A Hybrid Motion Classification Approach for EMG-Based Human–Robot Interfaces Using Bayesian and Neural Networks

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***Abstract*—In a human–robot interface, the prediction of motion, which is based on context information of a task, has the potential to improve the robustness and reliability of motion classification to control prosthetic devices or human-assisting manipulators. This paper proposes a task model using a Bayesian network (BN) for motion prediction. Given information of the previous motion, this task model is able to predict occurrence probabilities of the motions concerned in the task. Furthermore, a hybrid motion classification framework has been developed based on the BN motion prediction. Besides the motion prediction, electromyogram (EMG) signals are simultaneously classified by a probabilistic neural network (NN). Then, the motion occurrence probabilities are combined with the NN classifier's outputs to generate motion commands for control. With the proposed motion classification framework, it is expected that classification performance can be enhanced so that motion commands can be more robust and reliable. Experiments have been conducted with four subjects to demonstrate the feasibility of the proposed methods. In these experiments, forearm motions are classified with EMG signals considering a cooking task. Finally, robot manipulation experiments were carried out to verify the proposed human interface system with a task of taking meal. The experimental results indicate that the proposed methods improved the robustness and stability of motion classification.**

***Index Terms*—Bayesian network (BN), electromyogram (EMG) signal, human–robot interfaces, motion classification, motion prediction.**

I. Introduction

ELECTROMYOGRAM (EMG) signals, which are measured at the skin surface, are the electrical manifestations of the activity of muscles. It provides an important access to the human neuromuscular system. EMG has been well recognized as an effective tool to generate control commands for prosthetic devices and human-assisting manipulators. Up to the present, a number of EMG-based human interfaces have been proposed as a means for elderly people and the disabled to control powered prosthetic limbs, wheelchairs, teleoperated robots, and so on [1]–[5].

The core part of these human–robot interfaces is a pattern-classification process, where motions or intentions of motions are classified according to features extracted from EMG signals. Commands for device control are then generated from the classified motions. A variety of methods has been applied to motion classification. For example, Graupe *et al.* used an autoregressive (AR) model to represent EMG signal, and motions were determined based on the parameters of the AR model [1]. Kang *et al.* applied a Bayesian classifier for motion classification [6]. Probability is calculated based on cepstral coefficients of EMG signals, and the motion with the maximum probability is selected. In recent years, artificial neural networks (NNs) have been receiving increasing attention, and many approaches have appeared in the field of EMG pattern classification using multilayer perceptrons NNs [7]–[10], fuzzy NNs [11], [12], and probabilistic NNs [4], [13]. Various attempts have been carried out to improve the accuracy of EMG pattern classification using novel EMG features (or called as signal representations), such raw EMG signals and wavelet coefficients.

The performance of a human interface is largely limited by accuracy of motion classification. It must be noted that EMG is an exceedingly complicated and nonstationary signal. The feature patterns vary significantly depending on tasks and conditions of users. In addition, EMG signals are very likely affected by artifacts and noises. With regard to practical applications, it is still difficult to achieve sufficient accuracy and stable performance of motion classification *only* based on EMG signals. It requires many conscious efforts on the part of a user to operate a prosthetic device or a human-assisting manipulator.

In order to overcome these problems, Tsuji *et al.* introduced an entropy-based decision rule to reduce misclassification [9]. Entropy of a classifier's outputs gives a measurement of the amount of uncertainty of classification results. When entropy exceeds a predefined threshold, the motion decision rule suspends the judgment. In addition to this method, Fukuda *et al.* incorporated a task model into an EMG-based human interface to improve the classification performance for unstable EMG patterns [14]. This task model describes the sequences of motions in a task, including all possible motion transitions and branches, using a Petri net (PN) [15]. The task model determines a forthcoming motion according to the history of classification

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results. Outputs of a motion classifier, which are occurrence probabilities of motions, are then modified by a set of weights according to the PN task model. Thus, the probability of the motion determined by the task model is enhanced, while the other motions are depressed. However, the motion sequences and the modification weights must be manually designed. It is difficult to apply this method when we do not have enough knowledge to describe clearly all possible motion sequences in a task. Furthermore, the modification weights usually need to be determined by trial and error.

On the other hand, prediction of a user's future behavior based on context information has been used to improve efficiency and classification accuracy of human interfaces. For example, Darragh *et al.* developed a predictive typing aid to accelerate text entry [16]. This method predicts what a user is going to type from previously entered text, and the prediction is generated from an adaptively trained text model. In the speech recognition method proposed by Yamaoka and Iida, prediction of the next utterance is used to reduce ambiguity of candidates in classification [17]. It is also suggested that prediction of candidates in mathematical character classification can largely increase the accuracy [18]. In these researches, prediction is based on the idea that users repeat similar behavior under certain conditions, and the characteristics of tasks can be represented with a task model. Prediction of a user's intention, goals, preferences, and forthcoming actions, especially in cases of human interfaces, provides a high potential to reduce the number of candidates, assign high priority to some candidates, or re-rank the candidates concerned in classification. Such information can significantly ease the difficulty of pattern classification and virtually improve the classification accuracy.

