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Development of Human-Machine Interface for Teleoperation of a Mobile Manipulator

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Abstract: Human-robot control interfaces have received increased attention during the past decades for conveniently introducing robot into human daily life. In this paper, a novel Human-machine Interface (HMI) is developed, which contains two components. One is based on the surface electromyography (sEMG) signal, which is from the human upper limb, and the other is based on the Microsoft Kinect sensor. The proposed interface allows the user to control in real time a mobile humanoid robot arm in 3-D space, through upper limb motion estimation by sEMG recordings and Microsoft Kinect sensor. The effectiveness of the method is verified by experiments, including random arm motions in the 3-D space with variable hand speed profiles.

Keywords: Kinect sensor, robot, sEMG, SVM.

1. INTRODUCTION

The human society is increasingly dependent on machinery and robots. In order to interact with the uncertain and nonlinear external environments, the robots themselves have to be robust and adaptive against with the disturbances [1-3]. Especially, with networked controlled robots connecting the cyberspace with physical space, robots make a much more convenient life for people [4-7]. However, the human-robot interface plays an utmost significant role in view of the purpose to serve humans. On the other hand, many disabled people have difficulty accessing current assistive robotic systems and rehabilitation devices with a traditional user interface (such as joysticks and key boards), therefore more advanced hands-free human-machine interfaces are necessary. Myoelectric signals (MES) contain rich information, from which a user's motion intention, in the form of a muscular contraction, can be detected using surface electrodes.

Electrically powered prostheses with myoelectric control have several advantages over other types of prostheses since the sEMG is noninvasively detected on the surface of the skin, the user is freed of straps and harnesses required in body powered and mechanical switch control. Moreover, many potential applications for myoelectric control have been reported, including wheelchairs [8], gait generation [9], grasping control [10].

Hudgins *et al.* [11] utilized time-domain (TD) features and a neural network, resulting in classifying four types of upper limb motion with an accuracy of approximately 90%. This technique employed transient signals, rather than the steady-state signals associated with a isometric contraction. However the main drawback, of using the transient sEMG as a control input is that it requires initialization of a contraction from rest. This prohibits switching from class to class in an effective or intuitive manner. It severely impedes the coordination of complex tasks involving multiple degrees of freedom.

In the following 15 years, So many classifiers have been utilized to investigate the sEMG-based classification performance, such as linear discriminant analysis (LDA) [12], time-delayed artificial neural network (ANN) [13], and so on. In this paper, support vector machine (SVM) is employed to analyze different patterns. The SVM is a kernel-based approach with a strong theoretical background, which becomes an increasingly popular tool for machine learning tasks involving classification and regression. It has recently been successfully applied to sEMG classification applications [14].

At the same time, given that the sEMG-based control scheme is not reliable enough to implement self-contained control, other sensors including vision sensors would be a very great supplement. From the other hand, some body motion, such as the pronation, is not easy to detect by the vision sensor. Based on this reason, we merge the information from Microsoft Kinect sensor into our sEMG-based control scheme to make the system more robust and multifunctional.

The rest of this paper is organized as follows. In the next section, we introduce the system architecture. Section 3 presents the motion feature recognizer, including the SVM and Kinect. Section 4 provides the

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motion tracking scheme. In Section 5, we give the experiments results and analysis. Finally, in Section 6, the conclusions are presented.

2. SYSTEM ARCHITECTURE

The proposed teleoperation system is composed of a mobile humanoid robot, sEMG data acquisition device, and a Microsoft Kinect. A data acquisition board (DAQ-board) is used to process the sensor information and control the robot. The DAQ-board and the Kinect are connected via a serial port.

The service robot shown in Fig. 1 consists of a mobile platform with 2 wheels and a upper body simulating human. Its height is 165cm and weighs about 50kg. The upper body includes 2 arms. Given the position in Fig. 1 as the initial position, the shoulder motor's rotation range is from -90^o to 90^o; the elbow one can rotates a whole circle. All joints are driven by servo motors with corresponding encoders for feedback and each servo motor is controlled by its corresponding driver.

