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INSTITUTE OF PHYSICS PUBLISHING PHYSIOLOGICAL MEASUREMENT

Physiol. Meas. **24** (2003) 805–816 PII: S0967-3334(03)58936-5

Spatiotemporal characterization of paced cardiac activation with body surface potential mapping and self-organizing maps

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Received 29 January 2003, in final form 9 June 2003
Published 1 August 2003
Online at stacks.iop.org/PM/24/805

Abstract

In this study self-organizing maps (SOM) were utilized for spatiotemporal analysis and classification of body surface potential mapping (BSPM) data. Altogether 86 cardiac depolarization (QRS) sequences paced by a catheter in 18 patients were included. Spatial BSPM distributions at every 5 ms over the QRS complex were first presented to an untrained SOM. The learning process of the SOM units organized the maps in such a way that similar BSPMs are represented in particular areas of the SOM network. Thereafter, time trajectories and distance maps were created on the trained SOM from sequential maps in a selected paced QRS. The trajectories and distance maps can be applied as such for the localization of abnormal ventricular activation, as well as quantitative input for statistical classification. The results indicate that the method has potential for locating endocardial sites of abnormal ventricular activation, despite the patient material being too limited to provide a reliable statistical evaluation of the source localization accuracy.

Keywords: body surface potential mapping, neural networks, cardiac pacing, ventricular tachycardia

(Some figures in this article are in colour only in the electronic version)

1. Introduction

Catheter ablation of ventricular tachyarrhythmia sources is commonly used as an option, or to complement drug treatment or application of an implantable cardioverter defibrillator (Stevenson *et al* 1997). The treatment requires intracardiac mapping and pacing in an electrophysiological study (EPS) to localize the arrhythmogenic tissue. If the tachycardia cannot be treated by catheter ablation, the patient usually undergoes arrhythmia surgery where the results of the localization can be utilized. During the routine EPS, standard 12-lead electrocardiograms (ECGs) are used to guide the catheter to the arrhythmogenic area by comparing the signal morphology of a paced beat to the clinically verified tachycardia (Josephson *et al* 1981). Visualization of the coronary arteries and the catheter's position is performed with a fluoroscopic device.

Body surface potential mapping (BSPM) has been applied clinically to the diagnosis of several cardiac disorders such as myocardial infarction (Kornreich *et al* 1991), ventricular arrhythmias (Mitchell *et al* 1992) and coronary artery disease (Hänninen *et al* 2001), in which complementary non-invasive information to the standard 12-lead ECG is needed. For example, the localization accuracy of ventricular tachycardia sources during endocardial pace mapping based on the standard 12-lead ECG can be improved by the use of BSPM (SippensGroenewegen *et al* 1993, 1994). The localization of arrhythmia sources during catheterization is usually based on previously recorded databases for supraventricular (Liebman *et al* 1991, Nadeau *et al* 1993) or ventricular arrhythmias (SippensGroenewegen *et al* 1990, 1992). In BSPM database localization, the ECGs obtained during arrhythmia are averaged at each channel over the time interval from Q-wave onset to S-wave offset (QRS integral) and the resulting figures are plotted as a distribution on the body surface. The database localization of arrhythmias has also been applied in our patient material (Simelius *et al* 1996b).

Database matching is based on the assumption that a monomorphic and stable tachycardia originating from the same area of the heart will produce similar time-dependent potential distribution patterns on the body surface for every patient. This assumption is not strictly valid, but the localization accuracy has proved to be sufficient for clinical use (SippensGroenewegen *et al* 1993, 1994). On the other hand, the classification accuracy of the decision trees for standard 12-lead ECG is between 80 and 90% (Josephson *et al* 1981, Holt *et al* 1985, Kuchar *et al* 1989).