This paper proposes a predictive task model using Bayesian network (BN) for motion prediction in order to improve robustness and reliability of EMG-based motion classification. BN [19] is one of the popular techniques for user modeling and predicting [20]–[22]. For example, Albrecht *et al.* applied BNs to predict a user's next action, location, and quest in a multiuser dungeon (MUD) game [23]. BNs have also been used to model and predict human driving behaviors [24]. The advantage of BN lies in the following reasons: 1) Probabilistic expression in BNs is effective in dealing with uncertainty that is concerned with reasoning human behavior; 2) directed arcs between nodes give an intuitive and explicit representation of causal relationships, and the network structure can be devised by hand or learned from data; 3) the parameters, i.e., the conditional probability tables (CPTs), can be extracted from a database, and can be updated whenever new samples are available. In this paper, BN is utilized for modeling dependent relationships between two consecutive motions. Unlike the PN used in [14], we do not need to predefine detailed sequences of motions in the task model, but extract the conditional probabilities of motions from case data directly. Given context information of the previous motion, the task model predicts occurrence probabilities for each motion.

With the proposed task model, we further develop a hybrid motion classification framework for EMG-based human–robot interfaces. In this paper, we consider controlling a prosthetic hand with the motion commands classified from forearm EMG signals. Parallel to the motion prediction part using BN, a probabilistic NN is adopted for EMG pattern classification. We use a product rule [25] to combine the probabilities for the candidate motions, which are obtained from both the BN task model and the NN classifier.

The rest of this paper is organized as follows. Section II introduces the proposed BN task model. A hybrid motion classification framework for EMG-based human–robot interfaces is explained in Section III. Then, motion classification and robot manipulation experiments are presented in Sections IV and V. Finally, conclusions are given in Section VI.

II. Task Model using BN

A. Bayesian Network

A BN [19] is a graphical notation that encodes conditional dependence relationships among a set of events. It is a directed acyclic graph where the nodes are probability variables representing certain events. Generally, a BN can be defined as $G = (\mathbf{V}, \mathbf{A}, \mathbf{P})$, where $\mathbf{V} = \{V_1, V_2, \ldots, V_N\}$ is a set of nodes (variables), $\mathbf{A}$ is an assembly of directed arcs between the nodes, and $\mathbf{P}$ is a set of CPTs that are associated with each node. A directed arc from V_i to V_j, $(V_i, V_j) \in \mathbf{A}$, represents the conditional dependency between the variables, and this dependency is indicated with $P(V_j = a | V_i = b)$, which is the conditional probability for $V_j = a$ given that $V_i = b$.

B. BN Task Model for Motion Prediction

We assume that a task consists of a series of motions, $m(s)$ $(s = 1, 2, \ldots, S)$, where $m(s)$ represents the motion of the sth step. At each step, only one motion occurs. A set of M motions is considered in the task model $m(s) \in \{1, \ldots, m, \ldots, M\}$.

During a task, motion transition takes place between two consecutive steps, say from $m(s-1)$ to $m(s)$. The transition illustrates dependence between the motions. On the other hand, the motion at the sth step is related to one or more statuses of the motion at the $s-1$th step. For example, the location, where $m(s-1)$ is achieved, is one of these cues to predict $m(s)$.

In this paper, a BN, as shown in Fig. 1, is used to model the dependent relationships among four variables: m_c, m_p, l_p, and h_p. Here, m_c is the motion at the current step, m_p is the motion for the previous step, l_p indicates the location of motion m_p, and h_p represents user's hand position at the previous step. $P(m_p)$ and $P(h_p)$ are probability of motion and hand positon at the previous step, respectively. $P(l_p|h_p)$ represents the conditional probability of location at the previous step given the previous hand position, and $P(m_c|m_p, l_p)$ is the conditional probability of the current motion with respect to motion and location information at the previous step. There are N locations defined in the workspace $l_p \in \{l_1, \ldots, l_n, \ldots, l_N\}$. These locations are positions of the items used in the task and possible places, where users are expected to achieve some particular motions.

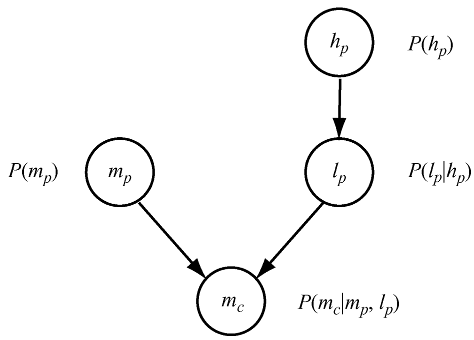

Fig. 1. Task model for motion prediction using a BN.

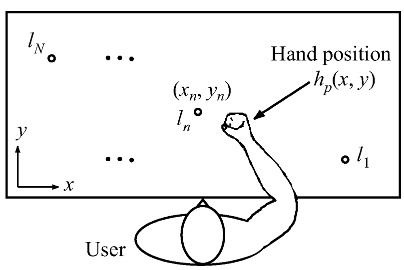

Fig. 2. Locations and the user's hand position in the workspace. Location of motion is determined according to coordinates of hand position.

There are three discrete nodes (m_c, m_p, and l_p) and one continuous node (h_p) in this BN. The conditional probabilities $P(m_c|m_p, l_p)$ can be estimated by counting the number of samples in a database. For example

$$\begin{aligned} P(m_c = m'|m_p = m, l_p = l_n) \\ &= \frac{P(m_c = m', m_p = m, l_p = l_n)}{P(m_p = m, l_p = l_n)} \\ &\simeq \frac{N(m_c = m', m_p = m, l_p = l_n)}{N(m_p = m, l_p = l_n)} \end{aligned} \quad (1)$$

where $N(m_c = m', m_p = m, l_p = l_n)$ denotes the number of samples in the database, which are $m_c = m'$, $m_p = m$, and $l_p = l_n$. $N(m_p = m, l_p = l_n)$ is the number of samples for $m_p = m$ and $l_p = l_n$. Frequencies of motion transitions as well as dependencies between motions and locations vary among individuals. A task model can be further adapted to a user by extract statistical information from databases of his task records.

