# Classifying MEG 20Hz Rhythmic Signals of Left, Right Index Finger Movement And Resting State Using Cascaded Radial Basis Function Networks

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## Abstract

A cascaded Radial-Basis Functions (RBF) network was devised to classify the magnetoencephalography (MEG) rhythmic signals of the left, right index finger movement and resting state.

Four right-handed subjects were instructed to perform self-paced index finger lifting in a rate of every 8 sec. MEG epochs from 4000 ms pre-movement to 3000 ms post-movement were digitized. Each trial was decomposed by Principal Component Analysis (PCA) and the task-related components were selected to reconstruct data followed by band-passed filtering around 16-20 Hz. Every five filtered epochs were averaged and processed by the Hilbert transform to produce a beta-band envelope. All the envelopes around sensorimotor channels were normalized and down-sampled to 100 samples. A movement feature vector was defined by concatenating two mean envelopes in the left and right channels. We defined a resting feature vector by averaging five envelopes randomly selected in the left and right channels respectively during the resting state, and then concatenating two means.

Two cascaded 3-layer RBF networks were constructed in which the first RBF network was to discriminate the movement from the resting state, while the second one was to distinguish the left and right index finger movement. The classification rates (rest, left, right) for four subjects achieve (100, 91, 66)%, (100, 80, 72)%, (100, 76, 73)% and, (100, 74, 94)%, respectively.

***Keywords*:** Radial basis neural network, Beta-band Brain rhythm, Brain computer interface

## Introduction

In recent years, great progress in neuroscience has inspired studies in developing brain computer interface (BCI) [1,2,3,4], a novel technique in assisting people to communicate with external environments or trigger surrounding devices by means of their brain signals. The effectiveness of such a system relies on two crucial components: an accurate classifier and distinguishable patterns of brain signals.

In this study, we proposed a cascaded radial basis function neural network, consisting of two 3-layer RBF neural networks [9], to classify the resting, right hand and left hand index finger lifting on the basis of MEG beta-band sensorimotor rhythm. The first 3-layer RBF neural network was employed to discriminate the movement from the resting state, while the second one to distinguish the left and right index finger movement. We applied the PCA and Amplitude Modulation (AM) method [5] to extract and produce the time-locked and phase-locked envelope waveforms of sensorimotor beta rhythm, which were used as feature vectors in the training of cascade RBF neural networks as well as in the classification stage. Due to the salient features of the RBF neural network that the input data can be better discriminated linearly when mapped into high-dimension space, the averaged classification rates of resting, right and left hand index finger movements achieved 100%, 80%, and 76%, respectively.

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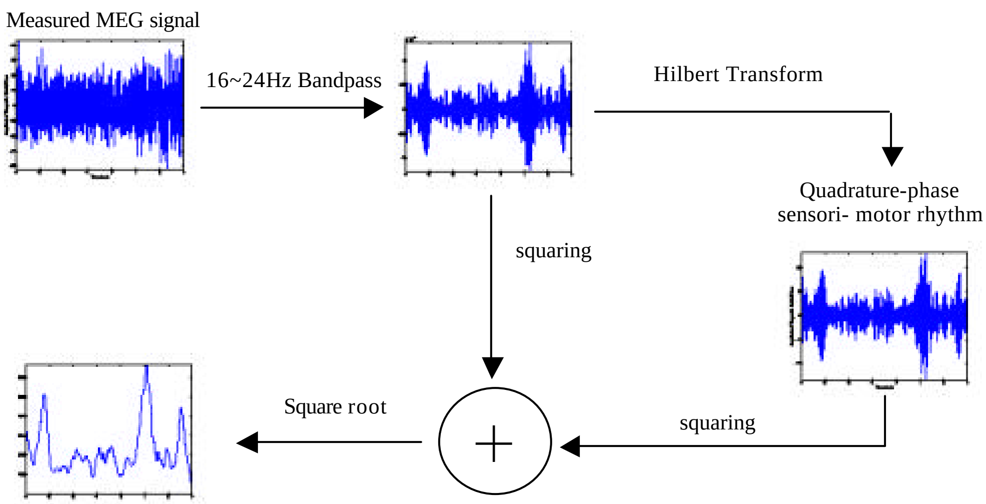


