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Controlling a Virtual Forehand Prosthesis Using an Adaptive and Affective Human-Machine Interface

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Abstract— **This paper presents the design of an adaptable Human-Machine Interface (HMI) for controlling virtual forearm prosthesis. Direct physical performance measures (obtained score and completion time) for the requested tasks were calculated. Furthermore, bioelectric signals from the forehead were recorded using one pair of electrodes placed on the frontal region of the subject head to extract the mental (affective) measures while performing the tasks. By employing the proposed algorithm and above measures, the proposed HMI can adapt itself to the subject's mental states, thus improving the usability of the interface. The quantitative results from 15 subjects show that the proposed HMI achieved better physical performance measures in comparison to a conventional non-adaptive myoelectric controller ($p < 0.001$).**

Key words: Affective measure, Human-Machine Interface, Virtual Reality

I. INTRODUCTION

a) Background

In the myoelectric prosthesis literatures, the *real-time/on-line* terms are commonly used to reflect how fast the control system can generate proper outputs after receiving the input signal(s)–response time. However, despite a short delay in response time, without having the capability of being updated over time, the control system will be faced with exponentially rising error over long-run operation, and its performance will degrade [1]. Nishikawa [2] performed a study regarding on-line motion classifiers using an Electromyogram (EMG) for motor skill evaluation. It was shown that the proposed method can cope with gradual changes in a myoelectric signal. However, because of the limited resources to perform large computational tasks, updating in real-time was impossible to accomplish for drastic changes in the EMG.

Kato et al. [3] controlled an EMG prosthetic hand by employing an adaptable neural network, which can manage data learning by examining the mapping to a training set of data in real-time. Fukuda et al. [4] used the EMG entropy level as a measure of the classifier input-output pairs' validity. They stated that if the developed EMG entropy was lower than a predefined threshold, then the reliability of the classified patterns could be high. Thus, the input-output pairs could be added to the neural network's on-line training set, while the oldest pairs were deleted from it.

b) Virtual Reality as Training Medium

Using a myoelectric prosthesis requires great mental effort and attention from a user, especially in an initial training phase. Thus, the interface of the prosthesis should have simplicity and interactivity. It should also motivate and encourage the user of the prosthesis to continue the training process and facilitate a positive transfer of learning to other contexts. According to recent studies [5], *Virtual Reality Environment* (VRE) technology provides adaptable and rich media to create environments for the assessment and training of motor deficits.

c) The Study Goal

Affection related emotion recognition is an important step in designing advanced human machine interfaces (HMI). Therefore, using bioelectric signals to detect emotions has recently gained the much attention in the field of human-machine interface. Since emotion can affect the performance of individual subjects, an intelligent HMI should be able to estimate or predict their emotional states as the higher-level context for improving service quality [6]. To solve the mentioned shortcomings in the real-time adaptation (cognitive interaction) of a myoelectric prosthesis' interface, we hypothesized that using the subject's emotional indices (affective measures) for updating the scheme of a prosthesis controller within an interactive medium could enhance the interface and consequentially improve the user's performance. Thus, we have designed and implemented a *collaborative and affective human-machine interface* (*a*HMI) and updated the interface control scheme using the user's mental states. Here, the manipulating commands for controlling a virtual forearm were extracted from Biceps and Triceps activities of a subject. By using a pair of electrodes placed on the frontal region of the subject's head, the relative bioelectric signals were recorded to explore the subject's affective measures.

Hence in this study, we would like to clarify the relationship among the mental workload, task demands, and performance. We hypothesize that the system's context awareness and interactivity will increase by employing the affective cues of a subject.

II. MATERIALS AND METHODS

a).Data Collection System

In this research, a Biopac system (*MP100* model and *ack100w* software version) [7] was used to acquire bioelectric-signals and was connected to a PC (1.73 GHz, 2 G Byte RAM) for further processing. Values of 1000 Hz and 5000 were selected as the sampling frequency and amplifier gain, respectively. A value of 0.1 Hz was chosen as the low cutoff frequency of the filter to avoid motion artifacts, and a narrow band-stop filter (48 Hz–52 Hz) was also used to eliminate the line noise. Fifteen volunteers, aged between 19 and 30, participated in this study to validate the experimental procedure and the robustness of our proposed method. All of the subjects were given necessary informed consents for their participation. The ethical guidelines approved by the school ethical board were strictly followed during the conduct of this study.

