

# A Study on Hybrid Model of HMMs and GMMs for Mirror Neuron System Modeling using EEG Signals

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**Abstract**—For our present life anytime, anywhere access to the network can communicate with the ubiquitous computing. it is essential to human life. We should be able to agree that communication will be enabled. For our present life, anytime, anywhere access to the network can communicate with the ubiquitous computing. Such as the ubiquitous era approached, interaction between the user and the computer has become an important issue. In this paper we use EEG signals to extract the user's intention recognition data, which the Mirror Neuron System Based on HMMs and GMMs to model the convergence of the hybrid model is proposed. This is based on a kind of biological signals using EEG signals to the user's intention recognition techniques have been studied. In addition, EEG signals is generated based on the model, using the user intention recognition method have been studied. The proposed model will be applied in the field of neuro robotics.

**Keywords**—Mirror Neuron System, HMMs(Hidden Markov Models), GMMs(Gaussian Mixture Models), EEG, Intention recognition

## I. INTRODUCTION

The last century, AI(Artificial Intelligent) field (problem solving, pattern recognition, decision-making) was a tremendous progress. The idea for the robot AI robot 'thinks' you want to empower people to start in the desires. AI robot, such as differences of level perceptual, emotional, and cognitive, was insufficient points. Therefore, we implemented a much more seamless system for human robot interaction is required. Meanwhile, today's information and communication technology breakthrough by the user computing system through anywhere, anytime access to information needed to build an infrastructure that can have been going. Accordingly, the ubiquitous and user-centered environment built on active service, the core technologies necessary to provide the domestic and foreign research institutes and universities have been actively focusing on. In ubiquitous computing environment, the circumstances of the computer and the user

intent is consistent with the self-awareness must be able to provide the best service. To implement this, a critical underlying technology is the user's intention recognition technology. Recognition technology is intended to process the information collected from various centers, fusion is applied to the reasoning and learning. Thus, to infer the intent of people, recognized as the technology to existing information and emotional situation for the individual to perform the recognition, there are many case studies[1][2].

According to the latest neuroscience research into the human brain called mirror neurons, the nerve was the existence of the doctrine[3][4]. Mirror neurons are brain cells in the premotor cortex. First identified in macaque monkeys in the early 1990s, the neurons also known as "monkey-see, monkey-do cells" fire both when a monkey performs an action itself and when it observes another living creature perform that same action[5]. Though it has been impossible to directly study the analogue of these neurons in people (since human subjects cannot be implanted with electrodes), several indirect brain-imaging measures, including EEG, have confirmed the presence of a mirror neuron system in humans[6]. The human mirror neuron system is now thought to be involved not only in the execution and observation of movement, but also in higher cognitive process, language, for instance, or being able to imitate and learn from other's actions, or decode their intentions and empathize with their pain[7][8].

There have been many studies Mirror neurons in the department of brain neuroscience, and psychology. But so far the engineering models of mirror neurons are the basic steps.

In this paper, the user intent recognition, a method for effectively is proposed for engineering modeling of mirror neurons. Original intent of the user to recognize the techniques used in the HMMs and GMMs are created by combining a hybrid model. This is based on a kind of biological signals using EEG signals to the user's intention recognition techniques have been studied. In addition, EEG signals is generated based

on the model, using the user intention recognition method have been studied. The proposed model will be applied in the field of neuro robotics. This paper is organized as follows.

In chapter 2, mirror neurons, and background information on user intent recognition is described, Section 3 describes the proposed hybrid model, and Section 4 describes the conclusions and future research.

## II. THEORY FOR SYSTEM

### A. Mirror neuron system in humans

Action observation studies in the mid 1990s using both TMS(Transcranial Magnetic Stimulation) and PET(Positron Emission Tomography) provided some evidence for the existence of the human MNS(Mirror Neuron System)[6][9]. Especially imitation was closely associated with MNS when researchers began to report the relation between mirror neurons and imitation in humans using MRI(Magnetic Resonance Imaging) and fMRI(Functional Magnetic Resonance Imaging). These reports provided the foundation for examining whether human areas relating to imitation of hand actions had mirror properties. Based on the research that mirror neurons discharge more during the execution than the observation of an action, and that an individual simultaneously observes and performs an action during imitation, it was predicted that human mirror neuron areas would show higher activity during execution than during observation of an action, and highest activity during imitation. This in sum reflects the activity attributable to action observation and execution[10][11].

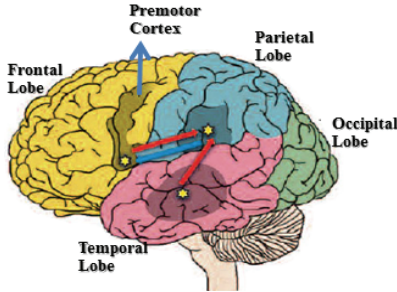


Figure 1. The distribution of mirror neurons

The human MNS is especially important for imitative behavior early in life. And imitation is a pervasive type of learning in humans, and the understanding of its primary neural mechanisms is noticeably important. It is associated with the user's intention recognition. Because, according to other people's words and actions that recognize the person's intent is for the most basic instincts. Therefore, when describing the behavior of actors, by analyzing the signals, as opposed to the user's intent is to identify.

