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Clinical Parameter Assessment in Magnetocardiography by Using the Support Vector Machine

K. Kim[1], H. Kwon[1], Y. H. Lee[1], T. E. Kim[1], J. M. Kim[1], Y. K. Park[1],
J. Y. Moon[2], Y. G. Ko[2] and N. Chung[2]
[1]Biomagnetism Research Center, Korea Research Institute of Standards and Science, Deajeon, S. Korea
[2]Division of Cardiology, Yonsei Cardiovascular Center and Cardiovascular Research Institute, Yonsei University College of Medicine, Seoul, S. Korea

Abstract—**We propose a method based on the support vector machine to assess a set of clinical parameters for MCG diagnoses. By using this method, we can conclude whether the parameters are suitable for classifying a specific disease, and we can extract the dominantly working parameters from the set. In this study, we test a well-known set of the field-map parameters for ischemia detection by using our method.**

Keywords—**Magneocardiogram, support vector machine**

I. Introduction

Magnetocardiogram (MCG) has many merits over the electrocardiogram (ECG); the MCG is more sensitive to tangential currents, vortex currents, and current flow between endocardium and epicardium. In addition, it is less dependent on variation in conductance outside the heart and fully non-contact. Such merits make the MCG a useful diagnosing tool for heart diseases such as myocardial ischemia. We can divide the diagnosis in MCG into four main methods: First, they gather a large amount of multichannel time series of MCGs for every kind of diseases and diagnose a disease by using the correlation between the patient's MCG and one from the database [1]. Second, they classify a disease MCG using machine learning algorithms, such as neural network and partial least square (PLS), and self-organizing map (SOM) for the multichannel time series [2]. Third, waveform parameters with a filtering process can be used. Fourth, they extract parameters from the spatial field map (FM) constructed by multichannel measurement. In these diagnosing methods, the first and second methods need heavy resources because they use the time series of the whole channels (the time resolution could be several milliseconds and tens of measuring channels would make about 10,000 parameters per a MCG). Therefore, if we have a small number of parameters that explain the clinical characteristics of an MCG well, those will be used for not only diagnosis, but also visualizing the characteristics. Recently, the extracted FM parameters in the ST-T interval–the angle of dipole, the changing rate of the angle, the changing rate of the pole distance, and the changing rate of the magnitude ratio between the poles--are very useful for diagnosing myocardial ischemia and coronary artery diseases [3-5]. However, it is obvious that the effectiveness of such parameters may change depending on what we want to decide or which of the diseases is diagnosed. Therefore, we need an assessment tool that a set of parameters is really appropriate for diagnosing the specific disease. A simple statistic process can conclude whether an individual parameter of the set is effective or not for the decision. Nevertheless, when there is complementary interference among the parameters for decision, we have to find an assessment method considering the systemic synergy among the parameters. In this point of view, a clustering method in parameter vector space was reported [6], but if the clusters for each disease are not completely separable, it is difficult to determine the classifying boundary (hyperplane classifiers).

We propose a multi-parameter evaluation method based on determination of the effective boundary between the constructed parameter vector clusters with a support vector machine (SVM) algorithm. The SVM is widely used in the field of pattern recognition and it has been proved very effective in binary decision-making and real world classification tasks [7,8].

In this article, we evaluate the disease separability of the popular FM parameters for the ST-T interval for the two following cases:

1) Detection of the non-ST-elevation myocardial infarction (the unstable angina with more than one vessel disease) in the group of patients who have no ST-elevation in their ECG.
2) Separation of the acute myocardial ischemia from the old MI.

The article consists of a brief review of the SVM algorithm, MCG measurement, the definition of the FM parameter, the SVM result for the case of the effective parameter set, the result for the case of the ineffective parameter set, and discussion.

II. Support Vector Machine

A SV classifier uses a pair of optimal hyperplanes that are defined as nonlinear planes with the maximal margin of separation between two classes. In our case, the two classes consist of a disease positive class and a disease negative class. We can plot l parameter vectors $\mathbf{x}_i$ on the d-dimensional vector space when we have l-training data set $\{\mathbf{x}_i, y_i\}$, $i = 1, \cdots, l,\ y_i \in \{-1, 1\}, \mathbf{x}_i \in \mathbf{R}^d$, where y_i is class label for $\mathbf{x}_i$. Suppose we have a hyperplane separating the positive from the negative. The points on the hyperplane will satisfy $\mathbf{w} \cdot \mathbf{x} + b = 0$, where $\mathbf{w}$ is normal to the hyperplane. For the linearly separable case, we have simple constraints, $(\mathbf{x}_i \cdot \mathbf{w} + b) y_i \geq 1$. Then all the positive vectors

