POLSKA AKADEMIA NAUK
MIĘDZYNARODOWE CENTRUM BIOCYBERNETYKI
INTERNATIONAL CENTRE OF BIOCYBERNETICS
WORLD HEALTH ORGANIZATION
COLLABORATING CENTRE FOR RESEARCH AND TRAINING
IN BIOCYBERNETICS AND BIOMEDICAL ENGINEERING

Address: 02-109 Warszawa, ul. Trojdena 4, Poland, Tel: (+4822) 6582877, Fax: (+4822) 6582872
Director: Prof. Dr. Maciej Nałęcz

LECTURE NOTES OF THE ICB SEMINARS

HIGH RESOLUTION ECG AND MCG MAPPING

Warsaw, October 2003

Edited by L. De Ambroggi
T. Katila
R. Maniewski

WARSAW 2004

THE USE OF BODY SURFACE POTENTIAL MAPPING IN THE IDENTIFICATION OF RISK FOR VENTRICULAR TACHYCARDIA

R. Bailón*, S. Olmos*, B.M. Horácek**, P. Laguna*

*Communications Technology Group, Aragón Institute of Engineering Research, University of Zaragoza, Spain

**Department of Physiology and Biophysics, Dalhousie University, Halifax, NS, Canada

Abstract

Based on the evidence that specific arrhythmogenic alterations manifest on body surface potentials, we attempted to identify patients at risk for ventricular tachycardia (VT) by means of body surface potential mapping (BSPM) recorded during sinus rhythm. The high dimensionality of BSPM data and the limited number of available patients make necessary a feature extraction step prior to the classifier design. Feature extraction was performed by means of linear expansions of two different time intervals: QRS and ST-T complexes. Two approaches were considered: the Karhunen-Loève transform (KLT) and spatio-temporal expansions. A multivariate linear discriminant analysis was applied to the extracted features to classify patients in two groups: VT and non-VT. Classification results achieved by spatio-temporal features (SE=83%, SP=86%) were similar to those obtained by KLT features (SE=78%, SP=93%) but with a lower computational cost. For comparison purposes, a method based on QRST integral maps, reported in the literature, was implemented, obtaining results within the same range (SE=88%, SP=72%).

1. Introduction

Ventricular tachycardia (VT) is a major factor of mortality in patients with heart disease. Several approaches have been investigated in order to identify the presence of arrhythmogenic regions in the ventricular myocardium, such as electrophysiological studies, ambulatory monitoring, exercise testing, 12-lead ECG and body surface potential mapping (BSPM). There is some evidence that specific electrophysiological alterations during sinus rhythm are associated with vulnerability to VT and manifested in body surface potentials. Therefore, BSPM analysis is particularly challenging since nearly all noninvasively-available electrocardiographic information can be captured. Previous works showed that subjects at risk for VT have unique map characteristics [1,2], e.g. the spatial distribution of QRST integrals over the torso was used in [3] to stratify patients at risk for VT.

In this work we attempted to identify patients at risk for VT by means of BSPM recorded during sinus rhythm. Due to the high dimensionality of BSPM data and the limited number of patients, it was necessary to reduce the dimensionality of the original BSPM space prior to the classifier design in order to avoid the so-called "Hughes phenomena" [4]. First, feature extraction was performed by means of linear expansions; then, a linear discriminant analysis was applied to the reduced feature space to stratify patients at risk for VT. Two approaches of linear expansions were studied: the Karhunen-Loève transform (KLT) and spatio-temporal (TS) expansions, proposed in [5] as a low-complexity approximation to KLT. For comparison purposes, the method in [3], based on QRST integral maps, was also implemented.