On the other hand, $P(l_p|h_p)$ is a continuous probability distribution. According to Bayes' law, $P(l_p = l_n|h_p)$ can be derived as

$$\begin{aligned} P(l_p = l_n|h_p) &= \frac{P(l_p = l_n, h_p)}{P(h_p)} \\ &= \frac{P(h_p|l_p = l_n)P(l_p = l_n)}{\sum_{l_p=l_1}^{l_N} P(h_p|l_p)P(l_p)} \end{aligned} \quad (2)$$

where $P(h_p|l_p)$ is the conditional probability of h_p at the location l_p. The location l_p is dependent on the coordinates of h_p (see Fig. 2). Suppose that $P(h_p|l_p = l_n)$ follows a 2-D normal distribution with the center at location l_n, which has the coordinates as (x_n, y_n) and standard deviations as σ_{xn} and σ_{yn}. Thus, with the coordinates of h_p, we have

$$\begin{aligned} P(h_p|l_p = l_n) \\ = \frac{1}{2\pi\sigma_{xn}\sigma_{yn}} \exp\left\{-\frac{1}{2}\left[\frac{(x - x_n)^2}{\sigma_{xn}^2} + \frac{(y - y_n)^2}{\sigma_{yn}^2}\right]\right\}. \end{aligned} \quad (3)$$

Also, given that $P(l_p)$ is a uniform distribution, (2) can be simplified as

$$P(l_p = l_n|h_p) = \frac{P(h_p|l_p = l_n)}{\sum_{l_p=l_1}^{l_N} P(h_p|l_p)}. \quad (4)$$

When context information of the previous motion step is added to the task model, belief updating is performed to give the probability of the user's forthcoming motion for prediction.

III. Hybrid EMG-Based Human-Robot Interface With Motion Prediction

A human–robot interface controlled with EMG signals is developed based on motion prediction using the BN task model. EMG signals measured from a user's forearm are classified in order to estimate his/her (intended) motions. The motions are then used as commands to control a prosthetic hand. The prosthetic hand can be directly attached to an amputee's body. The structure of this human–robot interface is shown in Fig. 3. This system consists of three major parts: 1) EMG pattern classification; 2) motion prediction; and 3) motion decision.

A. EMG Pattern Classification

First, EMG signals are processed to extract the feature patterns for classification. The EMG signals, which are measured from D pairs of electrodes, are rectified and filtered by a second-order Butterworth filter (cutoff frequency f_c). They are then digitized by an A/D converter with a sampling frequency of f_s. The sampled data are defined as $\mathrm{EMG}_d(t)$ $(d = 1, 2, \ldots, D)$ and are normalized to make the sum of D channels equal to 1.0. We have

$$x_d(t) = \frac{\mathrm{EMG}_d(t) - \mathrm{EMG}_d^{st}}{\sum_{d'=1}^{D}(\mathrm{EMG}_{d'}(t) - \mathrm{EMG}_{d'}^{st})} \quad (5)$$

where EMG_d^{st} is the mean value of $\mathrm{EMG}_d(t)$ that is measured while the arm is relaxed. The feature vector $\mathbf{x}(t) = [x_1(t), x_2(t), \ldots, x_D(t)]$ is used for pattern classification.

A probabilistic NN, which is called log-linearized Gaussian mixture network (LLGMN) [26], is used as the classifier. LLGMN is a three-layer feedforward NN. The structure of LLGMN is based on the Gaussian mixture model (GMM) and a log-linear model, and this NN is able to estimate probability density functions (pdfs) of input patterns. When used for pattern classification, LLGMN possesses an inherent advantage of achieving statistical classification using Bayes' decision rule and shows a good generalization ability. So far, LLGMN has been successfully applied to EMG pattern classification even in cases of amputee users [4], [14], [27]–[30].

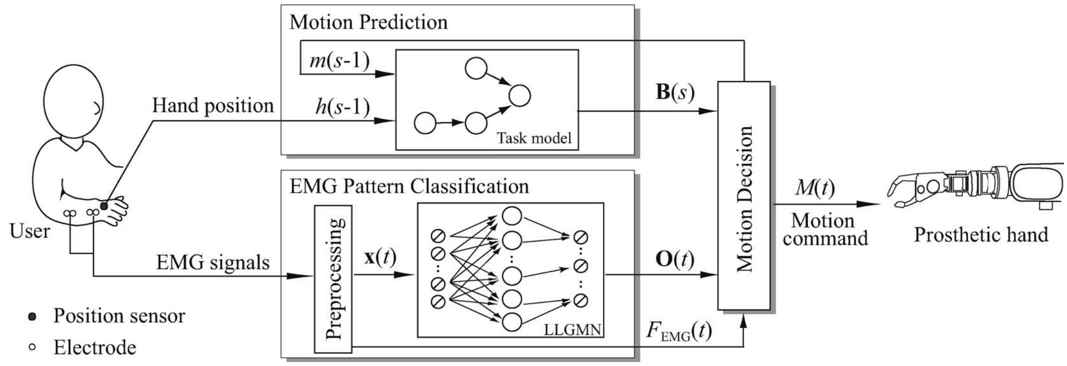

Fig. 3. Hybrid structure of an EMG-based human–robot interface, where the BN task model is incorporated for motion prediction.

Given an EMG feature vector $\mathbf{x}(t)$ $(t = 1, \ldots, T)$, the output of LLGMN $O_m(t)$ $(m = 1, 2, \ldots, M)$ represents the posterior probabilities of motion m. Then, the posterior probability vector $\mathbf{O}(t) = [O_1(t), O_2(t), \ldots, O_M(t)]$ is fed into the motion decision part.