So far, analysis methods for BSPM data during endocardial pace mapping have mainly focused on the detection of morphological differences of QRS integral maps at various pacing locations (Abildskov 1989). The integration procedure misses time-dependent features of the activation process, which can provide additional diagnostic information. Therefore, more dedicated analysis methods are needed to incorporate the temporal dynamics. We have studied self-organizing maps for the analysis of high-resolution BSPM data. Initial experiences with the method were described in conference reports (Simelius *et al* 1997, Reinhardt *et al* 1998) in which the results were classified manually. This paper reports more novel signal processing methods allowing automated classification and aiming at robust localization of cardiac excitation, such as endocardial origin sites of ventricular tachycardias.

2. Methods and materials

2.1. Body surface potential mapping

The design of our BSPM system design is based on the system developed at the University of Amsterdam (MettingVanRijn *et al* 1993). Our BSPM utilizes 123 channels for the ECG

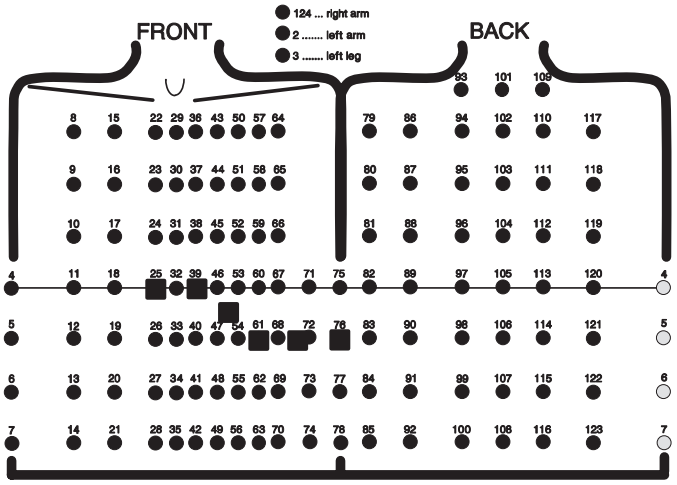


Figure 1. BSPM electrode positioning on the body surface. The horizontal line depicts the fourth intercostal space, and the six precordial standard leads are indicated by the filled squares.

recordings (Simelius *et al* 1996a). The signals are bandpass filtered to 0.16–300 Hz and sampled with a 1000 Hz sampling rate and 16-bit resolution. The data are transferred optically from the patient front-end to a PC using direct memory access transfer. The instrumental noise of the system is less than 1 μV_{rms}. In patient recordings, noise levels of 1.5 μV_{rms} have been measured. Further system characteristics and performance as well as the protocol for patient studies have been described elsewhere (Simelius *et al* 1996b, 1998). The electrodes are attached on flexible strips with an interelectrode distance of 50 mm (In Vivo Metric System, Healdsburg, CA). The electrode placement on the body surface is presented in figure 1.

2.2. Electrophysiological studies

We included in this study 18 patients with ventricular tachyarrhythmias scheduled for catheter ablation treatment or for an electrophysiological study. The mean age of the patients was 60.5 ± 14.0 years. The patients had no large structural changes in their hearts, although ten patients had a previous myocardial infarction.

Invasive EPS was performed in all patients using standard quadrupolar 5 French electrodes (Daig, St Jude Medical, USA) with 10 mm electrode spacing. The patients were in unsedated postabsorptive state, when they had been off antiarrhythmic agents for more than five half-lives. Electrode catheter placement, measurements of conduction and refractoriness as well as induction of ventricular arrhythmias were performed using standard electrophysiological techniques. Programmed ventricular stimulation was done with up to three extra stimuli from two ventricular sites using driving cycle lengths of 600 and 400 ms without the application of isoproterenol.

