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sEMG Pattern Classification Using Hierarchical Bayesian Model

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***Abstract*— This work addresses surface electromyogram (sEMG)-based muscle pattern classification using a generative model. By using a hierarchical Bayesian model, the proposed approach constructs an overall process model of recorded sEMG signals. By inferring probabilistically latent neural states which governs a collection of training sEMG data, classification is realized. To validate the approach, eight-class classification using four sEMG sensors on the limb actions is tested with five subjects. The proposed model achieves an overall 95% accuracy in the classification experiment. The results support that the proposed approach is very promising for sEMG pattern classification.**

I. Introduction

The surface electromyogram (sEMG)-based muscle activation observations have been extensively of interest as a non-invasive method for control or interfacing. Applications to control prosthetics or exoskeletons have been attempted and impressive results have been reported [1-9]. To successfully realize control or interface schemes, robust pattern recognition from sEMG is a key. Although discriminative classification methods were mainly investigated for sEMG pattern recognition, there were recently some attempts to apply Bayesian approaches for myoelectric control [10-11]. In particular, the hidden Markov model [10] and Gaussian mixture model [11] were applied for multiple limb motion classification using myoelectric signals. Bayesian approaches are generally known to be good at achieving an automatic and adaptive process without concrete information about the parameters and incorporating prior information as well. On the other hand, they typically involve high-dimensional integrals. A Bayesian model permits construction of a generative model, which can generally infer complex relationships between the output observations and some hidden variables. Although more complicated model organization is required, the recent advent of computational power and methodology make Bayesian approaches very attractive to resolve complex problems.

Even though a variety of methods were attempted so far, achieving stable and accurate performance is still challenging because the musculoskeletal system is very complex, and the sEMG signals are innately noisy and affected by conditions of the subject and tasks. A robust approach is expected to attain consistent results independent of subject. This work suggests a new approach to sEMG-based control or interface as another attempt to overcome demanding limitations.

This paper proposes newly a hierarchical Bayesian model which is derived from multi-time series of sEMG data. The proposed model assumes the probabilistic distribution of latent neural state variables which occur sEMG profiles. By constructing a generative probabilistic model, low-dimensional probabilistic relationships among a set of latent intention variables are formed and possible sequences of sEMG data are generated based on the relationships. The probabilistic structure of latent neural state variables makes it possible to classify activations from a set of sEMG profiles.

II. Hierarchical Bayesian model

A. Model Description

The proposed model is motivated from latent Dirichlet allocation (LDA), which is the simplest topic model. LDA is based on the intuition that documents, which are sets of words, exhibit multiple topics [12-14]. LDA models document collections which are produced from the latent topics by representing each topic to be a distribution over a fixed vocabulary. The proposed model interprets the intuition behind the topic model with respect to a collection of sEMG profiles. It is proposed to regard a sEMG signal profile over time as a sequence of data units. A sEMG data unit, corresponding to a word in topic model, contains features which play a role in a basic representation of data information. Then, a trial, which records sEMG signals from multiple electrode channels, is a collection of a sequence of units. Assuming there are latent neural states, comparable to latent topics in topic model, the trials are represented by random mixtures over latent intentions, where each latent neural state is characterized by a distribution over data units. This work proposes to use the Gaussian distribution to represent each latent neural state by taking into account the general features of sEMG signals. For application to pattern recognition, the model includes classification procedure. Most likely classes are successively selected assuming a trial is associated with a sequence of intentions.

Suppose that training data are collected in D trials for C class classification, and data sequence is made up of N data units in each trial. Under the assumption that K latent neural states are fixed, the proposed model, shown in Fig. 1, describes a generative process of data acquired at the dth trial as follows.