Figure 1. The flow chart of producing AM envelope waveform

Several different classifiers and feature patterns for BCI systems have been reported recently. Pfurtscheller et al. [1][2] used two bipolar EEG channels to measure the sensorimotor mu rhythms in left and right hemispheres when subjects were doing imagery movements. They used a learning vector quantization to classified signal on-line in a subject specific band which was determined by distinctive sensitive learning vector quantization. They also adopted adaptive autoregressive model to analyzed signal off-line and applied linear discrimination analysis to improve the detection of left and right hand movements. The reported error rates varied 5.8 and 32.8%. Polak et al. [3] measured the sensorimotor EEG signals in left and right hemispheres when subjects imagined that an object is moving up or down. They applied autoregression model and fast Fourier transform to extracted the frequency domain features and have attained 90% accuracy. Muller-Gerking et al. [4] applied common spatial filter to detect the left, right hand or right foot movements in single trial and reported 84%, 90% and 94% accuracies for three subjects, respectively.

## Material and method

*I. Instrument and Data recording*

A whole-head MEG (Neur- omag-306 vectorview; Neuromag Ltd., Helsinki, Finland) was used to record the magnetic fields of sensorimotor areas in the magnetically shielded room. The Neuromag-306 vectorview system has 102 sensor units. Each sensor unit contains a pair of gradiometers and one magnetometer. The magnetometer measures the magnetic flux ( $B_z$ ), normal to the sensor unit, while the gradiometers measure two tangential derivatives of $B_z$. Only magnetic signals measured by gradiometers were used. The vertical electro-oculogram (EOG) was applied to reject bad epochs induced by eye blinking during the recording.

Four subjects participated in our experiment. Each subject put his/her index fingers on an optical trigger pad, and was asked to perform either right or left self-paced index finger lifting movement at a rate of once around every eight seconds. Time interval between –4 s and 3 s relative to movement onset was chosen as an epoch.

*II. Data preprocessing using PCA and amplitude modulation*

The sensorimotor beta rhythm, which is different from internal artifact or external noise, was extracted and processed as feature patterns. PCA was applied to decompose each rhythmic epoch into temporally decorrelated components by means of an orthogonal matrix (which consists of the eigenvectors of the covariance matrix of rhythmic signals). Each column of the orthogonal matrix represents a scalp map, describing the relative projection weights of the corresponding temporal components at each of the MEG sensors. The scalp map and temporally decorrelated waveforms can be categorized into task-related and task-unrelated components. To facilitate the selection of task-related components, we constructed temporal templates (the beta-band rebound) using the Hilbert transform of averaged trials recording from the right and left index finger lifting task and spatial templates using the averaged topography map of somatosensory evoked field produced by the right and left medial nerve stimulations. Only the components that are highly correlated with spatial and temporal templates are selected and reconstructed for further processing.

The beta-band rhythmic signals are time-locked but not phase-locked to the movement onset and thus simple averaging technique producing blurred results is not suitable to extract sensorimotor rhythm. In order to extract the rhythmic signals and preserve their phase-lock to the event trigger, amplitude modulation (AM) [5] was utilized. The AM method first band-pass filtered (16-24 Hz) the MEG signal in each trial, and then used the Hilbert transform to compute the quadrature phase of the filtered rhythmic signals. The envelope waveforms of the beta-band rhythmic signals were computed using the following equation:

$$m(t) = \sqrt{M_{BP}(t)^2 + H(M_{BP}(t))^2}\ , \qquad (1)$$

where $M_{BP}(t)$ is the band-pass filtered MEG signals (see Fig. 1).

