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Bayesian Classification of Myocardial Excitation Abnormality Using Magnetocardiogram Maps for Mass Screening

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ABSTRACT

We propose a novel classification method based on the Bayes rule to utilize the magnetocardiogram (MCG) in noninvasive mass screening. The cardiac excitation is directly tracked by maps of the MCG field generated by myocardial excitation current through the excited wave front. To adopt the characteristics of the excited wave fronts as a parameter for the Bayes theorem, we developed a parameterization procedure that consists of a two-dimensional wavelet approximation and a cluster analysis of magnetic field maps. With the parameter determined by this procedure, the probability of a subject to belong to a disease group or to the normal group is estimated by the Bayes theorem. The subject is classified into the group of the highest probability. We applied the proposed method to ST-T period of MCG data of 6 old myocardial infarction (OMI) patients and 15 normal controls. The method showed sensitivity of 83%; specificity, 100%; positive predictive value, 100%; and negative predictive value, 94% in the classification of OMI patients and normal controls. The processing time is less than 5 seconds per one subject. It suggests a possible application of the proposed method in mass screening of abnormal MCG patterns.

KEY WORDS

Magnetocardiogram, Excited wave front, Myocardial infarction, Screening, Wavelet approximation, Gaussian mixture modeling, Bayes criterion

INTRODUCTION

MCG provides a visualization of electrophysiological field maps of the heart, and is considered as a potentially complementary and substitutive method for the electrocardiogram (ECG). Taking advantage of the non-contact registration and noninvasive measurement in clinical application, MCG should be valuable as an initial medical checkup. Therefore, we are developing a mass screening method to automatically distinguish abnormal patterns of cardiac excitation using MCG. In this paper, we propose a Bayesian classification method with newly developed parameterization techniques of magnetic field maps. The Bayes rule is a classifier algorithm that minimizes an error rate of false positives and false negatives, and widely used in pattern recognition [Christopher, 1995A]. The difficulty in applying the Bayes theorem to MCG classification is the parameterization of magnetic field maps. Data of a MCG field map in even one time window consists of tens of values of magnetic flux density that were measured at the respective measurement sites. In order to track the excitation pathway during one heart cycle, the magnetic field maps of more than a hundred analyzing time windows should be processed at once. We developed two-dimensional wavelet approximation and cluster analysis techniques to parameterize the magnetic field maps into a simple indicator, and applied it to the Bayesian classification of old myocardial infarction (OMI) patients and normal controls.

METHODS

MCG data. MCG examination was conducted on the MCG system (Hitachi Ltd., [Tsukada, 1998]) at the Institute of Clinical Medicine, University of Tsukuba, Japan. The system has 8 x 8 SQUID (Superconducting Quantum Interference Device) magnetometers at intervals of 2.5 cm in a 17.5 x 17.5 cm^2 measurement area. MCG data of 6 patients with OMI (2 inferior, 2 posterior, and 2 anteroseptal infarction) and 15 normal controls were taken at a sampling frequency of 1 kHz through a 0.1-100 Hz band pass filter and a notch filter of the power line frequency of 50 Hz. Data more than 20 heartbeats were averaged off-line using the points of R peaks in simultaneously measured ECG on the second lead for alignment, and baseline corrected. Coronary angiography was carried out to determine the area of the infarction in the patient with OMI. Clinical diagnoses of the normal controls were based on 12 lead ECG. In the analysis, we used the magnetic field maps of the repolarization phase (ST-T period) that corresponds in the last one third of the time course between the peaks of R wave and T wave.

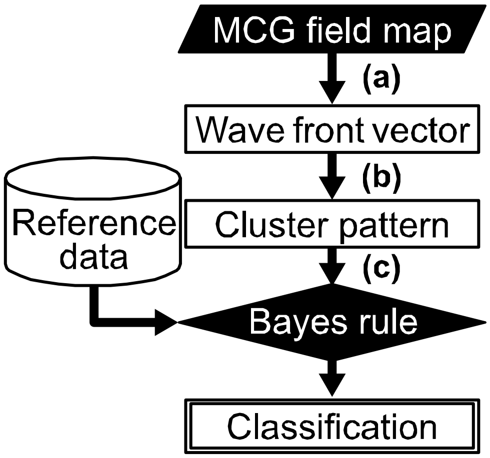

Figure 1. Flow chart of Bayesian classification of MCG.

Classification method. The classification method consists of two procedures of MCG field maps parameterization (**(a), (b)**), followed by the Bayesian classification **(c)**, as shown in Fig. 1.