### B. Intention recognition using EEG data extraction

In the previous study, when each of the letters imagine the ideation center and Broca's area was measured from the EEG signals. This is based on the person you imagine what a

particular word on when the change in EEG was found[12]. Using this data, data to recognize the user's intention were analyzed by ERSP(Event-Related Spectral Perturbation) and ITC(Inter-Trial Coherence) methods. We were building a database to recognize user's intention based on these data.

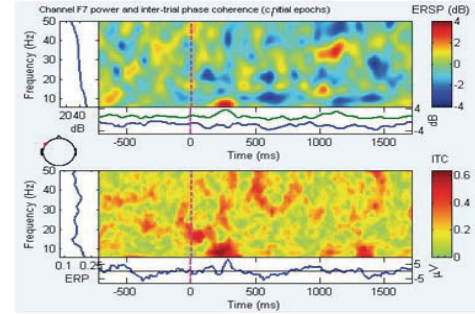


Figure 2. When we imagine letter C, spectrum of ERSP and ITC

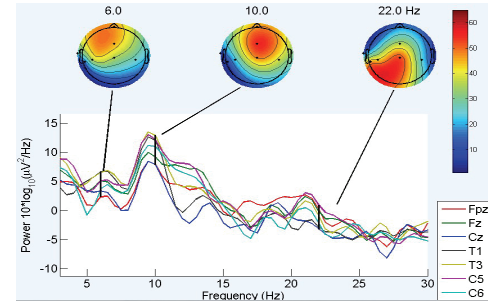


Figure 3. Analysis with EEGLAB, when we listen to dance music and the frequency by the average power spectrum EEG data

### C. Hidden Markov Models

HMMs (Hidden Markov Models) has been widely used in pattern classification, speech recognition and gesture recognition. In addition, the user with the user's intent is to produce a secreted sequence data to determine whether the top because you can see a problem in the field of intention recognition can be effectively applied[13][14].

HMMs Hidden States that we do not know the status of the probabilistic transition process Observable symbol that raises the probability of realistically modeling the transition process is a double stochastic process.

HMMs as the symbols  $\lambda = (\pi, A, B)$  is expressed as the number of hidden state variables, N, Observable symbol that when the number of M, has the following components[15].

- 1)  $Q = \{q_1, q_2, \dots, q_n\}$  : set of hidden states
- 2)  $V = \{v_1, v_2, \dots, v_m\}$  : set of observable symbol
- 3)  $O = \{o_1, o_2, \dots, o_{t-1}, o_t\}$  : sequence consists of observable symbol
- 4)  $\pi_i$  : initial probability vector of hidden state
- 5)  $A_{ij}$  : state transition matrix
- 6)  $B_{ij}$  : confusion matrix

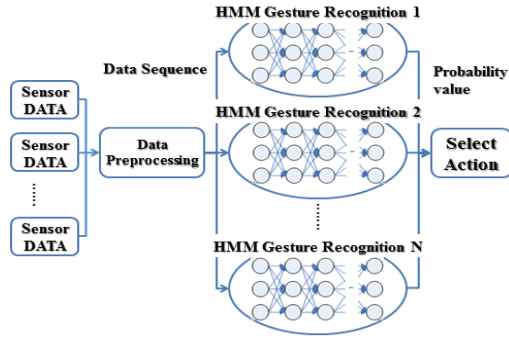


Figure 4. HMM models for recognizing the different behaviors

HMMs Hidden States that we do not know the status of the probabilistic transition process Observable symbol that raises the probability of realistically modeling the transition process is a double stochastic process.

HMMs as the symbols  $\lambda = (\pi, A, B)$  is expressed as the number of hidden state variables, N, Observable symbol that when the number of M, has the following components[15].

- 7)  $Q = \{q_1, q_2, \dots, q_n\}$  : set of hidden states
- 8)  $V = \{v_1, v_2, \dots, v_m\}$  : set of observable symbol
- 9)  $O = \{o_1, o_2, \dots, o_{t-1}, o_t\}$  : sequence consists of observable symbol
- 10)  $\pi_i$  : initial probability vector of hidden state
- 11)  $A_{ij}$  : state transition matrix
- 12)  $B_{ij}$  : confusion matrix

After the fact, the model defined by HMMs in order to use the following three problems (Evaluation, Decoding, Learning) must solve. Therefore, the three kinds of solutions to the problem, several algorithms have been widely used. When estimating the probability of the problem, Forward / Backward algorithm can be solved using, and determine the issue of optimal order is one of the Viterbi algorithm of dynamic programming techniques are used. Finally, estimate the parameters of the EM algorithm called the Baum-Welch algorithm is employed and can be solved[15]. For more information on HMM and then you can see in the paper[16].