Left and right ventricular pace mapping was performed using a quadrupolar 7 French steerable ablation catheter (EP Technologies/Boston Scientific Corp., USA) with 5 mm electrode spacing according to the principles presented by Josephson *et al* (1982a). In this technique, the endocardial surface of the left ventricle is divided into 12 and the right ventricle into six different pacing sites (Josephson *et al* 1981). The heart was paced from the tip of the

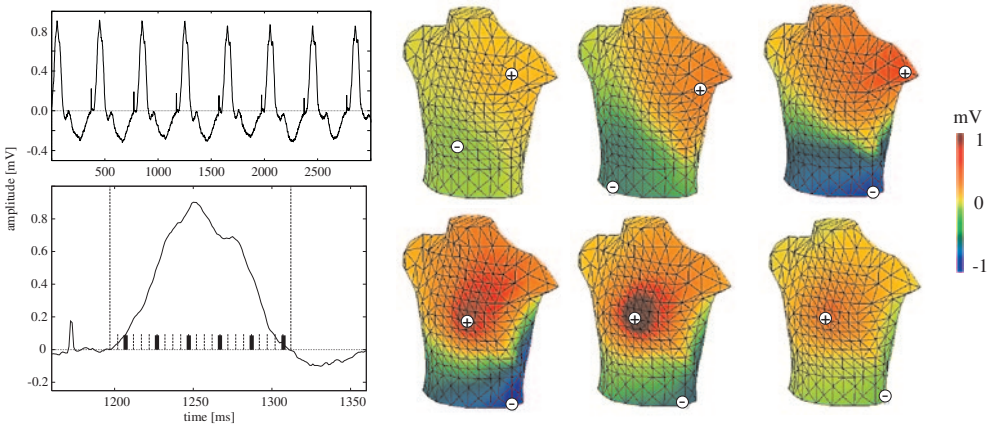


Figure 2. (a) Sampling of the paced ventricular beats. Maps at every 5 ms during the selected QRS are included for the SOM. (b) BSPM activation during ventricular stimulation displayed every 20 ms, denoted by thick ticks in (a).

mapping catheter with a current over the diastolic threshold at a rate close to the documented tachycardia rate. The 12-lead ECG (CardioLab^{R}, Prucka Engineering, Inc., Houston, TX, USA) and body surface potential mapping were recorded both during sinus rhythm and pace mapping. The position of the catheter tip was monitored using biplane fluoroscopy in right and left anterior oblique projections.

2.3. Sampling of paced maps

Altogether, 86 BSPM recordings were obtained from 16 distinctive pacing sites in 18 patients during catheter pace mapping. The minimum and maximum number of recordings per patient were 2 and 13, respectively. From each recording, the isoelectric baseline and three paced QRS complexes were selected manually. Also automatic baseline detection was tested (Jokiniemi *et al* 2003). The selected QRS complexes were then sampled at 5 ms sampling intervals from the beginning to the end of the depolarization. Figure 2(a) gives an example of the sampling process for a paced ventricular beat. Based on this procedure, altogether 8346 potential maps were extracted. The data obtained from the 123-channel recordings were interpolated on a triangulated 3D standard torso with 352 nodes as shown in figure 2(b). The interpolation algorithm is based on minimizing the surface Laplacian at all nodes of the torso (Oostendorp *et al* 1989).

2.4. Self-organizing map

The self-organizing map (SOM) is an artificial neural network architecture based on unsupervised, competitive learning (Kohonen 1995). The basic SOM maps the input data space $\mathcal{R}^n$ onto a discrete two-dimensional lattice of neurons in a topologically ordered fashion. For each neuron, a codebook vector m_i (dimension $\mathcal{R}^n$) is associated. Each input vector is compared with the codebook vectors, and the input is mapped to the location of the best match c. The comparison can be done by, e.g., minimizing the Euclidean distance:

$$c = \arg\min_i \|x - m_i\| \tag{1}$$

where x is the input vector. In the learning process the codebook vectors are updated according to the input vectors as

$$m_i(t+1) = m_i(t) + h_{ci}(t)[x(t) - m_i(t)] \tag{2}$$

where t is the learning time step, and $h_{ci}(t)$ is the neighbourhood kernel function. All neurons that belong to the neighbourhood kernel of the winner neuron c are updated according to the type of kernel. A simple 'bubble' kernel is defined as follows: let N_c be a set of neurons around the winner c. All the neurons in N_c are updated with same weight defined by a learning rate function $\alpha(t)$:

$$h_{ci} = \begin{cases} \alpha(t) & \text{if} \quad i \in N_c \\ 0 & \text{if} \quad i \notin N_c. \end{cases} \tag{3}$$

