN ISCHEMIC AND HEART-RATE RELATED ST-EPISODES

Non-linear Classification for an Online Capable Approach

S. Zaunseder
Fraunhofer IPMS, Maria-Reiche-Strasse 2, Dresden, Germany

W. Aipperspach, R. Poll
Institute of Biomedical Engineering, Dresden University of Technology, Dresden, Germany

Keywords: Ischaemia, Heart-rate related ST-episodes, Karhunen-Loève-Transformation, Ventricular repolarization, Artificial neural networks, Online classification.

Abstract: Transient ST-epsiodes 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; Stadler 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; Minchole 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

Zaunseder S., Aipperspach W. and Poll R. (2010).
DISCRIMINATION BETWEEN ISCHEMIC AND HEART-RATE RELATED ST-EPISODES - Non-linear Classification for an Online Capable Approach.
In *Proceedings of the Third International Conference on Bio-inspired Systems and Signal Processing*, pages 245-251
DOI: 10.5220/0002722802450251

Table 1: Used features to distinguish between ischemic and HR related ST-episodes. The symbol 'Δ' refers to features calculated as difference between the respective feature values of two intervals.

Group	Feature specification
HR	- Mean HR (Xing et al., 2007) - Δ HR (Faganeli and Jager, 2008; Minchole et al., 2007) - Maximum HR (Faganeli and Jager, 2008; Minchole et al., 2007)
HRV	- Low frequency high frequency ratio (Xing et al., 2007) - Center frequency (Xing et al., 2007)
Repolarisation	- ST-deviation (Langley et al., 2003) - Δ ST-deviation (Faganeli and Jager, 2008; Langley et al., 2003; Minchole et al., 2007) - ST-segment morphology (ST-segment sample values, Δ ST-Slope, Δ Legendre coefficients, ST-segment root mean square) (Faganeli and Jager, 2008; Zimmerman et al., 2003)
Depolarisation	- Δ Maximum QRS-slopes (Minchole et al., 2007) - Δ QRS morphology (KLT based Mahalanobis distance) (Faganeli and Jager, 2008)
Others	- Correlation between ST-deviation and heart rate (Minchole et al., 2007) - Group Delay (caluclated from Smoothed Pseudo-Wigner-Ville Distribution) (Xing et al., 2007)

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 corresponging with an episode → 4. Episode classification → 5. Repeat step 3-4 for all episodes.

The classification is typically based on a set of features $\mathcal{F} = \{F_1, F_2, ..., F_N\}$. 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).

Study	**Obtained results** in %				
	Se	*Sp*	$+P$	$-P$	*Acc*
(Faganeli and Jager, 2008)[a]	77.9	73.9	(93.5)[b]	(40.9)[b]	(77.2)[b]
(Langley et al., 2003)[c]	98.3	-	82.8	-	-
(Minchole et al., 2007)[d]	82.2	88.4	87.6	83.2	83.1
(Xing et al., 2007)[e]	-	-	-	-	86.2
(Zimmerman et al., 2003)[c]	63.8	-	48.2	-	-

[a] As basis for the definition of ST-episodes the single-channel annotations are used
[b] Values are calculated using the numbers given in the contribution
[c] Results obtained with the CinC challenge ST-episodes (including many events not constituting relevant ST-episodes as defined by annotation protocol B)
[d] 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
[e] Selected episodes (61 ischemic and 26 heart-rate related episodes from 21 patients) are used

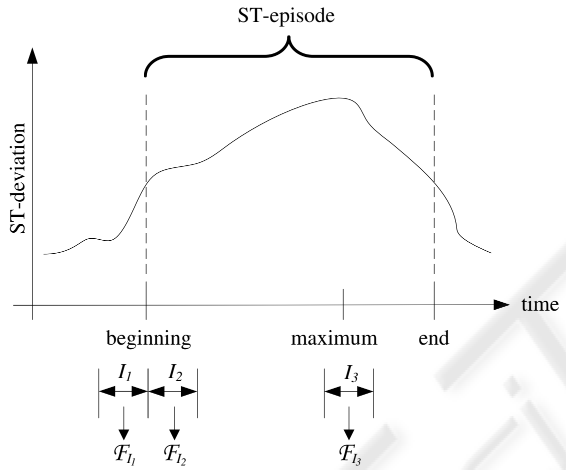

Figure 1: Intervals used to extract features. Although exact timing and number of the intervals may vary, the outlined timing (just before and after the annotated starting point (I_1 and I_2, respectively) and around the maximum ST-deviation (I_3) of the transient ST-episode) is common.