Fig. 2 shows the structure of the HMI based on sEMG and Kinect developed to allow controlling a mobile robot's manipulator. A surface sEMG device, produced by NCC, Shanghai, China, is used for recording sEMG. While the system is capable of collecting sEMG with sixteen channels, we only use six channels, because of the redundancy of the electrodes [14]. The electrodes are all active bipolar, pre-gelled ones, Each electrode's diameter is 10 mm, and the input impendence of the pre-amplifier is greater than $100M\Omega$, The collected data is transmitted through the IEEE 802.11 protocol (i.e., wifi). Kinect is a motion sensing input device developed by Microsoft [15]. It is based on software and range camera technology, which interprets 3D scene information from a continuously-projected infrared structured light. We use it for tracking the human skeleton and therefore recognize the human motion. The valid range of the sensor is approximately 0.7-6m.

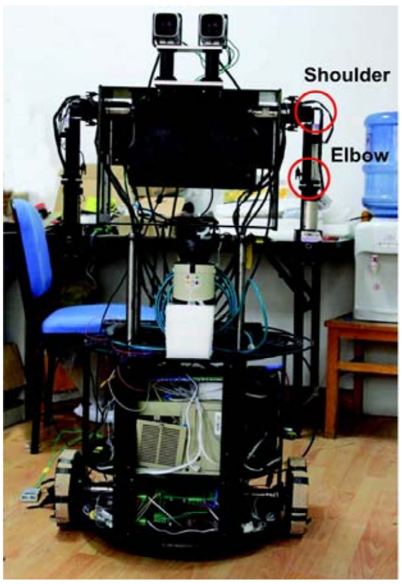


Fig. 1. The developed mobile service robot.

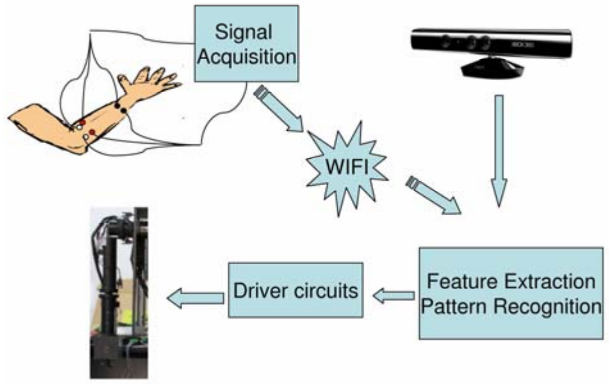


Fig. 2. The structure of the HMI.

3. MOTION FEATURE RECOGNIZER

3.1. Feature extraction

In [16], Tkach *et al*. studied the stability of the time-domain features for electromyographic pattern recognition, and find that mean absolute value, waveform length, and autoregressive coefficients are the most stable features under the effect of the shift of sEMG electrode location, variation in muscle contraction effort, and muscle fatigue. So the feature for recognition of sEMG signals we chosen consists of the three kinds of single feature:

1) Mean Absolute Value (MAV)

$$MAV = \frac{1}{N}\sum_{i=1}^{N} |x_i|.$$

2) Waveform Length (WL)

$$WL = \sum_{i=1}^{N} |\Delta x_i|; where \Delta x_i = x_i - x_{i-1}.$$

3) Autoregression Coefficients (AR)

This feature models individual sEMG signals as a linear autoregressive time series and provides information about the muscle's contraction state. It is defined as

$$x_k = \sum_{i=1}^{p} a_i x_{k-i},$$

where a_i represents autoregressive coefficients; p is the AR model order; x_i is the i–th sample; and N is the number of samples in a segment.