b).Electrode Placement

Three pairs of pre-gelled Ag/AgCl electrodes were placed on the subject's upper arm muscles (channels 1 and 2) and frontal region of the subject's head (channel 3 which is near Fp1 and Fp2) in a differential configuration to obtain the highest signal amplitude:

- *Channel 3:* based on [8], one pair of electrodes was placed on the subject's forehead region, close to the *Fp1* and *Fp2* regions in the international 10-20 electrode placement system for EEG recording. This channel is responsible for extracting the affective measures and cues based on the ACE scheme.
- *Channels 1 and 2:* The subject's *Biceps* and *Triceps* muscles were responsible for generating the movement commands for manipulating the virtual forearm.

c).Off-line Data Collection Protocol

In each recording session, the volunteer was asked to sit on a comfortable chair. For right-handed subjects, their left hands were used in the experiment and vice versa. Then, the prompt forearm and wrist were fixed using an adhesive strap to prevent movements in the elbow and wrist joints. Before each recording session, the volunteer was trained to generate two different isometric myoelectric signals using Biceps and Triceps muscles. Then, the subject was asked to take a rest and try to relax for a period of five minutes. After this period, *the quiescent* bioelectric signals from all three data channels were recorded for a one minute period, while he was still resting.

These quiescent signals were used to determine the *on-set* threshold to distinguish between the *rest* (no-action) and *active* states of the EMG classifier and also determine the baseline for estimating the mental workload. Then, the volunteer was asked to perform one of the mentioned isometric contractions moderately respect to maximum voluntary contraction level for each trial. The recording period in each trial was started 1 second after the beginning of the movement–to eliminate the transient effect of the EMG–and ended right after 2 seconds from the beginning of the recoding.

After a two-second rest, he was asked to repeat the movement again. The above movement-rest task was cycled 10 times. The resting period was chosen empirically to eliminate the fatigue effect during training. For each subject and based on the above protocol, the recording session took about 10 minutes.

d).Data Processing

The acquired raw data from channels 1 and 2 were passed through parallel *Butterworth* digital filter banks with predefined frequency characteristics from 30 Hz to 450 Hz to obtain the desired frequency bandwidth for the EMG. These signals were used to establish the physical interaction between the virtual forearm and the user. Furthermore, a band-pass filter (8 Hz–13 Hz) was employed on the raw data from channel 3 to select the EEG Alpha range.

By considering our real-time approach and referring to some detailed studies, a 256 ms non-overlapped segment length for channels 1 and 2 was chosen for our experiments [8]. Then, the RMS of the bioelectric-signals from channels 1 and 2 were calculated and normalized, and transformed to a non-linear simple feature space using a logarithm transform function within a non-overlapping window of 256 msec.

The acquired data from channel 3 (affective channel) was passed through an 8 Hz–13 Hz band-pass filter to select the EEG Alpha range. The filtered data from channel 3 was divided into non-overlapped 128-msec time slots. Then, the logarithm of energy entropy (H_{LogEn}) (hereafter, entropy or statistical entropy) for each time slot is calculated using the same method as described in [9]:

$$H_{LogEn} = -\sum_{i=0}^{N-1}(log_2(P_i(x)))^2 \qquad (1)$$

where x is the discrete random variable, N is the number of sampled data for x, and $P(x)$ is the probability distribution function of x.

e).The Classifier

According with the study of Mohammad Rezazadeh et al. [8], the input-output subtractive fuzzy clustering method was chosen as our classification approach to obtain a set of initial rules for the fuzzy inference system. Then, an Adaptive Neuro-Fuzzy Inference System (ANFIS) was employed for adjusting the obtained inference system's parameters.