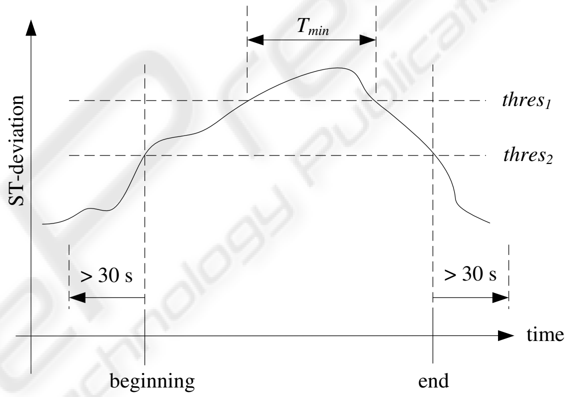

Figure 2: Annotation of relevant transient ST-episodes. In accordance with annotation protocol B of the LTSTDB, an episode is annotated if the minimum threshold $thres_1$ of 100 μV is exceeded for a minimum time T_{min} of at least 30 s. To find the boundaries of the episode, the ST-deviation must stay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

out the classification at the instant the ST-deviation is long-standing and pronounced enough to be referred to as an ST-episode. Thus, an online processing of ST-episodes becomes possible.

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 $T_{min} = 30\,\text{s}$ and $thres_1 = 100\,\mu\text{V}$. To confirm the beginning and end of an episode, the recording must run at least 30 s below threshold $thres_2$ of $50\,\mu\text{V}$. Each lead is annotated seperately. 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 epsiodes) are found. There is one constraint forcing us to exclude 10 episodes from the evaluation (9 epsiodes 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.

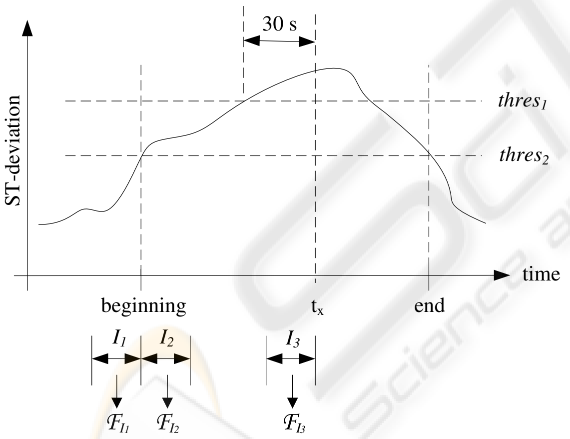

Figure 3: Maximum independent timing of intervals used to extract the features for the classification. Note, that the classification can be carried out at the instant a ST-deviation is referred to as an ST-episode follwing the annotation protocol B of the LTSTDB.

3.2 Used Time Intervals

Within a typical processing, one signal interval (e.g. I_3 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 attac is finished. Therefore we developed an approach using a different position of the time interval I_3. We use the instant t_x - the earliest instant at which the ST-episode is confirmed (according to annotation protocol B this applies when $thres1$ is exceeded for 30 s). The time interval I_3 is situated directly before t_x ("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 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 $\mathbf{x}$, also called pattern vector, of length N and its reconstruction $\mathbf{x}_{rec}$ calculated from a feature vector consisting of n KLT coefficients $kl_1 \dots kl_n$ with $n < N$. Due to its advantegeous 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 Φ. The basis functions are the eigenvectors of the covariance matrix $\mathbf{C}$ established by all training patterns

$$\mathbf{C} = E\left\{(\mathbf{X}-\mathbf{M})(\mathbf{X}-\mathbf{M})^{\mathrm{T}}\right\} \tag{1}$$

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

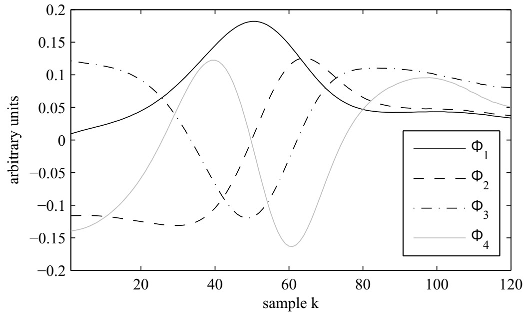

Figure 4: First 4 KLT basis functions calculated using the scheme outlined in section 3.3.3.

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 $\mathbf{stt}_i$ 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 intervall 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, $\mathbf{stt}_i$ is an isoelectric corrected ECG segment of variable length l.

The resulting vector of $\mathbf{stt}_i$ is filled in the pattern vector $\mathbf{x}_i$, 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 $stt(k)$ with $k > 120$ are discarded. In (Laguna et al., 1999) a resampling is applied to $\mathbf{stt}_i$ 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

$$CE_n = \frac{\sum_{i=1}^{n} \lambda_i}{\sum_{i=1}^{N} \lambda_i} \tag{2}$$

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

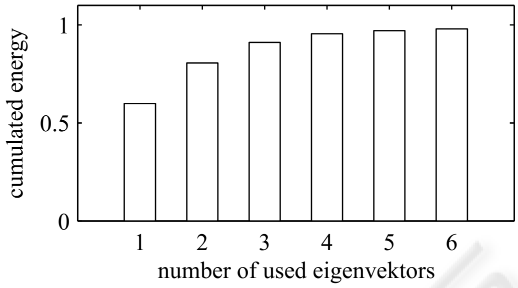

Figure 5: Cumulated energy using different numbers of KLT coefficients.