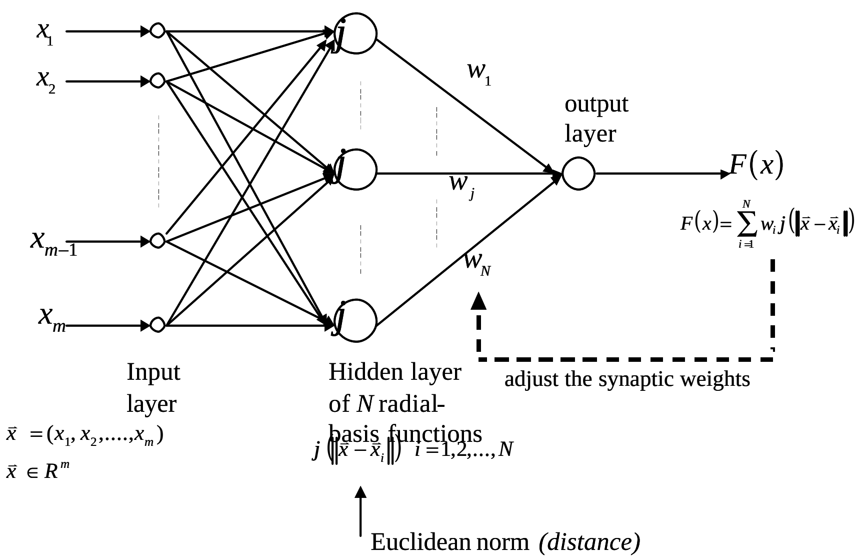


Figure 2. The hierarchy of RBF neural network

Every five AM waveforms from each channel were averaged to increase the signal-to-noise ratio. All the averaged envelopes across two channels in the left and right hemisphere covering sensorimotor areas were further normalized, down-sampled so that each envelope has 100 samples, and adjusted to have the same baseline, respectively. A movement feature vector was defined by concatenating two mean envelopes in the left and right channels. We defined a resting feature vector by averaging five envelopes randomly selected in the left and right channels respectively during the resting state, and then concatenating two means. In our experiment, 155 feature vectors, consisting of 65 trials of right hand movement, 30 trials of left hand movement, and 60 trials of resting states, were used in the training phase and 230 feature vectors, consisting of 100 of right hand movement, 100 of left hand movement, and 30 of resting states, were tested in the recalling phase of the CRBF neural network for each subject.

### *III. Radial Basis Function (RBF) neural network*

The RBF neural network [9] uses a nonlinear function to map the input data into high-dimension space so that they are more likely to be linearly separable than in the low-dimension space [6-8]. The hierarchy of (regularization) RBF neural network is depicted in Figure 2, which consists of one input layer, one hidden layer, and one output layer.

Each RBF network is designed to have a nonlinear transformation from the input layer to the hidden layer, followed by a linear mapping from the hidden layer to the output layer. The mapping between the input and output space is expressed by:

$$F(\vec{x}) = \sum_{i=1}^{N} w_i j(\|\vec{x}-\vec{x}_i\|), \text{ where } j(\vec{x}-\vec{x}_i) = e^{-\|\vec{x}-\vec{x}_i\|^2} \quad (2)$$

where $w_i$ represents the weighting from the $i_{th}$ hidden neuron to output neuron, and $\vec{x}_i$ represents the $i_{th}$ known feature vector with dimension *m*, *i* =1, 2, …*N*. The distance between input vector, $\vec{x}$, and center, $\vec{x}_i$, is mapped into high-dimension space by means of a Gaussian function ($j(\|\vec{x}-\vec{x}_i\|)$) in this study. In the phase of supervised learning, training feature vectors $\vec{x}_i$, *i* =1, 2, …*N*, and output desired output $F(\vec{x}_i) = d_i$ which is either 1 or -1 in our design, are given. For the sake of simplicity, the training feature vectors are used as centers. With the known *N* input feature vectors and the corresponding designed outputs, the weighting $w_i$ can be computed from the input-output relationship in equation (2):

$$Gw = d \quad (3)$$

where

$$G = \begin{bmatrix} j(\|\vec{x}_1-\vec{x}_1\|) & j(\|\vec{x}_1-\vec{x}_2\|) & \cdots & j(\|\vec{x}_1-\vec{x}_N\|) \\ j(\|\vec{x}_2-\vec{x}_1\|) & j(\|\vec{x}_2-\vec{x}_2\|) & \cdots & j(\|\vec{x}_2-\vec{x}_N\|) \\ \cdots & \cdots & \ddots & \vdots \\ j(\|\vec{x}_N-\vec{x}_1\|) & j(\|\vec{x}_N-\vec{x}_1\|) & \cdots & j(\|\vec{x}_N-\vec{x}_N\|) \end{bmatrix},$$

$$w = \begin{bmatrix} w_1 \\ w_2 \\ \cdots \\ w_N \end{bmatrix}, \quad d = \begin{bmatrix} d_1 \\ d_2 \\ \cdots \\ d_N \end{bmatrix}$$

By solving the linear system (3), the resultant weighting *w* vector is

$$w = G^{+}d \quad (4)$$

where $G^{+} = (G^T G)^{-1} G^T$ is the pseudoinverse matrix of G. Compared with other neural network which uses gradient-based optimization process to estimate the weightings, for example, the back-propagation recurrent neural network, the RBF neural network solve for a set of linear equations to avoid trapping in a local minimum and greatly reduce the training time. In the testing phase, input feature vectors, $\vec{x}$'s, can be linearly classified based on the values of $F(\vec{x})$'s.