f).Real-time Adaptation Algorithm

In this study, the classifier modifies itself according to the extracted features from channel 3. The HMI monitors the average $H_{LogEn}$of the subject's Alpha range within a predefined period (*TTM: Time to Monitor*) during the experiment. If the average entropy measure is beyond the predefined threshold within the TTM period, then the dimensional complexity and degree of disorder in the subject's Alpha sub-band is low. Thus, it can be concluded that the subject has an affordable mental workload while performing the requested task. Because the reduction of the subject's mental workload and an increase in performance are implied by the HMI, the classifier's performance (outputs) can be considered to be reliable and valid. Then, *algorithm I* is applied to the valid input-output pairs:

```
Algorithm I
// Previous (Last)   Inputs-Outputs Pair from channel 1 and 2; I: Input; O:
Output
ℙ = {IP-OP};
// New (Current) Inputs-Outputs Pair from channels 1 and 2
 ℕ = {IN-ON};
IF the average entropy channel 3 ≤ Entropy Validation Threshold Then
{
  DO       // For Every New Input-Output pair
  {
  IF ((‖INi −IPj‖  ≤ Valid Distance Threshold))AND((ON i= OP j)) THEN
  // Euclidean distance between New and Previous input-output pair
    {
    //Append those OLD Input-Output pairs to ℕ set which meet the above
    criteria
     ℕ = ℕ ⊕ {IP j- Op j};
    // Remove those Input-Output pairs from  ℙ  which meet the above
criteria
      ℙ = ℙ  ⊖ {IP j- Op j};
    }
    END IF
     ℙ  = ℕ;   // SET ℙ  main set which contains valid datum
      //Updating the importance factor for each input − output pair in  ℙ
    //Select Data in ℙ which has importance factor higher than predefined
    //threshold (ℙ active). The training algorithm will be applied to ℙactive to
    //obtain new fuzzy inference system (FIS) based on SFCM+ANFIS
   IF (the new FIS outperforms old FIS for the testing set from  ℙactive),
THEN
      SET new FIS as main FIS of the system
    END IF
END IF
```

Algorithm I decides whether to save the input history by calculating the Euclidian distance between the old and new input data. If the old inputs are within the predefined Euclidean distance from the new inputs and the outputs are the same, then the old data will be appended into new input-output pairs. However, appending old data to new ones may cause data redundancy and requires more storage space. Because the training time for the inference system increases in proportion to the size of the valid data set $\mathbb{P}$, the size of the data should not be too large to cope with real-time constraints. To resolve the data size problem, an *importance* factor is designated to each data in $\mathbb{P}$.

After each TTM, the importance factor is decayed exponentially by using *the forgetting rate* (i.e., the new coming valid data has an importance factor equal to 1, and it is reduced for the next TTM period). The data in $\mathbb{P}$ with a high importance factor is chosen as the active set $\mathbb{P}_{active}$. The SFCM + ANFIS method is then applied to $\mathbb{P}_{active}$ to obtain a new fuzzy inference system (FIS). If the new FIS outperforms the old FIS, it will be substituted for the old FIS. This process will recycle for the next TTM, if the channel 3 entropy level meets the described criteria.

g). Online Experimental Protocol

The experimental design was a within-subjects experiment with an interface control scheme as the factor. Prior to the online experiment, each participant was required to read through prepared training materials. An in-house virtual forearm which its kinematics and dynamics were selected based on *Denavit-Hartenberg* parameterization and Leva's study was used in this research. Each participant was asked to use two different interfaces for controlling the virtual forearm: *Condition 1* and *Condition 2.*

In the Condition 2 interface, the control unit was *not* in the active mode, which means the inference system was not modified and updated according to algorithm I. On the other hand, in the Condition 1, the control unit was in the active mode. In addition, to remove the influence of the learning process as much as possible, the sequence of using the interfaces was counterbalanced and the time interval between the two experiments was set at two weeks.

After initial training of the classifier, the subject was asked to participate in an online 60-min experiment protocol. Meanwhile, the bioelectric signals from all of the data channels were recorded and processed as described in the above sections. The RMS of biceps and triceps activations was passed through the designed controller as a control command for virtual forearm. The 60-min experimental scenario was as follows:

- *Moving the virtual forearm end point to the ball's coordinates.*
- *The ball will be attached to the virtual hand if it stays at the ball's coordinates for 2 seconds.*
- *Moving the virtual forearm accompanied by the ball to the basket's position.*
- *Release the ball by staying at the basket's position for 2 seconds (Fig. 1).*

. Each time the subject performed the above task properly, he gained a positive score and the corresponding completion time was simultaneously recorded. Then, the ball and basket positions were set randomly within the virtual environment for the next trial. The 60-minute experimental period was divided into three 20-minute time slots and each time slot had a different forearm movement speed. The speed levels were set in the following order for a complete 60-min experimental period: normal, slow, and fast.