(a) The '*wave front vector'* is determined from the magnetic field map of an analysis time window. Using a wavelet approximation, we choose positions at which the magnetic field map has positive and negative spatial extreme points. The cardiac excited wave front is considered to exist in the plane that is perpendicular to the chest and contains the line that connects the positive and negative extreme points. Therefore, we defined the position and the direction of the wave front vector as the center of these extreme points and the direction perpendicular to the direction from the positive extreme point to the negative extreme point, respectively; this is seen in Fig. 2. The wave front vector interprets the coronal center position and the travel direction of the excited wave front. Details of the determination procedure have been reported previously [Ono, 2002].

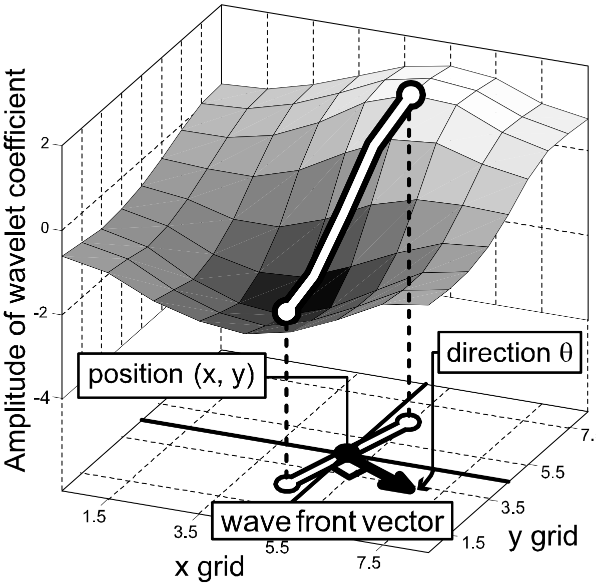

Figure 2. Determination of wave front vector.

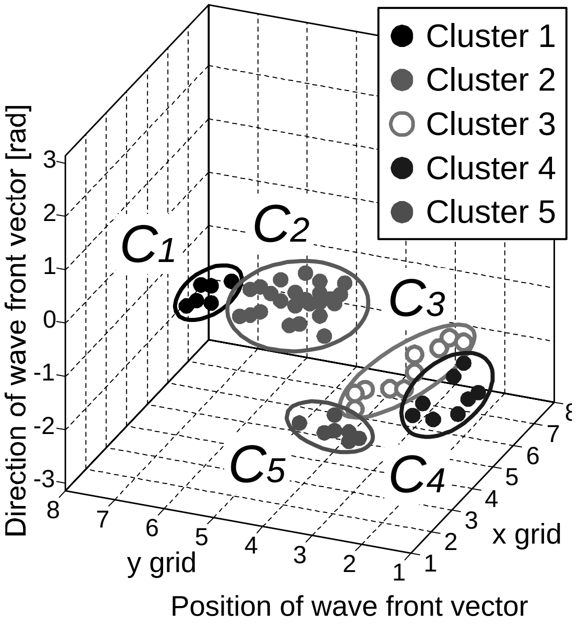

Figure 3. Clusters of wave front vectors.

(b) The subject's wave front vectors through all the analysis time windows are summarized in a '*cluster pattern*', which is then used for Bayesian classification. Since the number of the wave front vectors amounts to more than a hundred with each subject, it is not suitable to directly apply the Bayes theorem to the wave front vectors. The wave front vectors of all the subjects were divided into some clusters in advance. Using Gaussian mixture modeling (GMM) with expectation maximization algorithm [Christopher, 1995B], we applied 5 Gaussian models to all the wave front vectors in this study. As shown in Fig. 3, we describe these 5 clusters as C_1, C_2, ..., C_5, respectively. Then we determined the cluster pattern of a subject according to the distribution of his/her wave front vectors among the clusters. The Mahalanobis distances between the wave front vector and the mean position of the respective clusters are calculated, and the wave front vector is classified to the cluster that has the shortest Mahalanobis distance. All of the wave front vectors of a subject in the analyzing time windows are classified in this way. The cluster pattern (k-l) indicates that the population of the wave front vector in the cluster C_k is the largest and that in the cluster C_l is the second largest. If all of the wave front vectors are classified into one cluster C_k, the cluster pattern is (k). The Mahalanobis distance is used to take the trends of variance and covariance of the respective clusters into account. In order to apply the Mahalanobis distance, the cluster should be Gaussian distributed. Therefore we used GMM in the cluster analysis. We used the following equation to calculate the Mahalanobis distance:

$$d_t = \sqrt{(\mathbf{x}-\mathbf{m_t})^T \sum\nolimits_t^{-1} (\mathbf{x}-\mathbf{m_t})} \qquad (1)$$

where $\mathbf{x}$ denotes the wave front vector and $\mathbf{m_t}$ is the mean position of the cluster C_t; Σ_t^{-1} represents the inverse of the covariance matrix of C_t.