2. Materials and methods

2.1. Study population

The study population consisted of 705 patients: 259 normals (noMI/noVT), 69 with no evidence of a previous myocardial infarction (MI) but with a history of spontaneous VT (noMI/VT), 258 with no history of VT but a previous MI (MI/noVT) and 119 with a history of VT and previous MI (MI/VT). The diagnosis of MI was based on non-ECG evidence in the acute phase and the presence of diagnostic 12-lead ECG changes. Patients with a history of VT presented electrocardiographically documented spontaneous sustained VT in the absence of a reversible cause. Normal subjects had no clinical evidence of arrhythmias or heart disease on history, 12-lead ECG, physical and echocardiographic examination. All subjects were informed of the study's procedures, in accordance with the ethical guidelines approved by the institutional ethics committee.

2.2. Body surface potential mapping

BSPMs were recorded at the Victoria General Hospital, Halifax, NS, and at the Foothills Hospital, Calgary, AB, Canada, according to the same protocol and using acquisition systems with identical specifications (sampling rate of 500 Hz, amplitude resolution of 2.5 μV). The BSPM lead array had 120 leads: 3 limb and 117 unipolar chest leads (76 on the front and 41 on the back). BSPMs were recorded during sinus rhythm and supine position for 15 consecutive seconds. QRST complexes were identified and processed to yield a single averaged complex for each lead. The onset and end of ECG waves were determined from the averaged complexes. See [3] for further detail on acquisition system and ECG processing.

2.3. Feature extraction

Feature extraction was performed by means of linear expansions. Each BSPM was represented by a $N \times L$ matrix $\mathbf{X}$ (N samples, L channels) which can be decomposed as a linear combination of $N \times L$ elementary matrices $\mathbf{B_{ij}}$,

$$X = \sum_{i=1}^{N} \sum_{j=1}^{L} \omega_{ij} B_{ij}$$

The elementary matrices $\mathbf{B_{ij}}$ are often selected in order to pack most of the energy of $\mathbf{X}$ in a small subset of $r << NL$ weighting coefficients ω_{ij}. Two approaches of linear expansions were studied: KLT and TS expansions. Their characteristics and application to multichannel signals, like BSPM, were described in [5].

The basis functions of KLT are built from the dominant eigenvectors of the data covariance matrix. In the case of TS expansions, the basis functions are rank-one matrices of the form $\mathbf{B_{ij}}=\mathbf{t_i s_j}^T$, where $\mathbf{t_i}$ and $\mathbf{s_j}$ are the dominant eigenvectors of the average temporal and spatial covariance matrices, respectively. It was shown in [5] that for signals with separable autocorrelation function (i.e. the correlation matrix can be expressed as the Kronecker product of the temporal and the spatial covariance matrices) both approaches are identical.

The features extracted for BSPMs were the r-th dominant coefficients for KLT and TS approaches. The parameter r should be chosen as a compromise between energy representation and basis function generality. The rule of thumb $r < (\textit{training set size})^{1/2}$ was followed to avoid using basis functions overtunned to the training set.

2.4. Classification

A stepwise multivariate linear discriminant analysis was independently applied to KLT and TS features to classify patients into the VT (*noMI/VT + MI/VT*) and non-VT group (*noMI/noVT + MI/noVT*). The criterion used in the variable inclusion/rejection was the *Wilk's lambda* minimization. The number of stepwise selected variables followed the rule $\#variables < (smallest\ group\ size)^{1/2}$. Discriminant analysis assumes that classification variables are Gaussian within each of the groups. The Kolmogorov-Smirnov test was used to check the normality of the variables (a p-statistic value > 0.05 assessing the normality of a variable). Statistical analysis was performed using SPSS 11.5.
Classification results were quantified by the indexes: sensitivity (SE), specificity (SP), positive predictive value (P+), negative predictive value (P-) and exactness (EX).
The study population was divided into two sets: a training set of 200 subjects (50 *noMI/noVT* + 50 *MI/noVT* + 50 *noMI/VT* + 50 *MI/VT*) and a test set of 76 subjects (19 *noMI/noVT* + 19 *MI/noVT* + 19 *noMI/VT* + 19 *MI/VT*). The training set was used to derive the basis functions for feature extraction and the discriminant functions for classification. The test set was used to evaluate classification performance. It was also evaluated on the training set by means of cross-validation (*leave-one-out* method) to further support classification results obtained on the finite-size test set.