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 $X^I = \{\mathbf{x}_1, \mathbf{x}_2, \ldots, \mathbf{x}_M\}$ containing all M pattern vectors $\mathbf{x}_i$ derived from the interval I using the scheme described in section 3.3.2. Each of the pattern vectors is transformed seperatly 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 $\mathbf{med}$ is obtained, using the medians of all coefficient values. Around this median, a fixed radius r is defined. All feature vectors $\mathbf{b}_i \in \mathcal{B}^I$ within the predefined radius r using the Euclidean distance $\|.\|$ are considered as member in the set of potentially representative beats $\mathcal{B}^I_{rep} \subseteq \mathcal{B}^I$. This is to say $\mathcal{B}^I_{rep} = \{\mathbf{b}_i \,|\, \|\mathbf{b}_i - \mathbf{med}\| < r \,|\, i \in \{1, 2, \ldots M\}\}$. The representative feature vector is calculated as the average over all elements in $\mathcal{B}^I_{rep}$.

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

Table 3: Results of the evaluation using different interval timings.

Study	**Obtained results** in % $\pm$ confidence interval ($\alpha = 0.05$)				
	Se	*Sp*	$+P$	$-P$	*Acc*
max-based	96.83 ± 0.09	$87,45 \pm 0.36$	97.13 ± 0.08	$86,35 \pm 0.36$	95.09 ± 0.10
online-based	96.32 ± 0.10	85.00 ± 0.40	96.56 ± 0.09	84.13 ± 0.37	94.21 ± 0.10

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 ourselfes 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 stratified k-fold cross validation scheme ($k = 10$, random initialisation of the weight matrices of the MLP, $N = 100$ repetitions) (Kohavi, 1995).

The statistical evaluation is done using confidence intervals. Using the t-distribution the confidence intervals around the mean classification performance μ is estimated by

$$\bar{x} - t_{n-1;1-\frac{\alpha}{2}} \cdot \frac{s}{\sqrt{n}} \leq \mu \leq \bar{x} + t_{n-1;1-\frac{\alpha}{2}} \cdot \frac{s}{\sqrt{n}} \qquad (3)$$

Thereby $\bar{x} = \frac{1}{N}\sum_{i=1}^{N} x_i$ and $s = \sqrt{\frac{1}{N-1}\sum_{i=1}^{N}(x_i - \bar{x})^2}$. The result of the classification μ lies with a probability of $1 - \alpha$ in the given intervals.

3.4.3 Test Sets

Because of the different interval timing using the maximum based approach and the online capable approach two different test sets result. Within each test set for all three time intervals and two channels, the first four KLT coefficients are used (see figure 5), thus resulting in 24 KLT coefficients for each ST-episode.

4 RESULTS

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 $Se = \frac{\text{TP}}{\text{TP+FN}}$, specifity $Sp = \frac{\text{TN}}{\text{TN+FP}}$, positive predictivity $+P = \frac{\text{TP}}{\text{TP+FP}}$, negative predictivity $-P = \frac{\text{TN}}{\text{TN+FN}}$ and accuracy $acc = \frac{\text{TP+TN}}{\text{TP+FP+TN+FN}}$.

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 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

Blanchett, T., Kember, G. C., and Fenton, G. A. (1998). Klt-based quality controlled compression of single-lead ecg. *IEEE Trans Biomed Eng*, 45(7):942–945.

Castells, F., Laguna, P., Sornmo, L., Bollmann, A., and Millet-Roig, J. (2007). Principal component analysis in ecg signal processing. *EURASIP Journal on Advances in Signal Processing*, 1:1–21.

Dranca, L., Goni, A., and Illarramendi, A. (2006). Using decisiontrees for real-time ischemia detection. In *CBMS*, pages 719–726.

Exarchos, T. P., Papaloukas, C., Fotiadis, D. I., and Michalis, L. K. (2006). An association rule mining-based methodology for automated detection of ischemic ecg beats. *IEEE Trans Biomed Eng*, 53(8):1531–1540.

Faganeli, J. and Jager, F. (2008). Automatic distinguishing between ischemic and heart-rate related transient st segment episodes in ambulatory ecg records. In *CinC*, pages 381–384.