3.2. SVM

Given a set of training examples, each marked as belonging to one of two categories; $(x_1, y_1), \cdots, (x_n, y_n)$, where the x_i is a feature vector, and the y_i is the class label. The SVM is to construct an optimal hyperplane with maximum-margin and bounded error in the training data. The hyperplane can be shown as

$$\omega \cdot x + b = 0 \ \ \omega \in R^N, \quad b \in R. \tag{1}$$

In a mathematical way, the problem is equal to solve the following quadratic programming (QP) problem via the Lagrange function:

$$\max_{\alpha}\left(\sum_{i=1}^{n}\alpha_i-\frac{1}{2}\sum_{i,j}\alpha_i\alpha_j y_i y_j k(x_i,x_j)\right)$$
$$\sum_{i=1}^{n}\alpha_i y_i=0 \quad (2)$$
$$0\le\alpha_i\le C \quad \forall i.$$

The kernel $k(x_i, x_j)$, in (2), allows the algorithm to fit the maximum-margin hyperplane in a transformed feature space. It is often selected based on the data structure and type of the boundaries between classes. In this paper, we select the polynomial kernel as follows

$$k(x_i,x_j)=(rx_i\cdot x_j+coef)^d, \quad (3)$$

where r, $coef$ and d are the three parameters to adjust. "One-against-one" (OAO) technique is selected to solve the data-set slant problem in multiclass problems. By the approach, $k(k-1)/2$ (k is the number of classes) binary classifiers are trained to separate a pair of two classes. To classify a new sample, a class that gains most votes of the binary classifiers is chosen as the final output. The selection of parameters is presented in Section 5.

3.3. Kinect

In order to make full use of the Kinect sensor, we utilize the OpenNI (Open Natural Interaction) software [17]. OpenNI is a multi-language, cross-platform framework that defines APIs for writing applications utilizing natural interaction. OpenNI APIs are composed of a set of interfaces for writing NI (Natural Interaction) applications. This middle component makes a bridge between the user interface with the hardware, and facilitates the development of the system.

From the components in OpenNI, we can directly obtain the coordinates of the joints (except for the fingers), i.e., the skeleton of the user. Therefore, we do not need any statistical classifier. We can calculate the angle of each joint in real-time, and then the motion pattern is defined with relative angles between joints.

4. MOTION TRACKING

Trajectory tracking is an appealing field in robotics, and many tracking techniques have been proposed [18,19]. In this paper, the control scheme of the robot arm is PID control. Suppose that the desired position is q_d. During each sampling interval, the computer obtains the current positions q_c by position measurement. The position error can be obtained as:

$$e_k=q_d-q_c, \quad (4)$$

where e_k denotes the error array of the kth sample and q_d, q_c, e_k are all 6-dimensional vectors that correspond with the six joints of the two arms. The position error can be transferred to the corresponding voltage for the motor driver as follows

$$v=K_1e_k+K_2e_{k-1}+K_3e_{k-2}, \quad (5)$$

where v is the output 6-dimensional velocity vector, e_{k-1} and e_{k-2} denote the error array of $(k-1)th$ and $(k-2)th$ sampling, K_1, K_2 and K_3 are diagonal positive.

5. EXPERIMENTS

5.1. sEMG signals collection

Six-channel sEMG signals are collected from six locations on the forearm, as shown in Table 1. The signals are band-pass filtered (10-500 Hz) and notch filtered (50 Hz), sampled at 1 kHz. The data collected is used to present 7 states, as shown in Table 2. Before collection, the skin of the upper limb is cleaned with 70% alcohol swab to remove any oil or dust from the skin surface. Each contraction is held for 7s with 3-5s rest between adjacent contractions. This suite of seven contractions are repeated 42 times totally. The data collection is implemented on two days, and then be mixed and divided into two groups for training and testing. First, the original data needs to be segmented. A segment is a sequence of data limited in a time slot, which is used to estimate signal features. Real-time constraints enforce a time delay of less than 300 ms between the onset of muscle contraction made by a participant, and a corresponding motion in the controlled device [20]. We obtain 420 samples (i.e., feature vectors) for training each class, and the same amount for validation.