In this study, we assume that the amplitude level of EMG signals changes in proportion to the muscle force. The force information $F_{\mathrm{EMG}}(t)$ for the input vector $\mathbf{x}(t)$ is defined as

$$F_{\mathrm{EMG}}(t) = \frac{1}{D}\sum_{d=1}^{D}\frac{\mathrm{EMG}_d(t) - \mathrm{EMG}_d^{st}}{\mathrm{EMG}_d^{\max} - \mathrm{EMG}_d^{st}} \tag{6}$$

where $\mathrm{EMG}_d^{\max}$ is the mean value of $\mathrm{EMG}_d(t)$ that is measured while maintaining the maximum voluntary contraction of the arm. The force information is used to determine the onset and end of motions in the motion decision part.

B. Motion Prediction

The task model described in Section II is used for motion prediction. The motion and the hand position of a user are added to the task model as evidence. The motion of the previous step $m(s-1)$ is obtained from the results of the motion decision part. The hand position $h(s-1)$ is measured with a position sensor, which is attached on the user's wrist.

With the notation in Section II, the belief about the current motion, which is the conditional probability $P(m_c|m_p, h_p)$, can be calculated as follows:

$$P(m_c|m_p, h_p) = \frac{\sum_l P(m_c|m_p, l)P(l|h_p)}{\sum_m \sum_{l'} P(m|m_p, l')P(l'|h_p)}. \tag{7}$$

For the first motion step, the belief for motion prediction $B_m(1)$ $(m = 1, 2, \ldots, M)$ is set as $1/M$. As for the sth step $(s > 1)$, given that the context information of the $s-1$th step is $m(s-1)$ and $h(s-1)$, $B_m(s)$ is calculated for each motion as

$$B_m(s) = P(m(s)|m(s-1), h(s-1)). \tag{8}$$

After the belief propagation, the belief vector $\mathbf{B}(s) = [B_1(s), B_2(s), \ldots, B_M(s)]$ is output to the motion decision part.

C. Motion Decision

In order to recognize whether a motion has really occurred or not, the force information $F_{\mathrm{EMG}}(t)$ is compared with a predefined motion appearance threshold F_{th}. The motion is considered to have occurred if $F_{\mathrm{EMG}}(t)$ exceeds F_{th}. Thus, the duration of the sth motion step is the period $[t^s_{\mathrm{ON}}, t^s_{\mathrm{OFF}}]$

$$F_{\mathrm{EMG}}(t) \geq F_{\mathrm{th}}, \qquad t \in [t^s_{\mathrm{ON}}, t^s_{\mathrm{OFF}}] \tag{9}$$

where t^s_{ON} stands for the onset of the sth motion, and t^s_{OFF} is the end of the motion.

In the area of pattern classification, combining classifiers has been widely discussed, and various applications have utilized this scheme to improve efficiency and accuracy of classification [25], [31]. In this paper, the probabilities, which are outputs of LLGMN and the BN task model, are combined for motion decision. Since outputs of the BN task model are predictions based on the previous motion, rather than classification results based on a substantial event that resulted from the current motion. We set the outputs from LLGMN, i.e., the EMG pattern classification part, as the major part in the combination.

During the sth motion, a product rule is applied to obtain the probability of motion $P_m(t)$ $(m = 1, \ldots, M)$ as follows:

$$P_m(t) = \frac{w_m(t)O_m(t)}{\sum_{m'=1}^{M} w_{m'}(t)O_{m'}(t)}, \qquad t^s_{\mathrm{ON}} \leq t \leq t^s_{\mathrm{OFF}} \tag{10}$$

where the weight $w_m(t)$ is defined as

$$w_m(t) = \alpha\left(B_m(s) - \frac{1}{2}\right) + \frac{1}{2}, \qquad 0 \leq \alpha \leq 1. \tag{11}$$

Here, the interval of $B_m(s)$ $[0, 1]$ is transformed to $[(1-\alpha)/2, (1+\alpha)/2]$. This transformation is conducted in order to prevent misclassification due to $B_m(s) = 0$ for some motions. It should be noted that the parameter α determines the influence of motion prediction in the combination. The larger the parameter α is, the greater is the influence. The parameter α should be defined previously, and it can be adjusted according to a user's preference.

Moreover, the entropy of $P_m(t)$ is calculated in order to prevent misclassification. The entropy is defined as

$$H(t) = -\sum_{m=1}^{M} P_m(t)\,\log P_m(t). \tag{12}$$

If the entropy $H(t)$ is less than the threshold H_d, the motion with the largest probability is determined as the user's intended motion $M(t)$ according to Bayes' decision rule. Otherwise, the

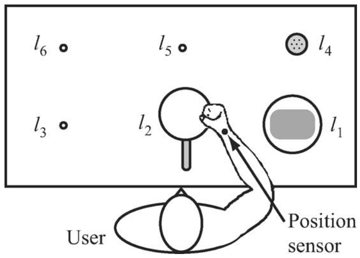

Fig. 4. Locations and items of the cooking task. l_1: Ingredients, l_2: a fry pan, and l_4: salt.

determination is suspended. Finally, $M(t)$ is used as control commands for the prosthetic hand.

IV. Motion Classification Experiments

Motion classification experiments were carried out in order to evaluate classification performance of the proposed method. Four male subjects voluntarily took part in these experiments. Subjects C and D had not participated in EMG classification experiments before. For comparison, the motion classification method utilized in [4] was used, which makes decisions *only* based on the outputs of LLGMN. The entropy-based decision rule was used in this comparison method. For the sake of simplicity, the comparison method is represented as LLGMN in the rest of this paper.