2.5. QRST integral

For comparison purposes, the method in [3] was implemented. Feature extraction was accomplished in two steps: first, QRST integral was computed on each lead as the algebraic sum of the sampled potentials within QRST complex multiplied by the sampling interval (2 ms); then, KLT was applied to the QRST integral maps. The r-th dominant coefficients constituted the set of features entering the discriminant analysis described in Section 2.4.

3. Results

Two different tiem intervals were considered in order to study depolarization and repolarization properties: QRS complex (160 ms centered at the the QRS fiducial point, defined as the median center of gravity of the QRS complex among all leads) and ST-T complex (450 ms from QRS end). QRS complex maps were represented by matrices QRS-BSPM dimensioned 81×117. ST-T complex maps were represented, after decimating the signal by a factor of 5, by matrices STT-BSPM dimensioned 45×117. STT-BSPMs were padded with zeros when ST-T complexes were shorter than 450 ms.
BSPM matrices were normalized to have unit energy ($\|\mathbf{X}\|=1$), in order to equalize the contribution of all subjects of the training set. The normalization was also performed in the test set because the interesting point was the relative contribution of each basis function to the whole BSPM. In this way, the ECG complexes' energy would not affect weighting coefficients.
Feature extraction was applied to QRS-BSPMs and STT-BSPMs as explained in Section 2.3. A total of 14 KLT features (denoted QRS-KL and STT-KL, respectively) and 14 TS features (QRS-TS and STT-TS) were considered. The discriminant analysis described in Section 2.4 was independently applied to different variable sets to discriminate between the VT and non-VT groups. The variable sets were the QRS-KL, STT-KL, QRS-TS and STT-TS features. Two other variable sets were considered, QRS-STT-KL and QRS-STT-TS, containing the

most significant KLT and TS features, respectively, from both intervals. A maximum number of 10 variables was allowed in the discrimination.

According to Kolmogorov-Smirnov test, all variables had normal distribution within each group, except for the most dominant STT-TS feature within the non-VT group. An *arcsin* transformation was performed to correct its lack of normality but classification results did not change.

Figure 1 shows the EX, as a function of the number of variables used, achieved in the test set by the different variable sets. There is a threshold above which EX is not increased, but even decreased, as using a higher number of variables. Classification indexes achieved in the test by each variable set are shown in Table 1.

The QRST integral method explained in Section 2.5 was applied to our study population. The EX, as a function of the number of variables, achieved in the test set is shown in Figure 1 and classification indexes are presented in Table 1.

Cross-validation classification results achieved by the different variable sets in the training set are shown in Table 2, mostly supporting the results obtained in the test set.