1. Sample $\theta_d \sim \text{Dirichlet}(\alpha)$
2. For each of sEMG data units ($n = 1, \ldots, N$),
   Sample $z_n \sim \text{Multinomial}(\theta_d)$
   Sample $d_n \sim p(d_n | z_n, \mu_{1:K}, \Omega_{1:K})$ from a multivariate

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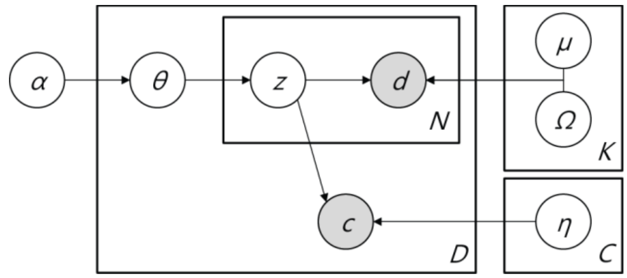

Figure 1. A graphical representation of the proposed model .

Gaussian distribution conditioned on z_n.

3. Sample $l \sim p(l|\bar{z}, \eta_{1:L})$ which represents a softmax distribution, where $\bar{z} = (1/N)\sum_{n=1}^{N} z_n$

θ_d is a K-dimensional Dirichlet random vector, and the parameter α is a K-dimensional vector whose element each is positive. Each trial is generated by again selecting from the Dirichlet random vector and repeating the entire process. Each z_n denotes a 1-of-K binary random vector with elements z_{nk} for k=1,…,K. $z_n, n = 1, \ldots, N$, is the latent neural state that induces sEMG sequence. To describe the kth latent neural state, the Gaussian parameters, mean vector μ_k and covariance matrix Ω_k, are fixed quantities. Given the quantities, a feature vector $d_n$of the data unit is drawn from the multivariate Gaussian distribution conditioned on z_n.

For application, class label l is drawn from the softmax distribution [15]

$$p(l|\bar{z}, \eta_{1:L}) = \exp(\eta_l^T \bar{z}) \,/\, \textstyle\sum_{i=1}^{L} \exp(\eta_i^T \bar{z}) \qquad (1)$$

where $\eta_{1:L}$ represents a set of L class coefficients, each η_l is a K-dimensional vector whose elements are real values. Unknown parameters to be estimated are α, $\mu_{1:K}$, $\Omega_{1:K}$, and $\eta_{1:L}$. Once the model is established, sEMG-based classification is possible for future test trial.

Raw sEMG profiles can be windowed with overlap. Each window is regarded as a data unit. In a window, features are appropriately designated. Feature extraction relies on physical and neurophysiological conditions for a problem to be solved. The feature used in this work is mean-absolute-value (MAV), which has been popularly used for onset detection due to its computational simplicity. Thus,

$$d_n = [\mathrm{MAV}_1 \quad \mathrm{MAV}_2 \quad \mathrm{MAV}_3 \quad \cdots \quad \mathrm{MAV}_C]^T \qquad (2)$$

where subscript indicates channel index assuming a trial recodes sEMG signals from C channels.

It is remarked that sEMG data unit is a basic element of information representation. This work assumes that a sequence of the sEMG units contains essential information encoded in sEMG data from a trial.

B. Parameter Estimation and Classification

Exact inference to compute the conditional distribution of latent neural states given the model is intractable. Instead, the recipe of the variational inference approximation used in LDA is similarly applicable [13]. In the middle of the inference approximation, variational parameters, γ and $\varphi_{1:N}$, are introduced; γ is a K-dimensional Dirichlet parameter and each φ_n parameterizes a categorical distribution over K elements where $\mathrm{E}[z_n] = \varphi_n$. Unknown model parameters are estimated through variational Expectation-Maximization (EM) algorithm. In the E step, variational parameters are updated. The update rule of the variational parameter γ is identical to LDA [13], therefore,

$$\gamma_k^{new} = \alpha_k + \textstyle\sum_{n=1}^{N} \varphi_{nk} \qquad (3)$$

Meanwhile, the update rule of the variational parameter φ_w is obtained by applying the technique introduced in [15] for the model which includes softmax classification as follows.

$$\varphi_{nk}^{new} = \kappa N(d_n|\mu_k, \Omega_k)\exp\left(\psi(\gamma_k) - \psi\left(\sum_{j=1}^{K}\gamma_j\right)\right)$$
$$\exp\left(\tfrac{1}{N}\eta_{lk} - (h^T\varphi_n)^{-1}h_k\right) \qquad (4)$$

where $h^T\varphi_n = \sum_{l=1}^{L}\prod_{n=1}^{N}\left(\sum_{k=1}^{K}\varphi_{nk}exp\left(\frac{1}{W}\eta_{lk}\right)\right)$, a linear function of φ_n , and $h = [h_1, \ldots, h_K]^T$. $\psi(\cdot)$ is a gamma function and κ is a normalization factor.