#### D. Gaussian Mixture Models

Gaussian probability distribution, albeit the most widely used distribution data, based on the average of the group together as a form of a unimodal only one possible representation is limited. Therefore, the general form of probability model capable of expressing need, this time to consider it the most easily combined with the multiple Gaussian model is being created. This is called GMMs (Gaussian Mixture Models). M simple probability density function (or component [component]) is defined as a linear combination of the entire probability density function is expressed as the following equation.

$$p(x | \Phi) = \sum_{j=1}^M p(x | w_j, \Phi) P(w_j) \quad (1)$$

Where  $w_i$  is a component,  $P(w_i)$  is the prior probability or mixed parameters. And  $p(X | w_i, \Phi)$  is the vector of the parameters  $\Phi$ , when told, is the probability density of the ingredients.  $X = \{x_k\}$  log-likelihood of the sample were as follows.

$$L(\Phi | x) = \sum_k \log p(x_k | \Phi) = \sum_k \log \sum_j p(x_k | w_j, \Phi) P(w_j) \quad (2)$$

Equation (2) does not have an immediate solution. Therefore, these problems can be solved using EM(Expectation Maximization)algorithm[17]. EM algorithm is performed in two stages, as follows: posterior probabilities was calculated using Bayes' theorem.

$$p(w_j | x_k, \Phi) = \frac{p(x_k | w_j, \Phi) P(w_j)}{\sum_l p(x_k | w_l, \Phi) P(w_l)} \equiv h_{kj} \quad (3)$$

Where the d-dimensional gaussian density components if you choose to be,  $p(x | w_j, \Phi) \sim N_d(\mu_j, \sum j)$  is as follows.

$$p(x | w_j, \Phi) = \frac{1}{(2\pi)^{d/2} |\sum j|^{1/2}} \exp[-\frac{1}{2}(x - \mu_j)^T \sum j^{-1}(x - \mu_j)] \quad (4)$$

So , the equation (3) can be expressed equation(4). As a result, equation (5) is represented by Gaussian probability.

$$h_{kj} = \frac{g_j |\sum j|^{-1/2} \exp[-\frac{1}{2}(x_k - \mu_j)^T \sum j^{-1}(x_k - \mu_j)]}{\sum_l g_l |\sum l|^{-1/2} \exp[-\frac{1}{2}(x_k - \mu_l)^T \sum l^{-1}(x_k - \mu_l)]} \quad (5)$$

However,  $g_i \equiv P(w_j)$

### III. HYBRID MODEL OF HMMs AND GMMs

Hybrid model based on the class variable mixture GMMs and HMMs based on the components are configured. Hybrid models take advantage of the positive aspects of each model used in the combination. Each of the types of models included in the training data, it is possible to collect specific information. For example, GMMs are more likely to capture the structural information. While HMMs in the sequence, the transition is to extract information. The choice of a single model, it can interfere with the performance of the classification. Before making a decision of the classification, the hybrid model has output to improve the stability of method and performance. We think this situation, combined results from two models that use a hybrid model of the sum rule is proposed. Sum rule for the probabilities of each model in estimating the error is known to be robust. Given a set of weights  $\{w_i; i = 1 \cdots L\}$  for L number of classifiers, and k classes, a given brain activity data, x is assigned to a model of  $M_n$ .

$$\sum_{i=1}^L w_i P(M_n | x_i) > \sum_{i=1}^L w_i P(M_l | x_i) \quad l = 1, \dots, k; l \neq n \quad (6)$$

A small training set to minimize the error rate classifier decides the value weighted. Figure 5. Illustrates the proposed model.

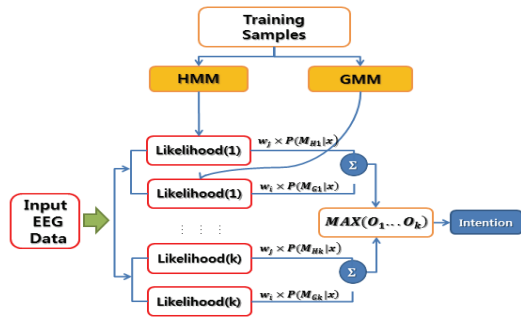


Figure 5. Hybrid model of HMMs and GMMs

HMMs and GMMs in Figure 5, M is the result of the hybrid model we ultimately need to find the error rate of recognition model, removing the maximum value of the optimized sequence.

### IV. CONCLUSIONS

In this paper, HMMs and GMMs as shown in Figure 5, the convergence of the proposed hybrid model. Hybrid models take advantage of the positive aspects of each model used in the combination. Each of the types of models included in the training data, it is possible to collect specific information. The choice of a single model, it can interfere with the performance of the classification. Before, both models making a decision on the classification of a performance and how to improve the stability of the output. Conventional HMMs to recognize only the user's intentions in the posterior probability classifier to minimize the error rate of Gaussian Neural Network based on GMMs were added. Error rate as shall be determined

appropriately weighted values and operations are expected to increase the speed and accuracy. Next simulation compares the performance of the proposed algorithm will be tested.

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