### *IV. Cascade RBF neural network*

In this paper, we implemented a cascaded RBF neural network to classify the subject's resting, right hand and left hand finger lifting states. Figure 3 shows one example

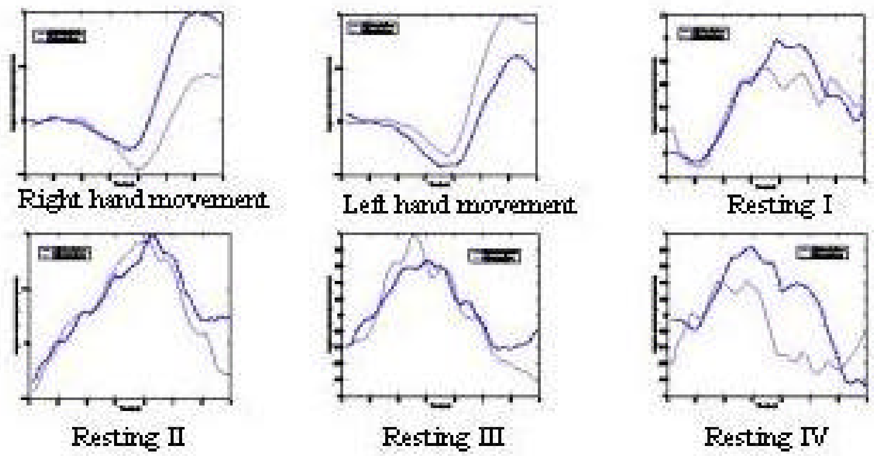


Figure 3. The beta-band sensorimotor AM waveforms of right hand, left hand index finger movements and resting state

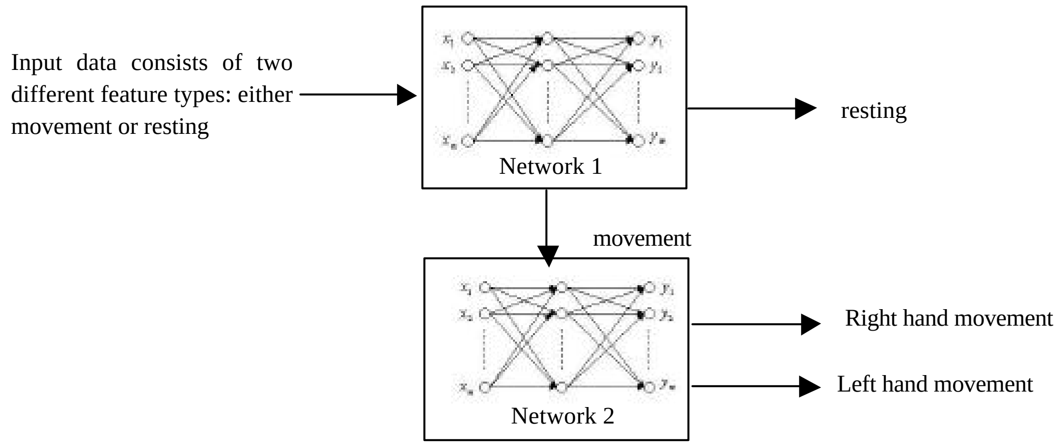


Figure 4. The hierarchy of cascaded RBF neural networks

of feature vector in left hand movement and right movement respectively, and four examples of feature vectors in resting state. The thick and thin curves represent the beta band sensorimotor AM waveform in left and right hemisphere respectively. Note that, around 1 sec after left and right index finger movement, the AM waveforms have stronger amplitude rebounds in contralateral hemisphere than that in ipsilateral hemisphere. Note that the differences between thick curve and thin curve in right hand movement are usually larger than that in left hand movement. Besides, AM waveforms in resting states are sometimes similar to the right and left hand movement waveforms, although they don't have regular AM waveform patterns. If single RBF neural network was considered and all the resting, left and right hand finger lifting AM waveforms were as input data in training the RBF neural network at the same time, we experienced that the three states cannot be distinguished accurately. Alternatively, we applied a cascaded RBF neural network (Figure 4) in which the first RBF network is used to discriminate resting state from moving state, and the second RBF network to distinguish left and right hand index finger movements. Each network composed of 200 nodes in the input layer. The numbers of nodes in the hidden layer for the first and second network were 155 and 95, respectively.