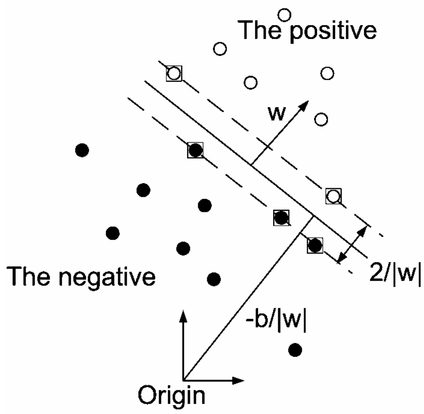

Fig. 1. Two-dimensional classifying hyperplanes for SVM.. The squared points are support vectors to determine the hyperplanes.

are placed in farther distance than $|1-b|/\|\mathbf{w}\|$ from the origin to the direction of **w** and all the negative vectors are placed in smaller distance than $|-1-b|/\|\mathbf{w}\|$. Hence, the margin between the positive and the negative is simply $2/\|\mathbf{w}\|$. Therefore, we can find the pair of the hyperplanes rendering the maximum margin by minimizing $\|\mathbf{w}\|$. We visualized the case of two-dimensional vector space (2 parameters per a sample) in Fig. 1. In the two-dimensional space, the hyperplanes converge into lines separating the positive from the negative. We can get the optimal solution by using the Lagrange multipliers on the constraints, i.e.,

$$\mathbf{w} = \sum_i \alpha_i y_i \mathbf{x}_i \ , \tag{1}$$

$$\sum_i \alpha_i y_i = 0 \ \text{ for } \ \alpha_i \geq 0 \ . \tag{2}$$

In Fig. 1, the squared points are 'the support vectors', which determine the hyperplanes and $\alpha_i > 0$ on the support vectors. Once the support vectors are selected, the hyperplanes can be constructed without help of the other training vectors. Even for the non-separable case, the SVM works by introducing positive slack variables in the constraints and (2) changes to $\sum_i \alpha_i y_i = 0$ for $C > \alpha_i \geq 0$, where *C* means a amount of penalty to errors from the non-separable vectors. [9]. Finally, the decision function for a sample, **x**, obtained from the training is

$$\mathrm{Sgn}\left(\sum_{i=1}^{Ns} y_i \alpha_i K(\mathbf{x}_i, \mathbf{x}) + b\right), \tag{3}$$

where *Ns* is the number of support vectors, $K(\mathbf{x},\mathbf{y})$ is the product kernel, $K(\mathbf{x},\mathbf{y}) = \Phi(\mathbf{x})\Phi(\mathbf{y})$ for a non-linear mapping into a higher dimensional space $\Phi(\cdot)$. In the prementioned linear case, $K(\mathbf{x},\mathbf{y})$ is simply $\mathbf{x}\cdot\mathbf{y}$; however, if we use a non-linear kernel like a radial basis function (RBF), $K(\mathbf{x},\mathbf{y})=\exp(-g\|\mathbf{x}-\mathbf{y}\|^2)$, we can construct a more flexible and better separable hyperplane. In order to achieve the optimal performance of the SVM, we should choose (*C*, *g*) that is proper to the training system. When we determine (*C*, g), it is not desirable to achieve high training accuracy because of the over-fitting problem. Thus, we use cross-validation. In *n*-fold cross-validation, we divide the training data into *n* subset of equal size. Then, we test one subset using the decision function trained on the rest *n*-1 subsets and we obtain how many data are correctly classified in percentage. The predicted figure can more precisely reflect the performance on classifying unknown data [10].

In our study, we use 4-fold cross-validation and average out 10 processes of the cross-validation to get a stable accuracy. We assume that the best accuracy over (*C*, *g*) is the maximum separability of the set of parameters with the training samples and we utilize the best accuracy in percentage as the measure to assess a set of parameters in a given problem.

III. MCG MEASUREMENT & PARAMETERS

The MCGs of all the subjects were measured with the KRISSMCG (Biomagnetism research center, KRISS, Deajeon, KOREA). The KRISSMCG installed in Yonsei cardiovascular center has 62 planar first-order SQUID gradiometers, which measure the tangential components of the cardiomagnetic fields [11]. Measuring tangential field components is effective to obtain the whole heart information with a relatively small area of sensor distributions [12]; however, in order to apply the popular FM parameters, we change the tri-polar field map patterns into the ordinary dipolar field maps by using minimum norm estimation [13]. Typical recording time was 30 s. The signal processing software provides automatic digital filtering, averaging, synthetic gradiometer formation and baseline correction for the acquired records.