A. Experimental Conditions

In the experiments, EMG signals were measured from five pairs ($D = 5$) of electrodes (NT-511G: NIHON KOHDEN Corporation). The electrodes were attached to user's forearm and upper arm: flexor carpi radialis (FCR), extensor carpi ulnaris (ECU), flexor carpi ulnaris (FCU), and biceps brachii (BB). Two pairs of electrodes were attached on the FCR and one pair on each of the others. The differential EMG signals were amplified by a telemetry system (MT11, NEC Medical Systems Corporation). The cutoff frequency of the Butterworth filter was 1 Hz, and the EMG signals were recorded at a sampling frequency of 1 kHz. Additionally, a 3-D position sensor (ISOTRACK II: POLHEMUS, Inc.) was used to measure the hand positions in the workspace.

A cooking task is used for test in these experiments. This task consists of four operations: 1) Turn on a gas ring; 2) put an ingredient in a fry pan; 3) add some salt to the ingredient; and 4) shake the fry pan. Six motions are considered in this task ($M = 6$: hand open, hand grasp, flexion, extension, pronation, and supination). We defined six locations in the workspace ($N = 6$), as shown in Fig. 4. Three items are used in this task, i.e., ingredients (l_1), a fry pan (l_2), and salt (l_4). A typical order of the motion series and location transitions in the cooking task is depicted in Table I.

Each subject performed 15 trials on the task. Data of the first five trials were used to train LLGMN and the BN task model, while the other trials were used for test. The training trials were performed with the order of operations as (1)–(2)–(3)–(4). The test trials were further divided equally into two groups:

TABLE I
Typical Order of the Motion Series and Location Transitions in the Cooking Task

Operation	m_p	l_p	m_c
(1)	-	-	Hand grasp
	Hand grasp	l_2	Pronation
(2)	Pronation	l_2	Hand open
	Hand open	l_1	Hand grasp
	Hand grasp	l_1	Hand open
(3)	Hand open	l_2	Hand open
	Hand open	l_4	Hand grasp
	Hand grasp	l_4	Pronation
	Pronation	l_2	Hand grasp
	Hand grasp	l_2	Hand open
(4)	Hand open	l_4	Hand grasp
	Hand grasp	l_2	Flexion
	Flexion	l_2	Flexion
	Flexion	l_2	Hand grasp
	Hand grasp	l_2	Hand open

Group I—the operation order is the same as the training trials and group II—the operation order is (1)–(3)–(2)–(4). Table II depicts the CPT $P(m_c|m_p, l_p)$ of subject A extracted from the training data. According to the previous researches on EMG motion classification [9], [10], [13], [27]–[30], $F_{\rm th}$ was set at 0.2 and H_d at 0.3. The parameter α was set at 0.8 with respect to a preliminary examination on change of classification rate for various values of α (see Section IV-D).

B. Motion Classification Results

An example of the experimental results of subject A is shown in Fig. 5. The operation order of this test trial is (1)–(2)–(3)–(4). This figure plots the five channels of EMG signals, force information $F_{\rm EMG}(t)$, outputs of the BN task model $B_m(s)$, the classification results of LLGMN, and the results of the proposed method. The gray areas indicate that no motion was achieved because $F_{\rm EMG}(t)$ was less than $F_{\rm th}$. Motions with label of "0" represent decision suspension due to a high entropy, and no motion command would be generated by the interface. The classification rates of LLGMN and the proposed method are 85.1% and 92.9%, respectively.

From the results of LLGMN, it can be found that most of the misclassifications occur at beginnings and ends of motion steps. These are chiefly due to the variation in EMG patterns during the transitional phases of motions. In contrast to the method that is only based on LLGMN, classification accuracy of the proposed method is substantially improved, and the results are much more stable during each motion step. Since the BN task model gives higher belief to the motions, which are predicted to appear at the current step, most of the misclassifications made by LLGMN are corrected by combining the output of LLGMN with the belief vector $\mathbf{B}(s)$. For example, at about 15 and 23 s, EMG patterns of motion 2 are incorrectly classified as motion 5 by LLGMN. With the proposed method, the belief of motion 2 (B_2) is higher than other motions during these motion steps so that the misclassifications are prevented.

Accuracy of the classification results for four subjects was investigated as well. Motion classification experiments were

TABLE II
CPT, $P(m_c|m_p, l_p)$, OF SUBJECT A FOR THE COOKING TASK

m_p	l_p	m_c					
		Hand open	Hand grasp	Flexion	Extention	Pronation	Supination
Hand open	l_1	0.00	1.00	0.00	0.00	0.00	0.00
Hand grasp	l_1	1.00	0.00	0.00	0.00	0.00	0.00
Flexion	l_1	0.167	0.167	0.167	0.167	0.167	0.165
...	...	...	...	...	...	...	...
Hand open	l_2	0.667	0.333	0.00	0.00	0.00	0.00
Hand grasp	l_2	0.60	0.00	0.20	0.00	0.00	0.20
Flexion	l_2	0.00	0.50	0.50	0.00	0.00	0.00
...	...	...	...	...	...	...	...
Hand open	l_4	0.00	1.00	0.00	0.00	0.00	0.00
Hand grasp	l_4	0.00	0.00	0.00	0.00	1.00	0.00
...	...	...	...	...	...	...	...
Supination	l_6	0.167	0.167	0.167	0.167	0.167	0.165