In the M step, model parameters are estimated given the variational parameters. Gaussian parameters in the latent neural state are computed:

$$\mu_k^{new} = \frac{\sum_{n=1}^{N}\varphi_{nk}\, d_n}{\sum_{n=1}^{N}\varphi_{nk}} \qquad (5)$$

$$\Omega_k^{new} = \frac{\sum_{n=1}^{N}\varphi_{nk}(d_n-\mu_k^{new})(d_n-\mu_k^{new})^T}{\sum_{n=1}^{N}\varphi_{nk}} \qquad (6)$$

Classification parameters $\eta_{1:L}$ can be estimated using conjugate gradient [25] which is applied to

$$\sum_{t=1}^{T}\eta_{l_t}^T\bar{\varphi}_t - log\left(\sum_{l=1}^{L}\prod_{n=1}^{N}\left(\sum_{k=1}^{K}\varphi_{tnk}exp\left(\frac{1}{W}\eta_{lk}\right)\right)\right) \qquad (7)$$

where $\bar{\varphi}_t = (1/N)\sum_{n=1}^{N}\varphi_{tn}$. α can also be optimized [19]. However, practically its value is fixed, for example, $\alpha = \left[\frac{1}{K}, \ldots, \frac{1}{K}\right]^T$ uniformly.

To perform classification for the future data, the same procedure as in [15] is applied, which results in the label selection such that

$$l^* = \arg\max_{l\in\{1,\ldots,L\}} E[\eta_l^T\bar{z}] = \arg\max_{l\in\{1,\ldots,L\}} \eta_l^T\bar{\varphi} \qquad (8)$$

III. Experiment

A. Subject

Five subjects volunteered for experiments (mean ± SD age = 25.4 ± 2.96 years). The relatively small range in age of the male subjects was intended to minimize the potential, confounding effects of age and gender during force generation. All of the participants were free of neuromuscular and musculoskeletal pathology. All of the subjects were given sufficient information about the purpose and procedures, and before participation, informed consent was obtained from each subject. The KAIST Institutional Review Board approved the proposed experimental protocol of this study.

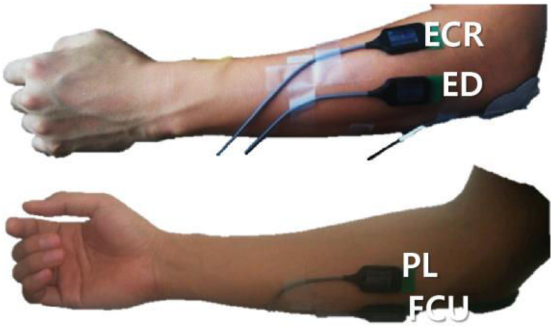

Figure 2. Electrode locations chosen for this study.

B. Experiment Design

In this study, limb actions were chosen to intuitively represent all possible actions: wrist flexion/extension, radial/ulnar deviation, pronation/supination, and hand grasp/open. The actions are easily executable, intuitive and various enough to be used for applications such as prosthetic or exoskeleton control [1, 3, 8, 10]. The goal of this study is classification of the nine wrist or finger postures, eight actions and one relaxation posture, using the proposed model and its evaluation. During actions, raw sEMG signals were measured using a commercial active surface electrode and filter-amplifier system (Bagnoli, Delsys Inc., USA). Four electrode locations were selected as shown in Fig. 2 considering particular muscles whose relevant functions contribute to wrist and finger actions; Flexor Carpi Ulnaris (FCU), Palmaris Longus (PL), Extensor Carpi Radialis (ECR) and Extensor Digitorum (ED). A minimal number of electrode sites were used so that signal interpretation of different actions can be made as much as possible across subjects. A fifth electrode was located on the upper arm as a reference to remove noises.