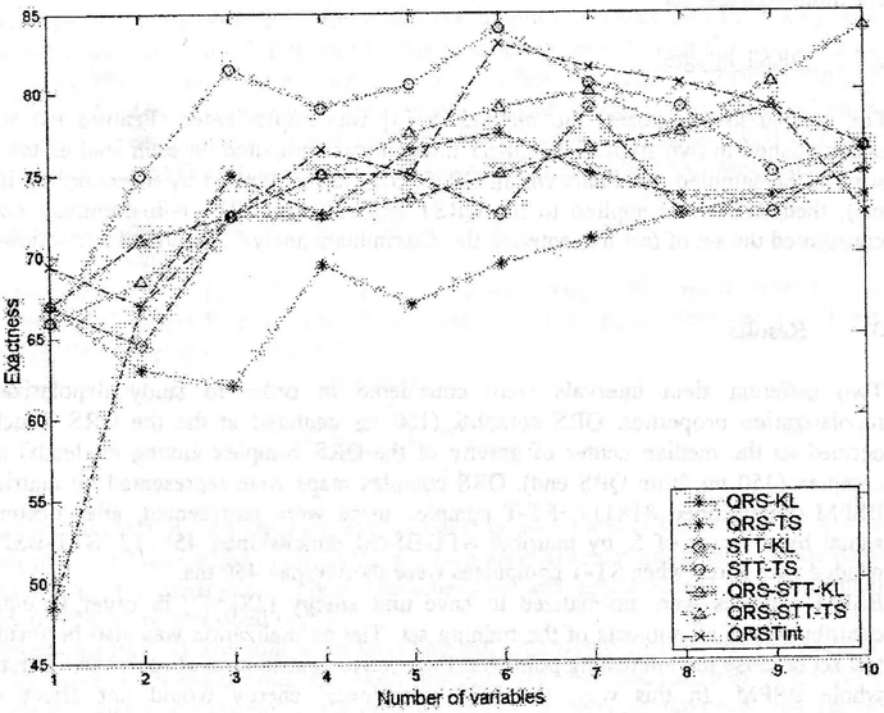

Fig.1. Exactness as a function of the number of variables in the test set

Table 1. Classification results in the test set.

Variable set	SE	SP	P+	P-	EX
QRS-KL	79	93	92	82	86
QRS-TS	81	83	83	81	82
STT-KL	76	80	79	77	78
STT-TS	76	84	83	78	80
QRS-STT-KL	78	93	92	81	85
QRS-STT-TS	83	86	86	83	84
QRSTintegral	88	72	76	86	80

Table 2. Cross-validation classification results in the training set

Variable set	SE	SP	P+	P-	EX
QRS-KL	79	93	92	82	86
QRS-TS	81	83	83	81	82
STT-KL	76	80	79	77	78
STT-TS	76	84	83	78	80
QRS-STT-KL	78	93	92	81	85
QRS-STT-TS	83	86	86	83	84
QRSTintegral	88	72	76	86	80

4. Discussion and conclusions

BSPM constitute a challenging technique in non-invasive cardiology since nearly all available electrocardiographic information can be captured. In this work we dealt with the identification of patients at risk for VT by means of linear expansions applied to BSPM recorded during sinus rhythm. In an attempt of designing the optimal classifier using all available information, we had previously implemented a *parametric-linear* classifier, a *parametric-quadratic* classifier and a *nonparametric* classifier, based on [4]. Our results showed that the number of subjects in the training set used to design the classifier was insufficient given the dimensionality of the data because of the so-called "Hughes phenomena" [4]. As a consequence the classifiers were overfitted to the particular study population and failed in prospective populations. Therefore, a feature extraction step was necessary to reduce BSPM dimensionality while maintaining the important diagnostic information. Finally, the classifier was designed from the reduced feature space.

Feature extraction was performed by means of linear expansions. The Fourier transform had been studied to reduce BSPM dimensionality [6], but the requirement of equally spaced samples constituted a restrictive limitation in the spatial domain. Two approaches were considered in this study: KLT and TS. KLT had been previously applied to BSPMs in other works to eliminate spatial [3,7,8] and temporal redundancies [9]. One of the limitations of KLT is the high computational load and complexity required for computing the basis functions and the transformed coefficients. In [5] TS expansions were proposed as a low-complexity approximation of the KLT, getting similar energy packing performances in a 12-lead ECG database. KLT and TS expansions were compared in this work in terms of diagnostic classification performance. The number of subjects in the training set limited to 14 the order of KLT and TS basis functions estimated avoiding the lack of generality. Higher order basis functions would collect particular details from the training set instead of the general behaviour of BSPMs.

The use of la linear classifier was funded on its simplicity, relative insensitivity to a limited-size training set and good performance even when unfulfilled underlying assumptions. It was observed the existence of a threshold in the number of classification variables used above which classification performance did not longer improved. The KLT and TS features obtained similar classification results, slightly varying depending on the population and variables used. This suggests that TS expansions can be used as an approximation to KLT not only for energy packing but also for diagnostic classification in BSPM analysis. The main advantage of TS expansions over KLT is the complexity reduction in the computation of the basis functions (from $O((NL)^3)$ to $O(N^3+L^3)$). The complexity in the computation of the weighting coefficients is lower for TS expansions than for KLT if $r>(N+L)$, which is not the case in this work.