Another commonly used kernel, the Gaussian one, is defined as

$$h_{ci}(t) = \alpha(t) \cdot \exp\left(\frac{-\|r_c - r_i\|^2}{2\sigma^2(t)}\right) \tag{4}$$

with

$$\alpha(t) = \alpha_0\left(\frac{1-t}{t_{\max}}\right) \qquad \sigma(t) = 1 + (r_0 - 1)\left(\frac{1-t}{t_{\max}}\right). \tag{5}$$

The parameters α_0 and r_0 are the initial learning rate and the neighbourhood radius, respectively. During the learning process, the neighbourhood radius and learning rate are diminished. The learning process leads to a smoothing effect on the codebook vectors in the neighbourhood and by continued learning to global ordering of the codebook vectors (Kohonen *et al* 1995).

The SOM adaptation process is achieved in four steps:

(a) *Setup and initialization:* various network parameters are provided for the SOM setup, such as number of neurons (codebook vectors), neighbourhood topology (rectangular or hexagonal), neighbourhood radius and learning rate function. The codebook vectors are then initialized with random data values.
(b) *Ordering:* the codebook vectors are ordered coarsely according to equation (2). In ordering phase the initial neighbourhood radius and learning rate are large.
(c) *Learning:* the codebook vectors are fine-tuned. Initial neighbourhood and learning rate are smaller than in the ordering phase. The number of learning steps is substantially larger than the number of ordering steps.
(d) *Evaluation of the SOM:* after the learning phase, the quality of the SOM is estimated, e.g., by calculating the quantization error and distortion, defined as ave$\|x - m_c\|$ and $\sum h_{ci}\|x - m_i\|^2$, respectively. The SOM can also be inspected visually.

In the present study, the predominant BSPM features were extracted by adaptively projecting the observed BSPM patterns onto a SOM. In the setup of the SOM we used a two-dimensional array for the network, with a hexagonal arrangement of the neurons. The number of neurons in the horizontal direction was set to 18 and in the vertical direction to 14, giving a total number of 252 neurons and codebook vectors for the SOM. In the ordering and learning phases, the codebook vectors were adaptively modified by subsequently presenting all measured BSPM patterns to the SOM. The adapted neurons can be viewed as specific detectors of their respective domains of BSPM patterns—in other words, the SOM can be seen as a mapping, where each 352-component BSPM pattern is projected to a single point in a 18×14 lattice.

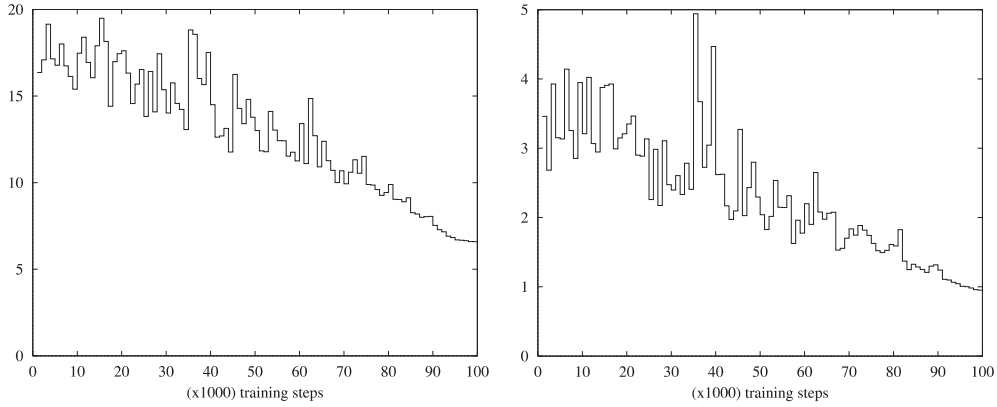


Figure 3. (a) Quantization error and (b) distortion measure as a function of the training steps. The vertical scale in (a) refers to the quantization error per channel, and in (b) to distortion measure multiplied by 10^{-9}.