## Results

The data preprocessing and the cascaded RBF networks were implemented using MATLAB (version 6.1, R12). All the data were analyzed off-line. The training time of cascaded RBF network took less than 15 second and recalling time for each testing vector was less than one second on PC (PIII 600MHz, 128M REM). The results of applying cascaded RBF neural network to classify 230 testing feature vectors of four subjects are summarized in Table 1. The first neural network has successfully classified the movement and resting features. The recognition rates, resulted from the second neural network, of left and right index finger movements (left, right) for four subjects are (91%, 66%), (80%, 72%), (76%, 73%) and, (74%, 94%), respectively. The recognition rates of the right finger movement are better than that of the left finger movement (except for subject D) since fewer training vectors were utilized for the left finger movement.

Table 1. The classification results obtained from the cascaded RBF neural networks

| | | | | | |
|---|---|---|---|---|---|
| The classification results obtained from the first RBF neural network | | | | | |
| | number of recognized trials/number of testing trials | | | | Averaged classification |
| | Subject A | Subject B | Subject C | Subject D | |
| Movement state | 200/200 | 200/200 | 200/200 | 200/200 | 100% |
| Resting state | 30/30 | 30/30 | 30/30 | 30/30 | 100% |
| The classification results obtained from the second RBF neural network | | | | | |
| | number of recognized trials/number of testing trials | | | | Averaged classification |
| | Subject A | Subject B | Subject C | Subject D | |
| Right index finger | 91/100 | 80/100 | 76/100 | 74/100 | 80.25% |
| Left index finger | 66/100 | 72/100 | 73/100 | 94/100 | 76.25% |

## Conclusions

In this paper, we have applied PCA and amplitude modulation method to extract beta-band envelope waveforms of left and right finger lifting, and proposed a cascaded RBF neural network, consisting of two RBF networks, to effectively classify the data in three different states. Based on the cascaded hierarchy, two-step classification process were performed: the first RBF neural network differentiates the resting and moving states, while the second one further discriminates right hand finger lifting from left hand finger lifting. The classification rates (rest, left, right) for four subjects achieve (100, 91, 66)%, (100, 80, 72)%, (100, 76, 73)% and, (100, 74, 94)%, respectively.

In the future, we plan to implement a real-time system for on-line recognition and apply the cascade RBF neural network to classify other brain rhythms with different patterns, for examples, occipital alpha rhythm, gamma rhythm, theta rhythm, tau rhythm, etc..

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## References

[1] G. Pfurtscheller, C. Guger, G. Muller, G. Krausz, C. Neuper, “Brain oscillations control hand orthosis in a tetraplegic”, *Neuroscience letters*, 292: 211-214, 2000.

[2] G. Pfurtscheller, C. Neuper, A. Schlogl, and K. Lugger, “Separability of EEG Signals Recorded During Right and Left Motor Imagery Using Adaptive Autoregressive Parameters”, *IEEE transactions on Rehabilitation Engineering*, Vol. 6, No. 3: 316-325, 1998.

[3] M. Polak, “Feature extraction in development of brain-computer interface: a case study”, *Proc. of the 20th Annual International Conference of the IEEE engineering in medicine and biology society*, 20: 2058-2061, 1998.

[4] J. Muller-Gerking, G. Pfurtscheller, H. Flyvbjerg, “Designing optimal spatial filters for single-trial EEG classification in a movement task”, *Clinical neurophysiology*, 110:787-798, 1999.

[5] P. Clochon, J. M. Fontbonne, P. Etevenon, “A new method for quantifying EEG event-related desynchronization: amplitude envelope analysis”, *Electroencephalography & Clinical Neuro-physiology*, 98: 126-129, 1996.

[6] T. M. Cover, Capacity problems for linear machines. Washington, DC: Thompson Book, Pattern Recognition: 293-289

[7] T. M. Cover, “Geometrical and statistical properties of systems of linear inequalities with applications in pattern recognition”, *IEEE transactions on electronic computers*, EC-14: 326-334, 1965.

[8] T. M. Cover, J. A. Thomas, Elements of Information Theory. New York: Wiley, 1991.

[9] S. Haykin, Neural Network: A Comprehensive Foundation. New York: Macmillan College Publishing Company, 1994.