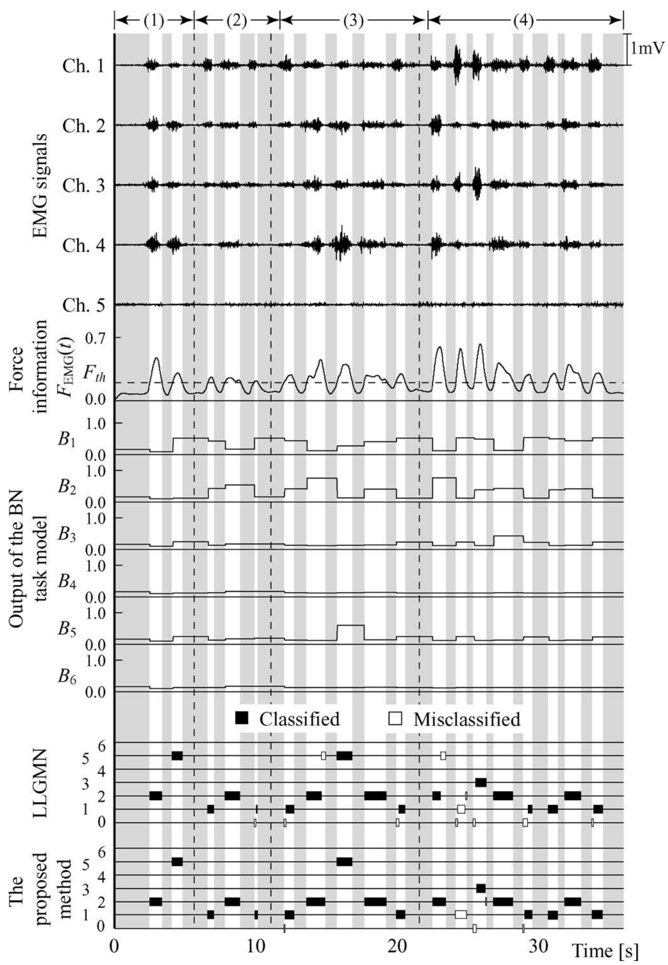

Fig. 5. Example of continuous classification results of the cooking task (subject A). The labels of classification results are as follows: 0—Decision suspension, 1—hand open, 2—hand grasp, 3—flexion, 4—extension, 5—pronation, and 6—supination.

conducted using all test trials. Figs. 6 and 7 show the mean values and standard deviations of classification rates for trials from test group I and group II, respectively. In both cases, the proposed method outperforms the comparison method. For test trails of group II, although the operation order is different from that of the training trials, improvements of classification results are confirmed for all subjects. Since the BN task model represents

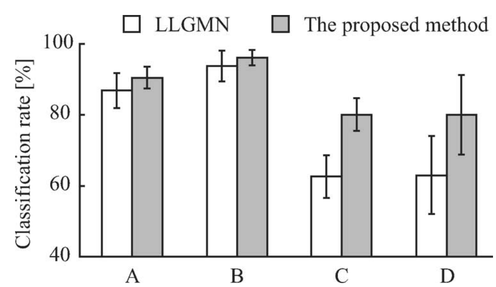

Fig. 6. Classification results of trails from test group I.

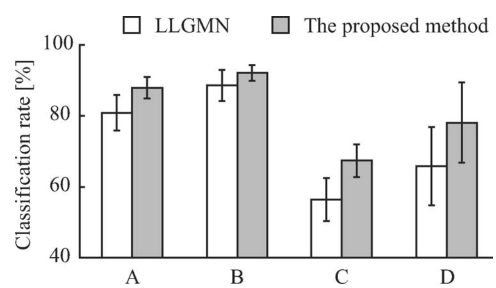

Fig. 7. Classification results of trails from test group II.

dependencies among variables of two consecutive motion steps, the proposed method is expected to provide high flexibility when dealing with practical motion series.

C. Increase of Classification Rates

The increase of classification rates is computed for each test trial. We define the increase ΔCR as

$$\Delta\mathrm{CR} = \mathrm{CR} - \mathrm{CR}' \tag{13}$$

where CR is the classification rate of the proposed method and CR$'$ is that of LLGMN. A summary of the increase of classification rate is listed in Table III. As demonstrated by the results, increase of classification rate has been achieved by the proposed method.

Furthermore, it can be found that ΔCRs of subjects C and D are larger than those of A and B. Thus, an increase ratio (IR) is

TABLE III
SUMMARY OF THE INCREASE OF CLASSIFICATION RATE (IN PERCENTAGE)

Subject	Test Group I			Test Group II		
	Mean	Min.	Max.	Mean	Min.	Max.
A	3.66	0.00	7.83	7.10	0.53	15.38
B	2.28	0.00	5.63	3.47	0.39	5.39
C	17.43	9.16	28.48	11.00	2.75	14.84
D	17.10	12.80	29.51	12.26	8.73	16.88

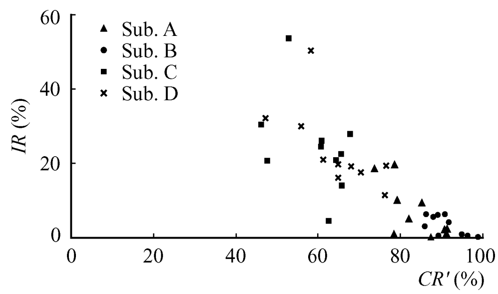

Fig. 8. IR versus classification rate of LLGMN (CR′).

evaluated as

$$\mathrm{IR} = \frac{\Delta \mathrm{CR}}{\mathrm{CR}'}. \tag{14}$$

The IRs versus CR′s for ten trials of each subject are plotted in Fig. 8. Generally, there is an increase in classification rate when CR′ decreases. If LLGMN makes a correct classification based on the EMG signals, the context information and characteristics of tasks, such as the transition between motions and information of locations, do not make much sense. When LLGMN fails, however, the motion prediction made by the BN task model helps a lot in the motion decision. This may be an encouraging result for users, like subjects C and D, who have not much experience in control with EMG-based human interfaces.