3. Results

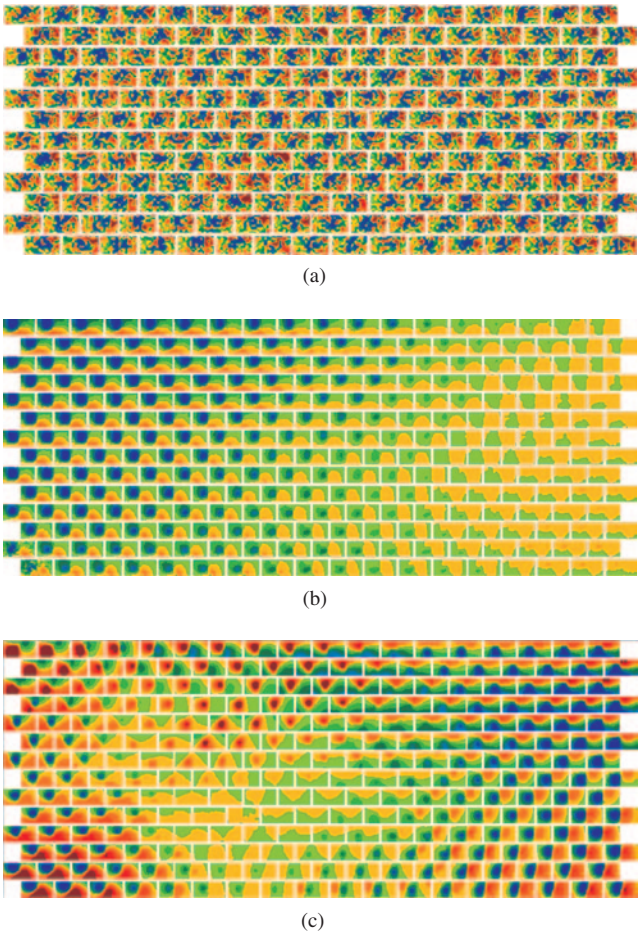
3.1. Training of the self-organizing map

The input data for the SOM comprise BSPM distributions obtained during ventricular pacing as described above. Every cell on the SOM represents a potential map on the body surface. All cells together constitute the *SOM codebook*, where each map is represented as a codebook vector. In the learning process we estimated the quantization error and distortion. They are presented in figure 3 as a function of training steps. The distortion measure is better adapted for large codebooks since it takes into account the neighbourhood function (Kohonen *et al* 1995). The development of a SOM during the learning process is shown in figure 4. After random initialization of the reference vectors, self-organization of the map starts and spreads over the network. The zero BSPM was fixed to the centre of the SOM.

The organization of a fully trained SOM in figure 4(c) shows that the map direction between neighbouring cells is changing smoothly on the SOM. In all teaching runs, the SOM organized to a good quality representation of the endocardium, i.e. adjacent sites on the endocardium mapped to adjacent points on the SOM. Moreover, the fully trained SOM did not include any meaningless or random maps. Of all teaching runs, the SOM that resulted in the lowest quantization error of the test set was chosen to be used in the classification.

3.2. Trajectories and distance maps

When a new potential map is presented to the trained SOM, the best matching node is found. Tracing the best matching nodes one by one for sequential potential maps results in a trajectory on the SOM. In order to provide data that are suitable for automatic classification, the trajectories of the paced beats on the SOM were quantified as follows: for each node of the SOM the shortest distance between the codebook vector associated with that node and all data vectors of the BSPM sequence was calculated. After logarithmic scaling a distribution of shortest distances over the SOM is obtained. This distribution is referred to as the *QRS distance map* in the following. Two typical trajectories and the corresponding