5.2. Recognition of sEMG signals

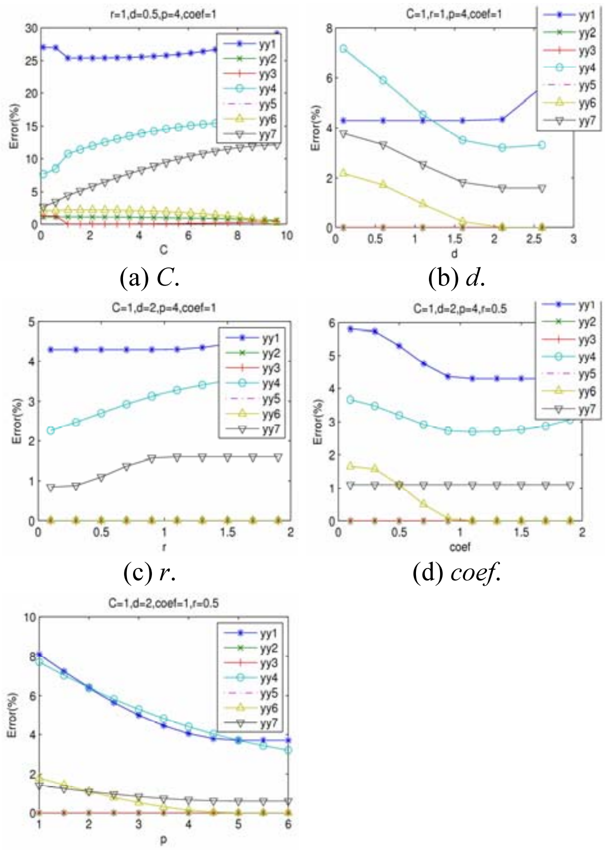
In order to find the best parameters of the polynomial kernel of the SVM and the order of the AR model, the parameters (C, d, r, $coef$, p) are changed one by one and the local optimal values of all the parameters will be picked with the best performance. The changing process and range of the parameters are showed in Fig. 3. From comparing those figures above, the picked parameters and the classification accuracy on validation data are showed in Table 3.

Table 1. The position of each channel.

Channel 1	Flexor Carpi Radials
Channel 2	Extensor Carpi Radial
Channel 3	Round Pronator muscle
Channel 4	Extensor Carpi Ulnaris
Channel 5	Long abductor muscle of thumb
Channel 6	Superficial flexor tendon

Table 2. The motion state.

State 1	Rest
State 2	Wrist Flexion
State 3	Wrist Extension
State 4	Forearm Pronation
State 5	Forearm Supination
State 6	Fist
State 7	Hands Open



(a) *C*. (b) *d*.

(c) *r*. (d) *coef*.

(e) *p*.

Fig. 3. The parameters chosen.

Table 3. The chosen parameters and results.

Parameters	$C = 1$, $d = 2$, $r = 0.5$ $coef = 1$, $p = 4$
States	Recognition Accuracy(%)
State 1	96.3
State 2	100
State 3	100
State 4	96.3
State 5	98.9
State 6	100
State 7	99.4

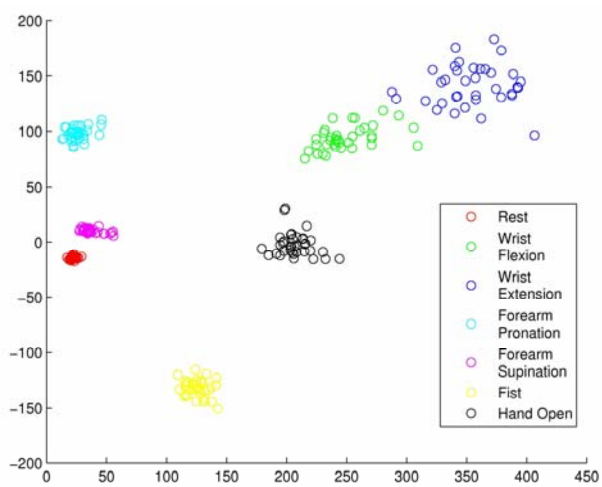


Fig. 4. Feature vectors of reduced dimensions.

The multifeatures (MAV + WL + $AR4$) produce a 36-dimensional feature vector. In order to verify the effectiveness of the selected features set, principle component analysis (PCA) is applied to reduce the dimension of the original feature vectors from 36 to 2, and which can be plotted on a plane. 50 feature vectors in each class, the results are shown in Fig. 4. Analyzed from the figure, the seven classes are easily distinguished by the feature set.