Goldberger, A. L., Amaral, L. A., Glass, L., Hausdorff, J. M., Ivanov, P. C., Mark, R. G., Mietus, J. E., Moody, G. B., Peng, C. K., and Stanley, H. E. (2000). Physiobank, physiotoolkit, and physionet: components of a new research resource for complex physiologic signals. *Circulation*, 101(23):E215–E220.

Jager, F. (2006). *Advanced Methods And Tools for ECG Data Analysis, Chapter 9: Introduction to Feature Extraction*, pages 245–264. Artech House.

Jager, F., Moody, G. B., and Mark, R. G. (1998). Detection of transient st segment episodes during ambulatory ecg monitoring. *Comput Biomed Res*, 31(5):305–322.

Jager, F., Taddei, A., Moody, G. B., Emdin, M., Antolic, G., Dorn, R., Smrdel, A., Marchesi, C., and Mark, R. G. (2003). Long-term st database: a reference for the development and evaluation of automated ischaemia detectors and for the study of the dynamics of myocardial ischaemia. *Med Biol Eng Comput*, 41(2):172–182.

Kohavi, R. (1995). A study of Cross-Validation and Bootstrap for Accuracy Estimation and Model Selection. In *IJCAI*, pages 1137–1145.

Laguna, P., Moody, G. B., Garca, J., Goldberger, A. L., and Mark, R. G. (1999). Analysis of the st-t complex of the electrocardiogram using the karhunen–love transform: adaptive monitoring and alternans detection. *Med Biol Eng Comput*, 37(2):175–189.

Langley, P., Bowers, E., Wild, J., Drinnan, M., Allen, J., Sims, A., Brown, N., and Murray, A. (2003). An algorithm to distinguish ischaemic and non-ischaemic st changes in the holter ecg. In *CinC*, pages 239–242.

Maglaveras, N., Stamkopoulos, T., Diamantaras, K., Pappas, C., and Strintzis, M. (1998). ECG pattern recognition and classification using non-linear transformations and neural networks: a review. *Int J Med Inform*, 52:191–208.

Minchole, A., Jager, F., and Laguna, P. (2007). Discrimination between demand and supply ischemia episodes in holter recordings. In *Conf Proc IEEE Eng Med Biol Soc*, volume 2007, pages 2579–2582.

Minchole, A., Skarp, B., Jager, F., and Laguna, P. (2005). Evaluation of a root mean squared based ischemia detector on the long-term st database with body position change cancellation. In *CinC*, pages 853–856.

Moody, G. and Jager, F. (2003). Distinguishing ischemic from non-ischemic st changes: the physionet/computers in cardiology challenge 2003. In *CinC*, pages 235–237.

Moody, G. and Marc, R. (1982). Development and evaluation of a 2-lead ecg analysis program. In *CinC*, pages 39–44.

Papadimitriou, S., Mavroudi, S., Vladutu, L., and Bezerianos, A. (2001). Ischemia detection with a self-organizing map supplemented by supervised learning. *IEEE Trans Neural Netw*, 12(3):503–515.

Papaloukas, C., Fotiadis, D. I., Likas, A., Stroumbis, C. S., and Michalis, L. K. (2002). Use of a novel rule-based expert system in the detection of changes in the st segment and the t wave in long duration ecgs. *J Electrocardiol*, 35(1):27–34.

Rumelhart, D., Hintont, G., and Williams, R. (1986). Learning representations by back-propagating errors. *Nature*, 323:533–536.

Smrdel, A. and Jager, F. (2004). Automated detection of transient st-segment episodes in 24 h electrocardiograms. *Med Biol Eng Comput*, 42(3):303–311.

Smrdel, A. and Jager, F. (2008). An algorithm to estimate the st segment level in 24-hour ambulatory ecg records. In *CinC*, pages 701–704.

Stadler, R. W., Lu, S. N., Nelson, S. D., and Stylos, L. (2001). A real-time st-segment monitoring algorithm for implantable devices. *J Electrocardiol*, 34 Suppl:119–126.

Taddei, A., Costantino, G., Silipo, R., Emdin, M., and Marchesi, C. (1995). A system for the detection of ischemic episodes in ambulatory ecg. In *CinC*, pages 705–708.

Thakor, N. V., Webster, J. G., and Tompkins, W. J. (1984). Estimation of QRS complex power spectra for design of a QRS filter. *IEEE Trans Biomed Eng*, 31(11):702–706.

Xing, W., Liang, X., Zhongwei, S., Zibin, Y., and Yi, P. (2007). Heart rate variability analysis of ischemic and heart rate related st-segment deviation episodes based on time-frequency method. In *NFSI-ICFBI*, pages 162–164.

Zimmerman, M., Povinelli, R., Johnson, M., and Ropella, K. (2003). A reconstructed phase space approach for distinguishing ischemic from non-ischemic st changes using holter ecg data. In *CinC*, pages 243–246.