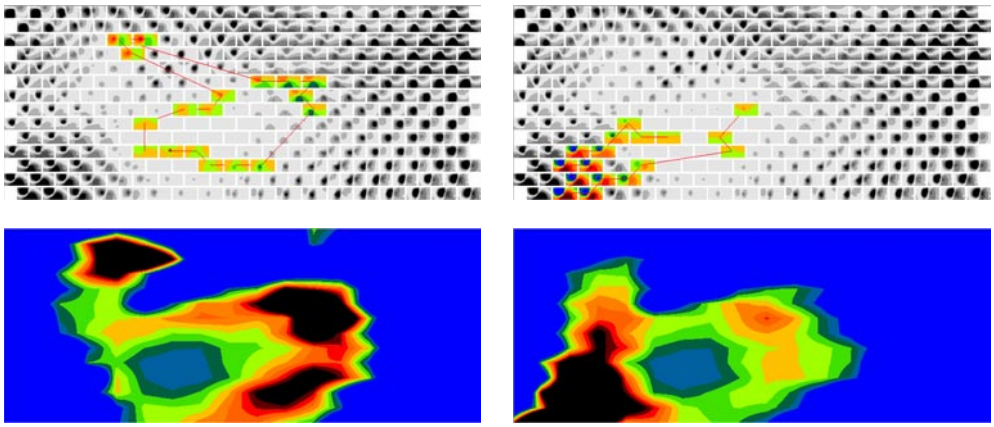
(a)

(b)

(c)

Figure 4. SOM development during the training process: (a) a random initialization of the SOM is followed by (b) an ordering phase using 1000 training steps. (c) The fully trained SOM is obtained after 100 000 training steps.

distance maps are shown in figure 5. In figure 5(a) the trajectory is somewhat discontinuous and the distance map contains dark islands with light coloured areas between them. This results from discontinuous projection of the BSPM patterns onto the SOM; the feature can be used in both estimating the quality of the SOM mapping and visual classification of unknown data. The distance maps calculated from QRS sequences of one subject are presented in figure 6, and some maps of eight subjects in figure 7. From the figures it can be seen that the distance maps from adjacent pacing sites resemble each other. Also the distance map resulting from same pacing sites in different subjects are alike. For example, paced QRS sequence from the right ventricle apex (Josephson site 14) produces in all the subjects a map that contains small distances (dark colours) in the upper right part of the map. Physically this means that those QRS sequences contain maps that resemble codebook vectors in the upper right part of the SOM. The subject no 0021 had an anteroapical myocardial infarction. This explains partly the almost identical distance maps resulting from all the apical pacings.



(a) (b)

Figure 5. QRS trajectory and corresponding distance map of paced ventricular beats from (a) the left ventricular apex (Josephson site 1), and (b) the right ventricular outflow tract (Josephson site 17). The red (grey) dots in the trajectories indicate the earliest timepoints in the sequences.

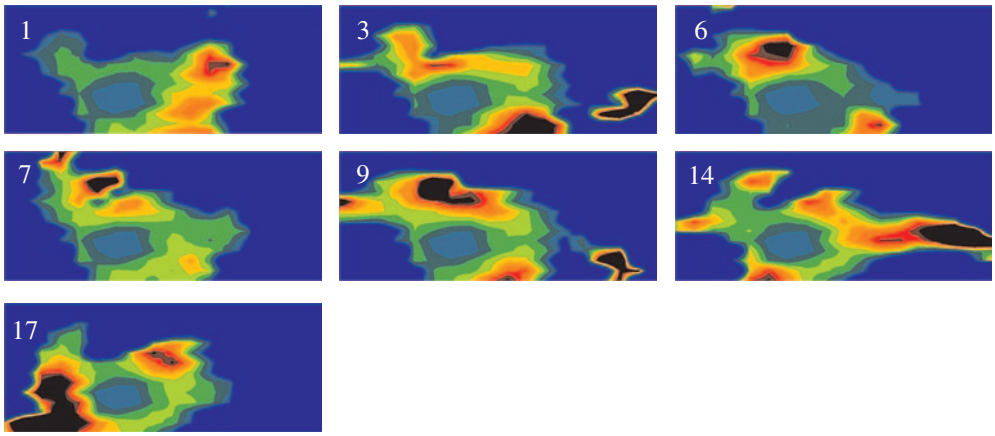


Figure 6. Calculated distance maps of seven pacing sites in one subject with ventricular tachycardia.