D. Influence of BN on Classification Results

Motion classification experiments were conducted using various values of parameter α. It was set as 0.0, 0.2, 0.4, 0.6, 0.8, and 1.0, respectively. For each subject, five trials of test data were classified. Mean values of the classification rates for each α are shown in Fig. 9. It can be found that the classification rate rises when α increases, especially for subjects C and D. In the case of $\alpha = 0.0$, the classification results are only based on LLGMN. By increasing the influence of BN, better classification performance is available. Remember that for the combination of the neural classifier (LLGMN) and the motion prediction model (BN), we set the former as the major part. The parameter α is set as 0.8 in this study.

V. ROBOT MANIPULATION EXPERIMENTS

The simulation experiments in the previous section demonstrate the feasibility and effectiveness of the proposed method. This section introduces robot manipulation experiments conducted using the proposed EMG-based human–robot interface.

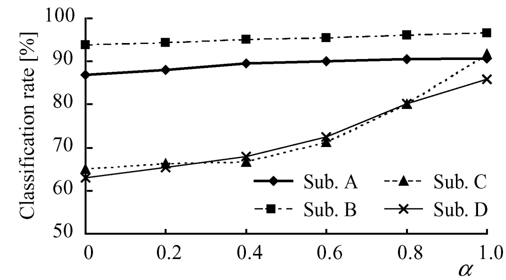

Fig. 9. Classification results for various values of parameter α.

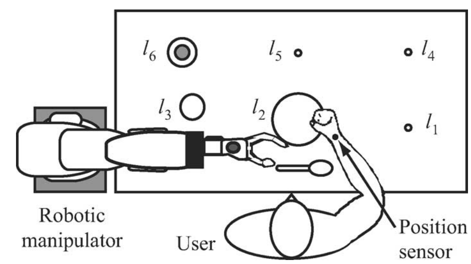

Fig. 10. Workspace of the task of taking meal. A robotic manipulator is set on the left side. The items in the workspace are a disk and a spoon (l_2), a glass (l_3), and a bottle of water (l_6).

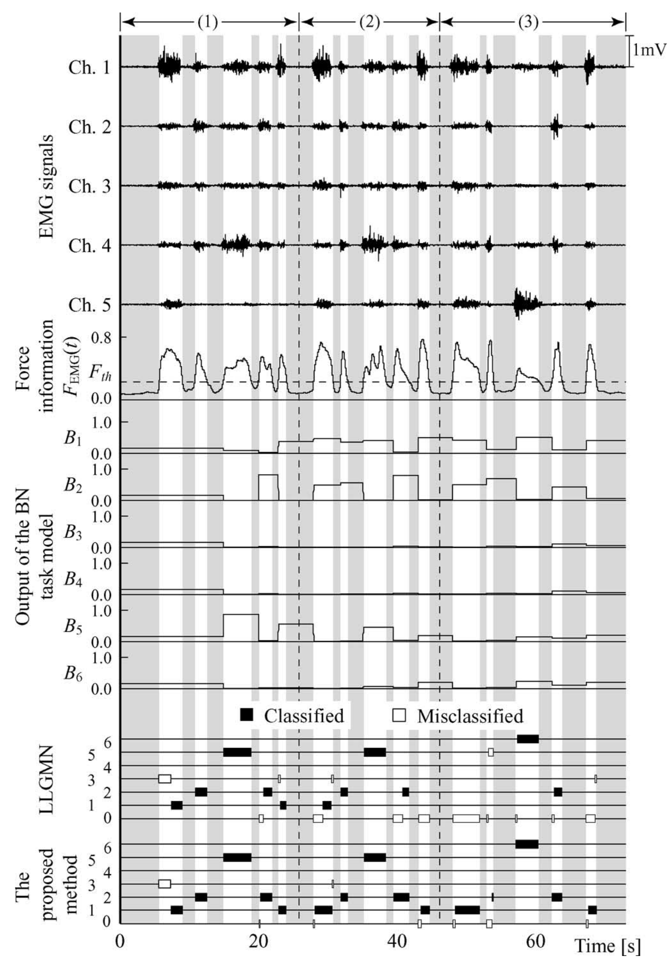

Fig. 11. Sample session of experimental results of a manipulation trial (task of taking meal; subject A). The labels of classification results are as follows: 0—Decision suspension (no motion command is generated for the manipulator), 1—hand open, 2—hand grasp, 3—flexion, 4—extension, 5—pronation, and 6—supination.