(c) The conditional probability of the parameter to belong to patient or normal group is estimated by the Bayes theorem. The Bayes theorem predicts the probabilities of a subject to belong to the respective groups to classify:

$$P(A_k \mid B) = \frac{P(A_k)P(B \mid A_k)}{\sum_{l=1}^{s} P(A_l)P(B \mid A_l)} \qquad (2)$$

where $\{A_k \mid k = 1, \ldots, s\} \subset A$, $P(A_k) > 0$. In this case A_k is either the group of inferior OMI (G_i), anterior OMI (G_a), anteroseptal OMI (G_s), or normal (G_n) subjects and B is the cluster pattern. The probability density of a subject belonging to each of the group A_k is denoted as $P(A_k)$. The probability density that a subject has the cluster pattern B given that the subject belongs to the group A_k is denoted as $P(B|A_k)$. The conditional probability $P(A_k|B)$ that a subject belongs to the group A_k given that his/her cluster pattern is B, is estimated with these prior probabilities of $P(A_k)$ and $P(B|A_k)$. The estimated conditional probabilities for the cluster pattern to belong to the groups of G_i, G_a, G_s, and G_n are indicated in Table 1. In the application of the Bayes rule, the probability belonging to G_n and the sum of the probabilities belonging to G_i, G_a, and G_s are compared. Each subject is classified into Normal/OMI group when the former/latter probability is larger.

CP	Estimated probabilities				Bayes rule
	OMI			Normal	
	G_i	G_a	G_s	G_n	
1	0%	0%	0%	100%	Normal
2	0%	0%	0%	100%	Normal
5	0%	50%	50%	0%	OMI
2-3	100%	0%	0%	0%	OMI
2-4	0%	34%	0%	66%	Normal
3-4	50%	0%	50%	0%	OMI

Table 1. Cluster pattern (CP) and the corresponding Bayes rule.

RESULTS

The result of the classification of OMI patients and normal controls is shown in Table 2. The method showed sensitivity (the percentage of patients recognized by the method) of 83%; specificity (the percentage of normal controls recognized by the method), 100%; positive predictive value (the percentage of patients among the subjects who are classified as positive (OMI) by the method), 100%; and negative predictive value (the percentage of normal controls among the subjects who are classified as negative (Normal) by the method), 94%, respectively. The total calculation time to classify a subject from the MCG data was less than 5 seconds with MATLAB software on a personal computer (1.8 GHz Intel Pentium4 CPU with 1GB RAM). Note that we used the same MCG data for classification as well as for the definition of clusters of wave front vectors and Bayes rule since we had small samples. In the practical use of this method, the clusters and the Bayes rule should be defined beforehand with large samples and new MCG data should be classified with it.

Diagnosed Classified	OMI (+)	Normal (-)
OMI (+)	**5**	0
Normal (-)	1	**15**

Table 2. Clinical diagnosis and classification result.

DISCUSSION

The difference in the characteristics of the excited wave fronts among patients and normal controls was clearly distinguished by the cluster patterns. As shown in Table 1, the excited wave fronts of OMI patients during the repolarization phase had the tendency to exist in the different position and direction from those of the normal controls. In myocardial infarction, the excited wave front may be obstructed and diverted when passing the infarction area. It is thought that this change in the pathway of excited wave fronts caused the different distribution of the cluster pattern in OMI patients. In addition, the cluster pattern of OMI patients had a good correlation with the positions of artery stenosis that was examined by coronary angiography, as shown in Table 3. The result suggests the possibility of MCG in the screening of stenosed position of arteries. In summary, the use of the presented techniques is acceptable to the practical mass screening with the short processing time. Future studies should also evaluate the capability of the presented method with larger samples.

Subject	Infarction area	Stenosed position (AHA)				CP
		#1	#3	#6	#7	
p1	Inf.	**90%**	**100%**			**3-4**
p6	Ant. sep.	**99%**	**75%**		99%	**3-4**
p3	Ant.			**90%**	**75%**	**5**
p5	Ant. sep.			**90%**	**90%**	**5**
p2	Inf.		100%		75%	2-3
p4	Ant.	100%			75%	2-4

Table 3. Positions of coronary artery stenosis and cluster pattern. Abbreviation; Inf. (inferior), Ant. (anterior), Ant. sep. (anteroseptal).

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