3.3. Classification—a case study

The distance maps of all paced beats can be used as input for a classifier such as a learning vector quantization (LVQ) method. In the LVQ algorithm, vector quantization is used to directly define the class borders according to the nearest-neighbour rule (Kohonen *et al* 1995). The accuracy of the LVQ classification depends on the amount of training data, the number of codebook vectors assigned to each class and on the proper learning rate.

The LVQ codebook learning was done with a jackknifing method: distance maps of one patient were left out of the training set and used as a test set. The number of subjects and the localization results for each class are shown in table 1. When all the distance maps were classified according to the ventricle, where the catheter was, the results were good. Also

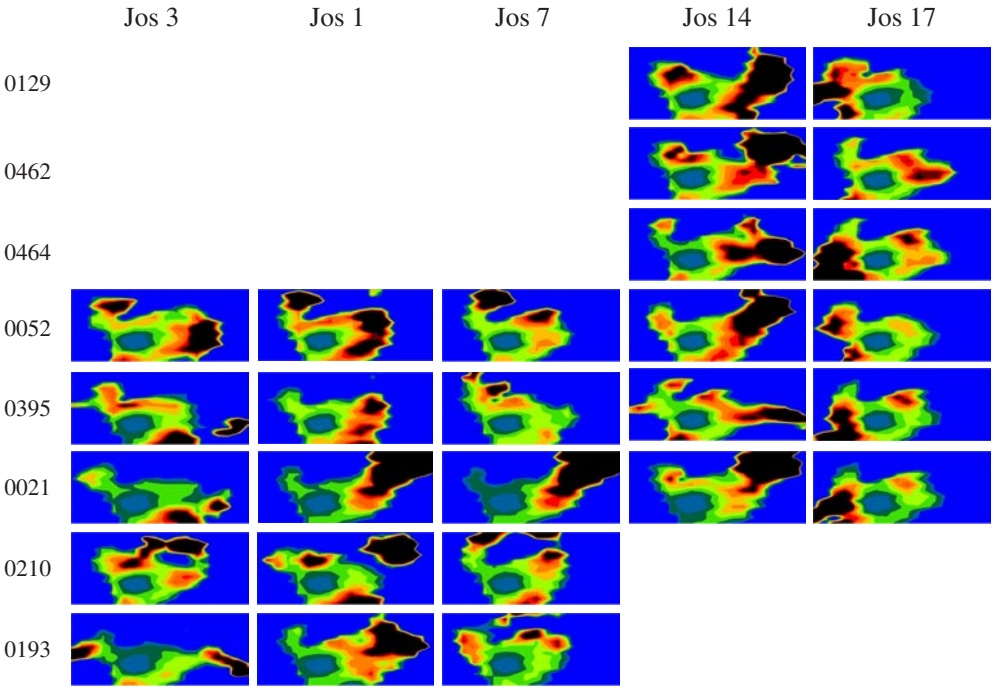


Figure 7. Calculated distance maps of five pacing sites in eight different subjects.

Table 1. Recognition accuracy obtained by LVQ classification of different pacing locations (see Josephson *et al* (1981)).

Pacing location	Number of patients	Accuracy (%)
Jos1	5	0
Jos2	5	0
Jos3	5	28
Jos5	4	12
Jos6	3	0
Jos7	6	5
Jos9	3	0
Jos11	4	17
Jos14	12	43
Jos17	11	63
LV	9	91
RV	14	83

from classes with many subjects (Josephson sites 14 and 17), the results were encouraging. However, for the left ventricular pacings the localization accuracy was poor; this results mainly from the size of the dataset. The same QRS sequences were used for teaching the SOM and calculating the distance maps that were used as LVQ input. This is not a problem as such, but the errors due to badly projected data (trajectories with large gaps) tend to grow in further neural processing.