The sensitive part to ischemia in MCG is the ST-T segment. Thus, the FM parameters were found in the ascending part of the T-wave between $T_{max}/3$ and T_{max}. The four FM parameters mainly observe the direction of the vector (from minus pole to plus pole), change in the angle of the vector, change in the distance between the poles, and change in the ratio of the pole magnitudes in the above-mentioned interval. Specifically, the latter three parameters are called 'dynamics' parameters. The dynamics means rapid change inside a time interval of 30 ms between $T_{max}/3$ and T_{max}. Generally, a diagnosis of myocardial ischemia is made when at least one of these four FM parameters exceeds the corresponding critical value [4,5].

IV. RESULT

A. A set of effective parameters

There are many reports besides [3-5] that the FM parameters are feasible for the diagnosis of acute myocardial ischemia when they are applied to the patients whose ECG does not show pathological abnormalities such as ST

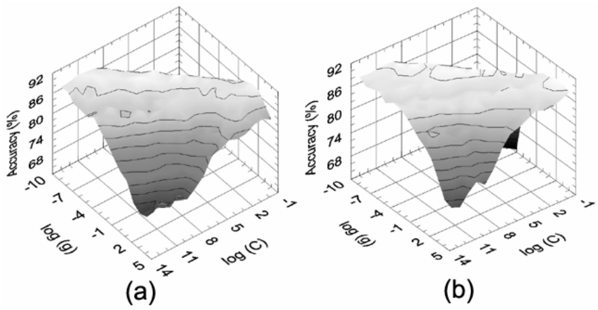

Fig. 2. Cross validation results for a set of effective parameters. (a) Cross validation for the four FM parameters with (C, g). (b) Cross validation for the three dominant parameters with (C, g). Note that the 2-based logarithmic scale is used.

elevation or depression. On that account, we can expect that the FM parameters will make a fairly good score in our SVM assessment.

Included in the study were a total of 80 patients without pathological abnormalities in the ST-T segment of their ECG: 30 patients, who were angiographically determined to have more than one vessel disease on their coronary artery, and the rest 50 controls in whom ischemia was ruled out from their symptoms and ECG results. With the conventional diagnosis (the disease is positive when at least one of the four FM parameters exceeds the corresponding critical value), the 24 of 30 patients (sensitivity; 80%) were recognized as true positive and the 48 of 50 controls (specificity; 96%) were recognized as true negative. The critical values of the FM parameters for our system were the angle range of -112^{o} to $+20^{o}$, the angle dynamics of 50^{o}, the distance dynamics of 34 mm, and the ratio dynamics of 1.2.

In order to validate the parameters with SVM, we conducted cross validation over (*C, g*) for the RBF kernel (Fig. 2(a)). As we have expected, the maximum accuracy was fairy high (88% at (*C, g*)=(16, 0.0625)) and we could conclude that the FM parameters are suitable for diagnosing unstable angina with vessel disease. In addition to this, we can evaluate which parameter is dominantly effective for the diagnosis by looking at the weighting vector, **w** in (1). In this case, the normalized **w** was (0.53, 0.20, 0.80, 0.19) for the RBF kernel and (0.41, -0.02, 0.90, 0.12) for the linear kernel, respectively. Therefore, the dominant parameters are the angle, the distance dynamics, and the ratio dynamics. With the three parameters, we again conducted cross validation over (*C, g*) for the RBF kernel (Fig. 2(b)). The maximum accuracy was 88.5% at (*C, g*)=(8, 0.125). Note that there is little difference betweens the two cases. Three-parameter vectors can be visualized on the 3-D space. Fig. 3 shows the classification results with the SVM hyperplane for the case. In both the RBF kernel (Fig. 3(a)) and the linear kernel (Fig. 3(b)), the three parameters successfully separate the classes. Note that the separation for this case will be successful with only two parameters (the angle and the distance dynamics) in Fig. 3(c). This is because the parameter of the ratio dynamics had a small value in the **w** vector.

B. A set of ineffective parameters

In the preliminary study [14], we constructed a two-dimensional heart simulation model and reported that the myocardial currents in acute ischemic tissue rather than in chronic infarcted tissue give much more dynamic change (even generation of vortex currents). Fig. 4 shows the propagation of isochrones and the corresponding field maps for infarction and ischemia, respectively, at the instant of repolarization. The creation and annihilation of the current vortex shown in Fig. 4(c) make dynamic change in the field map whereas the change in the field map of infarction (Fig. 4(b)) is quite stable. From this result, we can suppose that the latter three ‘dynamics’ parameters in the four FM parameters would be used to separate the acute ischemia from the old myocardial infarction (MI).