C. Experimental Procedure

The experiments consisted of three sessions: pre-test, maximal voluntary contraction (MVC) check, and test. During the pre-test session, each subject experienced the familiarization session in which the subject became comfortable with the experimental equipment and practiced the experimental protocols. After the pre-test session, the subjects were asked to sequentially perform four wrist actions, radial deviation, flexion, extension, and ulnar deviation at MVC following the instruction on the computer screen. Each wrist action was asked to be performed for two seconds. Strong verbal encouragements were provided. Maximum contraction values were recorded to be regarded as 100% MVC. In each experiment, each subject was asked to perform wrist actions sequentially at strong but comfortable contraction level. In each test session, the order of wrist actions is radial deviation, flexion, extension, ulnar deviation, pronation, supination, hand grasp, and hand open for five seconds. Relaxation posture is taken between any two sequential actions with the same interval. The movement sequence began with relaxed natural posture of wrist and hand initially. Each subject repeated the movement sequence five times at each muscular contraction level. Therefore, five sessions per subject were recorded. The subjects could relax between each session to avoid muscular fatigue, which could affect the sEMG signal in the subsequent trial.

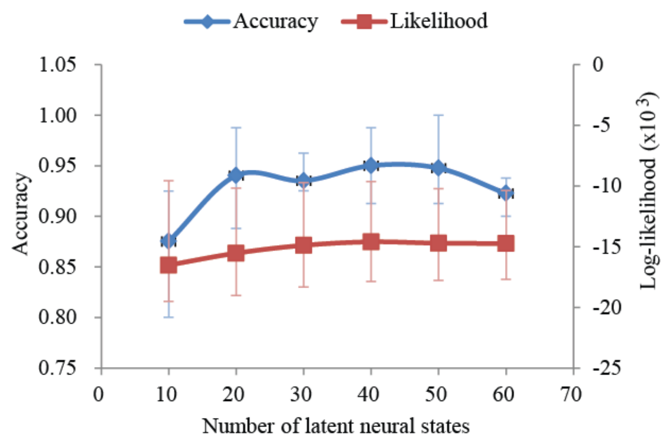

Figure 3. Accuracy and likelihood over the number of latent neural states averaged across subjects.

Table I Accuracy according to the number of latent neural states

	S1	S2	S3	S4	S5	ave
10	0.913	0.875	0.800	0.863	0.925	0.875
20	0.913	0.988	0.888	0.938	0.975	0.940
30	0.925	0.925	0.938	0.925	0.963	0.935
40	0.913	0.988	0.925	0.938	0.988	0.950
50	0.938	1.000	0.913	0.950	0.938	0.948
60	0.938	0.913	0.900	0.925	0.938	0.923

D. Signal Processing

The sEMG signals were recorded simultaneously with a data acquisition system (NI 6221, National Instrument, USA), and were then sampled at 1 kHz. The sEMG signals were band-pass filtered (5–450 Hz) using the zero phase fourth order Butterworth filter and power line noise were rejected with an activated notch filter. Baselines of the sEMG signals were shifted using mean values during initial 10 seconds and then the sEMG signals were normalized using MVC values. The time window per a data unit was set to be 250 msec with 50 msec overlap and the feature, MAV, was extracted in each window.