5.3. Data fusion

In the experiment, we need to control the robot using the information from Kinect and sEMG device. Based on the intuition of arm motion and limits in degree of freedom in manipulator, the chosen motion is the rest, the pronation and supination of the forearm, as well as the arm lifting. Different motion can be recognized by different sensors. The first three kinds of actions are recognized from sEMG signals collected by the sEMG sensor, and the third one will be recognized from the joints coordinates obtained from the Kinect. Therefore, the sEMG signals collected from the forearm are fed into the sEMG-motion recognizer, where feature vectors are first extracted, and then SVM would classify it to the most possible motion type. As for the Kinect, the data fed into the corresponding motion recognizer is the coordinates of elbow joint with Kinect being the origin point.

The recognition scheme of sEMG-motion recognition is as follows. When the system detects and recognizes the rest state, the manipulator would go back to its origin location, and when the pronation or the supination is detected and recognized, the manipulator would pronate or supinate to a fixed location. The recognition results are continuously generated with analyzing each segment of the data stream, and the current result would be recorded. If the current recognition result is the same with the last one, motion will not be triggered, otherwise the new state would be recorded, and the corresponding event would be triggered.

For the Kinect sensor, the scheme is almost similar. We can obtain the displacement between the elbow and the shoulder from their coordinates. When the displacement is nearly zero, it is recognized as the natural droop of the arm. The recognition of the lift motion is recognized as follows. We need to detect the state of the natural droop as the initialization of recognition firstly. Then when the displacement reaches a set threshold in a limited time, which can be adjusted by the motion speed of the user, the lift event is triggered. The detection system would be initialized again when the detection period is over or the motion has been recognized.

5.4. Control results and analysis

The control experiment is shown in Fig. 5. Fig. 6 illustrates the interface of the ourselves-developed software. On top left of the software, the real-time waveform collected from the sEMG device is displayed, and the results of the recognition are showed below. The

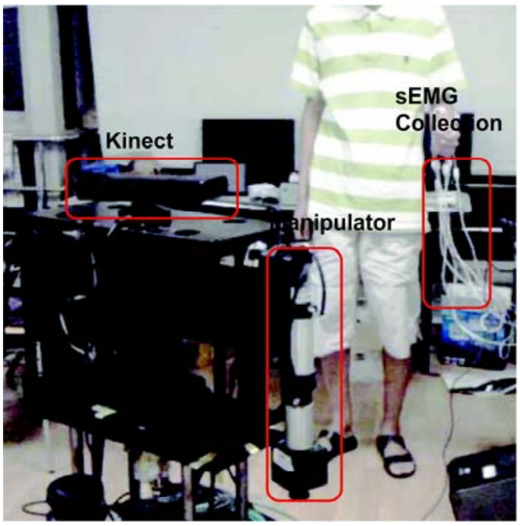


Fig. 5. The experimental environment.

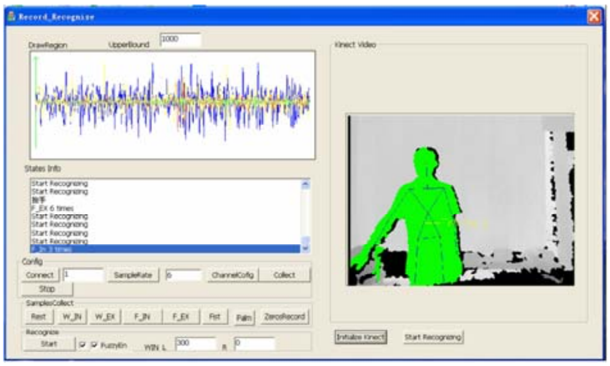


Fig. 6. The interface of the software.

participant was facing the kinect, using his left arm to control the robot arm. The whole scene in front of the kinect (Fig. 5) is fed into it, and then the user's body and the coordinates of every joints would be detected automatically by OpenNI. In order to provide a clear feedback to the participant, the body part is indicated in green color and the joints are depicted in lines on the green body.