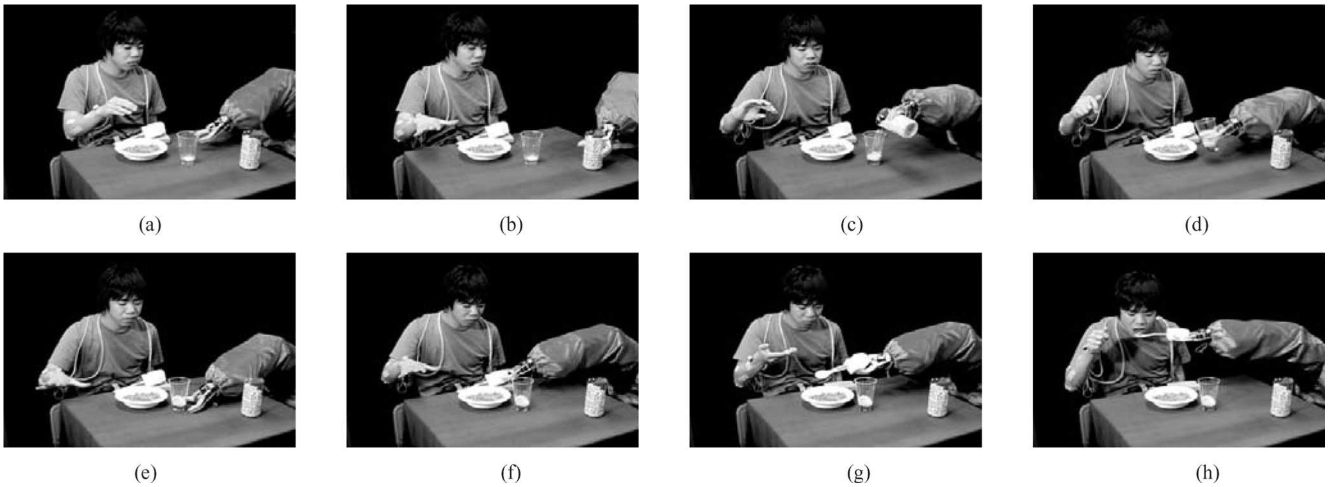

Fig. 12. Scenes of the robot manipulation experiments (subject A). (a) $t = 0.0\,\mathrm{s}$. (b) $t = 5.2\,\mathrm{s}$. (c) $t = 14.2\,\mathrm{s}$. (d) $t = 30.0\,\mathrm{s}$. (e) $t = 39.2\,\mathrm{s}$. (f) $t = 48.3\,\mathrm{s}$. (g) $t = 55.0\,\mathrm{s}$. (h) $t = 62.3\,\mathrm{s}$.

The subjects were instructed to perform a taking meal task, which includes three operations: 1) Pour some water into a glass; 2) drink water; and 3) eat soup with a spoon. The schematic view of the workspace is presented in Fig. 10.

A robotic manipulator is set on the left of the workspace. The robotic manipulator consists of a prosthetic hand (Imasen Laboratory) and a robot arm (Mitsubishi Electric Corporation). Motion of the prosthetic hand is controlled with the commands $M(t)$, which are generated by the motion decision part. The prosthetic hand can achieve six different motions corresponding to the six forearm motions of users. The robot arm supports the prosthetic hand and transports it to positions in the workspace according to a user's hand position. The prosthetic hand is detachable from the robot arm, and an amputee can attach it to his/her body to replace the amputated arm. This robotic manipulator was developed by Fukuda *et al.* [28], [30], and it has been used in previous research. For details, see [4] and [14].

The experimental conditions of EMG measurement and position sensing are as the same as those in Section IV. The parameters for motion decision are as follows: $F_{\mathrm{th}} = 0.22$, $H_d = 0.3$, and $\alpha = 0.8$.

Fig. 11 shows a sample session of experimental results of a manipulation trial (subject A). In the first motion step (around 6 s), misclassification can be found for both methods. It should be noted, however, that no context information is available for the first step; therefore, the classification results of both methods are the same. For later motion steps, the proposed method *corrected* most of the misclassification of the comparison method. With the proposed method, the subject achieved the task successfully. The classification rate of the proposed method is 86.4%, with an increase of 17% from the result of LLGMN. Some scenes of the robot manipulation experiments are shown in Fig. 12.

VI. Conclusion

In this paper, we have proposed a new task model based on BNs and applied it to an EMG-based human–robot interface system as an assist to support motion classification. Since BNs extract the statistical dependency between two continuous motions, the task model outputs the conditional probabilities as belief for motion prediction according to context information. The belief then can be easily combined with output of a probabilistic NN classifier to improve stability and accuracy of motion decision. Additionally, the probabilistic parameters in the task model are obtained by training with a database, and online learning methods [32], [33] are possible to keep adaptability for a user. Finally, experiments of EMG motion classification and robot manipulation have proved the feasibility and effectiveness of the proposed method.

On the other hand, it is still quite difficult for the proposed task model to provide a precise prediction, especially considering uncertainty in human behavior. There are many researches working on improving the accuracy of BN-based human modeling. This is out of the range of the present paper. Here, we use a weak predictor, i.e., a BN with simple structure, as a subpart in the proposed hybrid motion classification framework. The BN part does not directly give an *answer* but gives a suggestion for motion decision based on the characteristics of task flows, user's operation process, and his preference so that a much more robust and reliable classification result can be obtained.

In this paper, the structure of the BN task model is manually designed; it is not learned from a database. Actually, the task model shown in Fig. 1 is not the only form that can be used in this study. Motion, location, and hand position of the previous motion step are only a small part of the status related to a user's operation. Alternative designs of the BN task model are possible, using context information like user's posture, duration of a motion, and other related features.

In our future research, we would like to increase the number of subjects in the experiments, and a statistical analysis of experimental results is needed to investigate the proposed method. On the other hand, in order to demonstrate the validity of the proposed method for disabled users, we would like to conduct evaluation experiments with amputee subjects. Also, we will focus on the improvement of the proposed method. For example, the combination rule used in this paper would be enhanced. Moreover, in order to deal with human–robot interface applications in daily life, extension of the BN task model is needed. For this purpose, hierarchical structure of BN task models and combining of the proposed task model with PN is another interesting prospect.

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