Included in the study were a total of 18 patients with symptoms of unstable angina: 11 patients, who were angiographically determined to have more than one vessel disease on their coronary artery, and the rest 7 patients with the past MI history and no occlusion of the vessels, in whom akinesia of the MI region was observed echocardiographically. We classify the former group as the

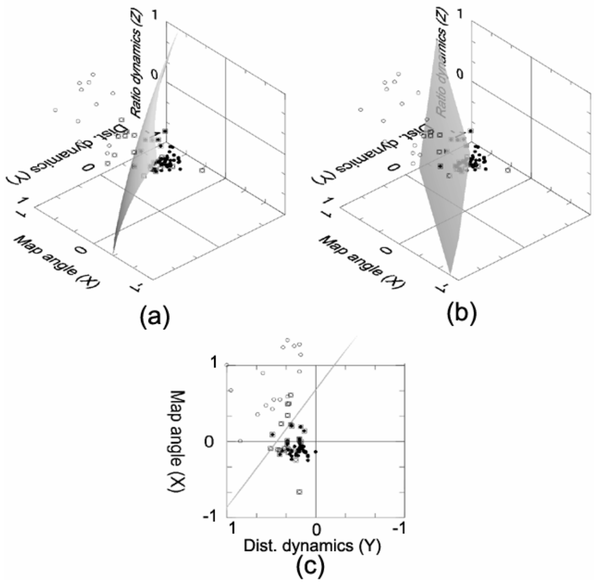

Fig. 3. Classifying hyperplanes for the dominant three parameters with (a) an RBF kernel and (b) a linear kernel. The empty circles are the parameter vectors for the patients and the filled circles are for the controls. The squared points are the support vectors to determine the hyperplanes. (c) represents that just two of the four FM parameters are enough to separate the case.

acute ischemia and the latter as the old MI, respectively. In the conventional diagnosis, the 7 of 11 acute ischemia patients (sensitivity; 63%) were recognized as true positive and the 4 of 7 old MIs (specificity; 57%) were recognized as true negative. Here, we used only the three dynamics parameters with the same criteria as those used in the previous section.

In order to validate the parameters with SVM, we conducted cross validation over (*C*, *g*) for the RBF kernel (Fig. 5(a)). The result shows a rather low accuracy on the entire area of (*C*, *g*). The planar area of high accuracy in the figure means that the hyperplane is located outside of both the positive vectors and the negative vectors (Fig. 5(b)); hence, the meaningless accuracy is simply 61% (11/18).

This result indicates that the three dynamics parameters of the FM are not suitable to separate the acute ischemia from the old MI. The reason for this result is that the FM parameters using two major poles (the maximum strength and the minimum strength) do not reflect the small dynamic structures in the field map (Fig. 4).

V. Discussion

The aim of this study is to assess a set of clinical parameters for classification of a specific disease. A theoretical estimation of error bound for SVM was also reported [15], however, we believe that the practical cross validation in this work is feasible for the assessment and visualization of the characteristics of proposed parameters.

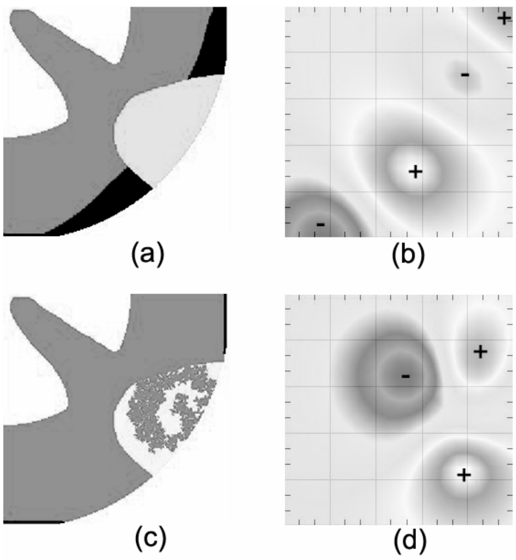

Fig. 4. Comparison between (a) infarction and (c) ischemia. In (a) and (c), the black region is repolarized tissue and the grey region is depolarized tissue. The light grey region is the infarcted tissue for (a) and the ischemic tissue for (c), respectively. (b) and (d) is the corresponding field maps for (a) and (c), respectively. Note that the field maps are just parts of the total field maps covering the entire heart.

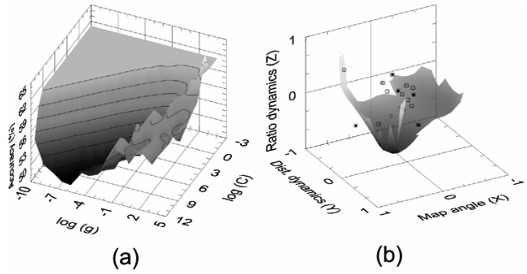

Fig. 5. (a) Cross validation result for a set of ineffective parameters with (C, g). Note that the 2-based logarithmic scale is used. (b) The resultant hyperplane for the RBF kernel (C, g)=(4, 8).

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