4. Discussion

4.1. Advantages of the SOM

QRS integral maps have been utilized in most BSPM studies for localizing infarctions and arrhythmias. Such maps compress the spatiotemporal information of the whole QRS complex into one spatial distribution. In contrast, the SOM approach is to our knowledge the first approach which takes advantage of both the whole spatial distribution and the temporal development during the QRS. The SOM method also uses data of several QRS sequences, and can utilize data from patients both with and without myocardial infarctions (MI). In contrast, QRS integral matching requires separate databases for MI and non-MI patients (SippensGroenewegen *et al* 1990, 1992).

The SOM approach is expected to result in an improved and consistent localization accuracy while also providing more detailed information for the clinician treating the patient. For example, two different arrhythmia sequences may generate almost identical QRS integral maps, while they produce distinctly different QRS traces. Therefore, the distance maps are suitable for using with any classification method.

In the creation of the distance maps from trajectories, a fundamental assumption is made. Namely, since the directional information of time is lost in the conversion process, it must be assumed that the activation of the heart cannot produce two different sequences of potential maps, wherein the only difference is in the order of the maps. In other words, it is assumed that the arrhythmic activation of the heart cannot propagate so that it produces in reverse order a similar sequence of maps as another activation. Considering the electrophysiological properties of cardiac tissue and the generation of the electrocardiogram, this assumption is very well founded.

The method is fast, and the SOM used for localization can be upgraded easily with new patient recordings. Our future aim is to obtain for each paced beat a probability distribution describing the likelihood that it belongs to a particular pacing location. Moreover, the method performs in a predictable manner for new beats falling between the teaching beats, which is behaviour similar to that of the QRS integral method (Potse *et al* 2000).

4.2. Limitations of the study

Our patient data included very few VT beats, and the study was therefore limited to the data obtained during ventricular pacing. The main limitation is the relatively small number of patients and pacing sites; especially the number of subjects with structurally normal hearts paced from both ventricles is inadequate. The problems related to the small training set can be seen in discontinuous SOM trajectories resulting from some pacing locations in the training data. For reliable statistical classification, the learning dataset should contain about the same number of sequences for each pacing class; the dataset of about 15 patients for each class should improve the results substantially.

The earlier results that were based on manual classification demonstrated the strength of the SOM approach. The powerful visualization of cardiac activation is a helpful tool in localization of the arrhythmia sources. However, the current approach where a further classification step was carried out by another neural network system revealed the weaknesses of the method. More specifically, it became obvious that the use of SOM alone produces such a strong compression of the information in the activation sequence that further compression results in degradation of localization accuracy, especially if the training datasets are not large enough. Moreover, the loss of detail through the use of distance maps leads to some ambiguity in the interpretation of the trajectories. As a conclusion, it would perhaps be best to offer both

the trajectories and the distance maps to the cardiologist for interpretation, along with a library of trajectories and distance maps representing various arrhythmia sources.

5. Conclusions

We have developed a novel method for non-invasive characterization and classification of cardiac activation from BSPM data. As compared to QRS integral maps which display only average spatial information on the whole QRS complex, the SOM-approach uses both spatial and temporal QRS information. The method is fast and the SOM used for localization can be upgraded easily. Moreover, the method does not require selection of a single beat but can utilize a longer tachycardia sequence as input. The results are promising, but further studies and more patient material are still needed to test the method for clinical BSPM localization of VT.

Acknowledgments

This study was supported by the Training and Mobility of Researches (TMR) Programme of the European Union (EU), grant no ERBFMBICT972854, the Academy of Finland, the Aarne Koskelo Foundation (Finland), the Wihuri Foundation (Finland) and the Finnish Cultural Foundation.

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