IV. Results

As in [1], performance measure was based on leave-session-out cross-validation error. That is, the proposed model was trained with four sessions and tested with a remaining session. An average accuracy is obtained from five runs for test per each session. Figure 3 shows classification accuracies and converged likelihood values during training over the number of latent neural states of selected subjects among the five. The results indicate relatively high contraction level performances are generally better than relatively low contraction level performances. Although accuracy changes over the number of latent neural states, 40 latent neural states look an appropriate choice to obtain reasonable overall accuracies of 95 %. Table I summarizes

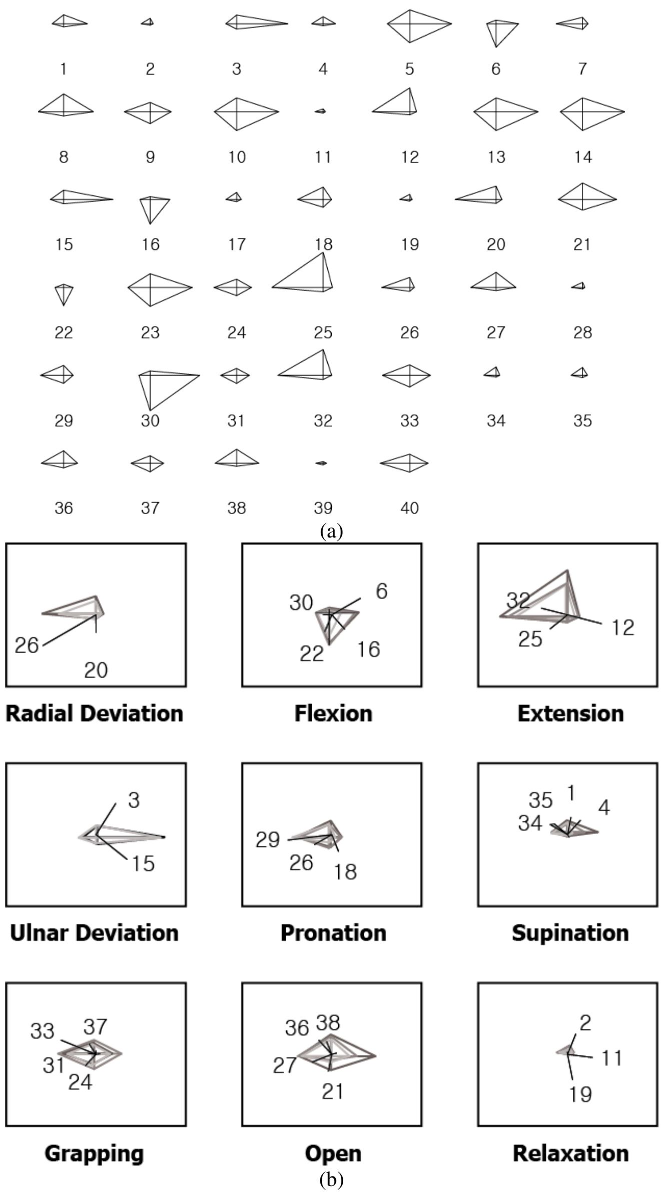

Figure 4. (a) Visualization of mean vectors of latent neural states, (b) relative scales of major neural states per action.

the performance results over subjects. Accuracies are generally above 90%, which is competitive in comparison with previous reports [1, 3, 8, 10].

To see the trained model in detail, the estimated latent neural states from a subject's model are illustrated in Fig. 3(a). Each rectangular shape visualizes the 4-dimenional mean vector, sEMG values of FCU, PL, ECR and ED, clockwise from right direction, of each Gaussian distribution representing a latent neural state. Each neural state is labeled from 1 to 40. Given data of a particular trial, in Fig. 3(b), relative contribution scales of major influential latent neural states are visualized per each action including the relaxed posture. Regarding that elements in γ represent the relative influence proportions of latent neural states, latent neural states corresponding to large elements, which cover up to 90% of each action, were selected to be the major influential latent neural states for each action. As a result, two to four major latent neural states were selected per action as in Fig. (b). The visualization shows relative amplitudes of the four electrodes per action, which were encoded in the model.

V. Conclusion

This paper suggested hierarchical Bayesian model-based classification of sEMG signals. Given training data, the generative model finds latent neural states and their combined structure, which are key components of classification. The experimental evaluation indicates that the proposed approach seems very promising. Even though further exploration is required, this work proposes that hierarchical Bayesian model may be an effective choice for sEMG pattern recognition. Further enhancement is under investigation.

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