Classification performances of depolarization and repolarization features support the previous findings that vulnerability to VT alters depolarization [10] and repolarization [11] properties and suggest that these alterations may be correlated since only a slight improvement is achieved when jointly considered.

QRST integral maps have been widely analyzed as a marker of vulnerability to VT [1-3,8]. In our study population classification performance achieved by QRST integral maps (SE=88%, SP=72%) was within the same range of KLT and TS features (SE≈80%, SP≈90% in average). Our results suggest that the relevant information for identifying patients at risk for VT is contained in the spatial distribution of BSPM rather than in the temporal waveform, since the spatial distribution of a single measurement per beat (QRST integral) obtained similar results than when the whole QRST complex was considered.

The main limitation of this work is the insufficient number of patients available, given the data dimensionality, to design the classifier, which was found to be common in BSPM studies [12]. It was extremely important to extract a reduced feature space without lost of diagnostic information and avoiding the overtunning.

In a further study, the discriminant KLT and TS features should be physiologically interpreted to understand how the arrhythmogenic substrate may manifest through them.

Acknowledgements

This work was supported by projects TIC 2001-2167-C02-02 from MCYT and P075/2001 from CONSID-DGA.

References

1. Abildskov J., Green L., Lux R.: Detection of disparate ventricular repolarization by means of the body surface electrocardiogram; in: Zipes D., Jalife J. (Eds.). Cardiac electrophysiology and arrhythmias, New York, Grune & Stratton, 1985, 495-499.
2. Gardner M., Montague T., Armstrong C., Horácek B., Smith E.: Vulnerability to ventricular arrhythmia: Assessment of mapping of body surface potential, Circulation, 1986, 73, 684-692.
3. Hubley-Kozey C., Mitchell L., Gardner M., Warren J., Penney C., Smith E., Horácek B.: Spatial features in body surface potential maps can identify patients with a history of sustained ventricular tachycardia, Circulation, 1995, 92, 1825-1838.
4. Fukunaga K.: Introduction to statistical pattern recognition, San Diego, CA, Academic Press, 1990.

5. Olmos S., Martínez J., Sörnmo L.: Spatio-temporal linear expansions for repolarization analyisis, Computers in Cardiology, 2002. Memphis, TN, USA, IEEE Computer Society Press, 2002, 689-692.

6. Monro D., Guardo R , Bourdillon P , Tinker J.: A Fourier technique for simultaneous electrocardiographic surface mapping, Cardiovasc. Res., 1974, 8, 688-700.

7. Lux R., Evans A., Burguess M., Wyatt R., Abildskov J.: Redundancy reduction for improved display and analysis of body surface potential maps. I. Spatial compression, Circ. Res. 1981, 49, 186-196.

8. Ambroggi L.D., Bertoni T., Locati E., Stramba-Badiale M., Schwartz P.: Mapping of body surface potentials in patients with the idiopathic long QT syndrome, Circulation, 1986, 74, 1334-1345.

9. Evans A., Lux R., Burgess M., Wyatt R., Abildskov J.: Redundancy reduction for improved display and analysis of body surface potential maps. II. Temporal compression, Circ. Res., 1981, 49, 197-203.

10. Faugère G., Savard , Nadeau R., Derome D., Shenasa M., Page P., Guardo R.: Characterization of the spatial distribution of late ventricular potentials by body surface mapping in patients with ventricular tachycardia, Circulation, 1986, 74, 1323-1333.

11. Okin P., Devereux R., Fabsitz R., Lee E., Galloway J.M., Howard B.: Principal component analysis of the T wave and prediction of cardiovascular mortality in American Indians. The Strong Heart Study, Circulation, 2002, 105, 714-719.

12. Kozmann G., Lux R., Scott M.: Sample size and dimensionality in multivariate classification: Implications for body surface potential mapping, Comput. Biomed. Res., 1991, 24, 170-182.