The real-time states of the robot's elbow and shoulder joint are recorded, as shown in Figs. 7 and 8, respectively. Analyzed from the figures, there are some states that do not last enough time, and even not reach the set degree, resulting in a peek in the figure. It's due to that the user's joint goes back to the rest state quickly after doing some other motion, and the manipulator performs a real-time motion tracking. In Fig. 8, because the lift motion must conquer the gravity of the machinery, the speed switching from droop to lift is much slower than the adverse switch. The time spent in Table 4 also illustrates such a phenomenon, while the time spent by the pronation and supination is almost the same. Through this, we conclude that although that the recognition delay of sEMG-based control scheme between the onset of the manipulator and the user's motion state is 300ms, yet because of the physical property of the mechanical device, the delay is amplified. In this experiment, because the two components are independent, the system

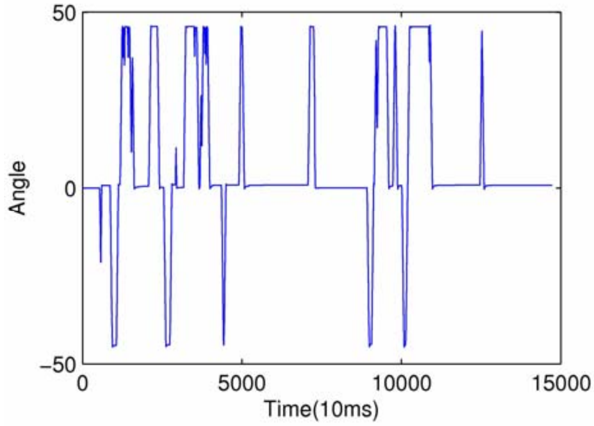


Fig. 7. The pronation and supination of the robot's forearm.

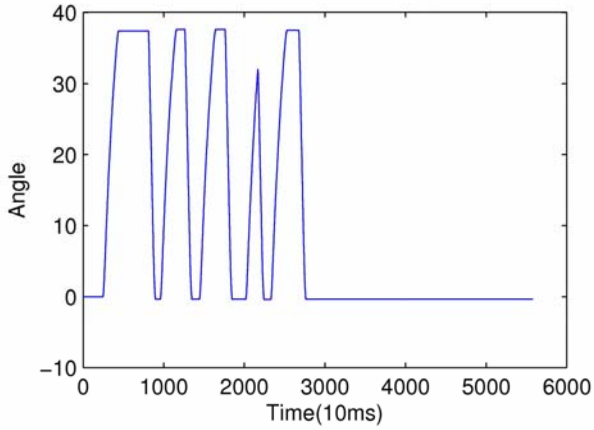


Fig. 8. The lift of the robot's arm.

Table 4. The time spent by the motion.

Motion	Time(ms)
From rest to pronation	710
From pronation to rest	810
From rest to supination	640
From supination to rest	790
From rest to lift	2050
From lift to rest	1000

can response the movement of the elbow and shoulder simultaneously, which can been seen from the start part in Figs. 7 and 8.

6. CONCLUSIONS

In this paper, we have merged the kinect with the sEMG-based recognition to control the robot's arm in real-time. Kinect provides a powerful human-machine interface, making people free of hand-held devices using computer vision technique. However due to its limits, motion like pronation and supination of forearm, which do not cause depth change in vision, cannot be detected by kinect. By combining the sEMG-based control, we utilized an SVM classifier to analyze the difference between seven motion patterns, and analyzed the effects of feature set of sEMG and the parameters of SVM kernel. The sEMG-based control compensated the shortage of the kinect. The experimental results show the effectiveness of our proposed approach.

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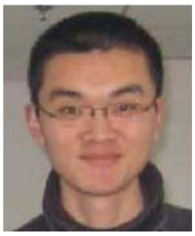

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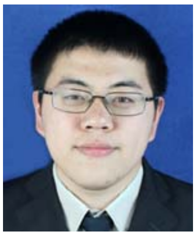

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