III. RESULTS AND ANALYSIS

a). Performance Metrics:

Table 1 shows the objective performance metrics (obtained score and completion time) achieved by the healthy subjects under two different experimental conditions: one is with real-time adaptation (Condition 1) and another is without real-time adaptation (Condition 2). It should be noted that the myoelectric controller in Condition 2 was performed as a traditional non-adaptive myoelectric controller did. It is clear that by using the affective measures feedbacks to update the inference system, the subjects achieved higher scores in Condition 1 (p<.001). In addition, the score and completion time were highly correlated with each other (r = -0.93, p < 0.001), because the score increased in a case where the subject could complete more tasks at a shorter time.

b). Physical Workload and Muscular Fatigue:

Furthermore, the obtained score and completion time depended on the degree of muscular fatigue imposed by the interface.

Fig. 1 A subject during task performance (left) ;Snapshot of virtual forearm (right) within virtual environment.

Table 1 Objective performance metrics achieved by the healthy subjects under the ACE-on and ACE-off states

Experimental Metric For Healthy Subjects	Experimental Time Slot		
	Normal Speed	Slow Speed	Fast Speed
Score			
- **Condition 1**	113 ± 5	78 ± 7	92 ± 5
- **Condition 2**	102 ± 5	63 ± 6	78 ± 6
- ***p*-value**	<.001	<.001	<.001
Completion Time in ms			
- **Condition 1**	13 ± 3	31 ± 4	19 ± 3
- **Condition 2**	18 ± 5	35 ± 6	22 ± 3
- ***p*-value**	<.001	<.001	<.001
Slope of Biceps EMG Entropy			
- **Condition 1**	-.19 ± .04	-.23 ± .04	-.21 ± .04
- **Condition 2**	-.24 ± .06	-.27 ± .03	-.22 ± .02
- ***p*-value**	<.001	<.01	<.01
Slope of Triceps EMG			
Entropy	-.14 ± .03	-.17 ± .03	-17 ± .03
- **Condition 1**	-.16 ± .04	-.19 ± .03	-.18.02
- **Condition 2**	<.001	<.05	<.05
- ***p*-value**			
Slope of Alpha band Entropy			
- **Condition 1**	.03 ± .01	.04 ± .02	.04 ± .02
- **Condition 2**	.07 ± .04	.22 ± .03	.19 ± .02
- ***p*-value**	<.001	<.001	<.001

In a fatigued muscle, the fibers fire in a more synchronized way to compensate for the loss of muscle strength and exert the force adequate to handle the task. Therefore, the entropy in the fatigued muscle decreases. Table 1 shows that the slope of EMG entropy reduction in Biceps and Triceps muscles is about 15% (average of all time slots) lower in the Condition 1 in comparison with the Condition 2. This means that by using the affective feedbacks, the degree of muscular fatigue will be reduced. The slopes of the Biceps and Triceps entropies are also negatively correlated with the obtained score (r = -0.91 for Biceps and r = -0.82 for Triceps).

The average decreasing rate of EMG entropy in channels 1 and 2 shows that these metrics are lower in the normal speed level compared to the other levels. In addition, more muscular fatigue occurs during the transition from the normal speed level to the slow and fast speed levels. It should be noted that these results can also be achieved by monitoring EMG amplitude or middle frequency.

c). Mental Workload:

Table 1 shows that by using the affective feedbacks and real-time adaptation algorithm, the slope of the EEG Alpha range entropy remained in the same range. However, in Condition 2, this slope increased as the level of difficulty increased. The Alpha range entropy reduction (or retention) means the subject's brain worked in a more organized and less complex way (see Section 1.3). In addition, the Alpha band entropy is negatively correlated with the obtained score during the experiment (r = -0.83, $p < 0.05$).

IV. CONCLUSION

In this study, we proposed a real-time adaptable human machine interface (HMI) for controlling a virtual forearm based on the affective states of a user. The proposed HMI attempts to adapt itself to its user's affective status while the user is trying to undertake the experiment. It is clear that, beside physical fatigue, as long as the Alpha entropy increasing rate is less than a predefined threshold (entropy *validation threshold)*, it can be used as an indication of the normal mental workload during the task operation and the reliability of the classifier's outputs. Furthermore, despite the increasing slope of the EMG entropy during the experiment, the slope of the Alpha range entropy remained the same as Condition 1. However, this phenomenon did not occur when the affective control scheme had the inactive status. In this case, the slope of the Alpha band increased simultaneously with muscular fatigue. We can conclude that by using the affective control scheme, the degree of mental demand remains on the same scale. In other words, the interface does not cause the subject a mental overload when the affective control scheme is employed. It is a mixed initiative adaptation by which the control unit collaborates with the user. Thus, the usability of the proposed HMI will be enhanced compared to conventional HMIs, which will increase the usability and performance of the interface

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