A novel virtual reality rehabilitation system for upper-extremity amputee by fusion analysis of sEMG and depth image data

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Abstract. Upper-limb myoelectric prosthesis is commonly-used to improve the life quality of upper-extremity amputees. Before the use of this prosthesis, the rehabilitation training program under virtual reality environment can help the amputees to enhance the muscle strength of the residual arm and get used to the prosthesis earlier. Nevertheless, the current programs often focused on the training of hand motion instead of both the hand motion and arm motion. Thus, this study proposed a novel virtual reality rehabilitation system for upper-extremity amputee by fusion analysis of the surface electromyography (sEMG) and depth image data. Firstly, based on four time-domain features extracted from eight-channel sEMG signals, we applied support vector machine (SVM) algorithm to recognize the hand motion classes (hand-open or hand-close). Secondly, based on color and depth images, the arm motion could be recognized and tracked by using image processing algorithm. Finally, by fusion analysis of the recognition results, we designed two kinds of rehabilitation programs. It preliminarily showed good performance results on recognition of participant's (able-bodied subject's and amputee's) hand motion and arm motion. This rehabilitation system will help to improve the efficiency of upper-limb myoelectric prosthesis.

Keywords: Human Interface, Medical Electrophysiologic Signal Processing, Image Processing, Virtual Reality, Upper-Extremity Amputee

1. INTRODUCTION

Amputation is a serious problem happened all around the world. The prevalence of amputations was 1.6 million in 2005, with projections that the prevalence may double by the year 2050 [1]. In the existence of 350,000 persons with amputations in USA, 30% is upper-extremity amputee [1]. The transradial amputations make up the majority of upper-extremity amputations. In order to improve the amputee's life quality, upper-limb prosthesis is often applied. Nevertheless, many people reject or abandon the prosthesis. One important reason is that they feel uncomfortable and unaccustomed to the prosthesis [2, 3]. Therefore, the rehabilitation training before the use of prosthesis is very crucial, due to its enhancement of strength of residual arm muscles.

Rehabilitation training system under virtual reality environment is common-used on disease recovery (i.e., recovery of stroke, cerebral palsy, and phantom limb pain) [4-6]. For amputation rehabilitation, the virtual reality system was often used when the amputee prepared to use the myoelectric prosthesis [7, 8]. The surface electromyography (sEMG) from amputee's residual arm muscles were collected and analyzed to control the virtual prosthesis in the virtual reality environment. This system could help the amputees to get used to the myoelectric prosthesis before they wore the real prosthesis. However, they often focused on the control of virtual hand motion instead of both the hand motion and arm motion. In the real world, it is necessary to move the prosthesis anywhere with any gesture. Thus, it is significant to record the movement data of not only hand motion but also arm motion.

The data of arm motion could be obtained through a lot of manners. The depth camera is a tool to obtain the 2D and 3D spatial information of the object, by capturing the color image and depth image [9, 10]. It is popularly applied in virtual reality and augmented reality. Therefore, in this study, we aimed to design a novel virtual reality rehabilitation system for upper-extremity amputee by fusion analysis of the sEMG and depth image data.

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2. MATERIALS AND METHODS

2.1. Subjects

Three able-bodied male subjects and one unilateral transradial male amputee were recruited in this study. The able-bodied subject's hand was hidden by using a glove, in order to mimic the residual arm. Each subject signed the written informed consent before the experiment, while the procedures for this study were approved by the Institutional Ethics Committee and conformed to the Declaration of Helsinki.

2.2. System Components

A commercial wireless biological signal acquisition system (Myo, Thalmic Labs, Canada) with 8 bipolar EMG electrodes was used to acquire sEMG data (sampling rate: 200 Hz). For both able-bodied subject and amputee, all 8 electrodes were placed on the proximal forearm as shown in Fig. 1a.

A depth camera (RealSense D435i, Intel Corp., USA), which can simultaneously record the color and depth images, was applied in this study. It was placed in front of the subjects on the surface of a desk (Fig. 1b).

Both the Myo system and the RealSense system have developed SDK for accessing the data. We used visual C++ and OpenCV tool to load these SDKs. A virtual training interface was developed to acquire EMG and image data, by using the SDKs.

Fig. 1 System for sEMG and image recording. (a) sEMG system. (b) Depth camera and virtual training interface.

2.3. Fusion Analysis of sEMG and Image Data

In this study, the virtual training system for amputees consisted of two parts (Fig. 2).

One part was the control of the virtual hand while the other was the control of the virtual arm. These two parts were respectively based on the sEMG data and image data. Through the fusion analysis of recognition outcomes from the sEMG and image data, the amputees could control the virtual upper-extremity to do the training program such as object grasp.

For control of virtual hand, four temporal features were extracted from the SEMG signals of forearm muscles in order to recognize the motion classes. These sEMG features were mean absolute value (MAV), number of zeros crossings (ZC), number of slope sign changes (SSC), and waveform length (WL). The definition of feature was displayed as following:

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

$$WL = \sum_{i=1}^{N-1}|x_{i+1} - x_i| \tag{2}$$

$$ZC = \sum_{i=1}^{N-1}[\operatorname{sgn}(x_i \times x_{i+1}) \cap |x_i - x_{i+1}| \geq threshold]$$

$$\operatorname{sgn}(x) = \begin{cases} 1, & if\ \ x \geq threshold \\ 0, & others \end{cases} \tag{3}$$

$$SSC = \sum_{i=2}^{N-1}\{f[(x_i - x_{i-1}) \times (x_i - x_{i+1})]\}$$

$$f(x) = \begin{cases} 1, & if\ \ x \geq threshold \\ 0, & others \end{cases} \tag{4}$$

Where x_i is the i th sample in a segment and N is the number of samples in a segment.

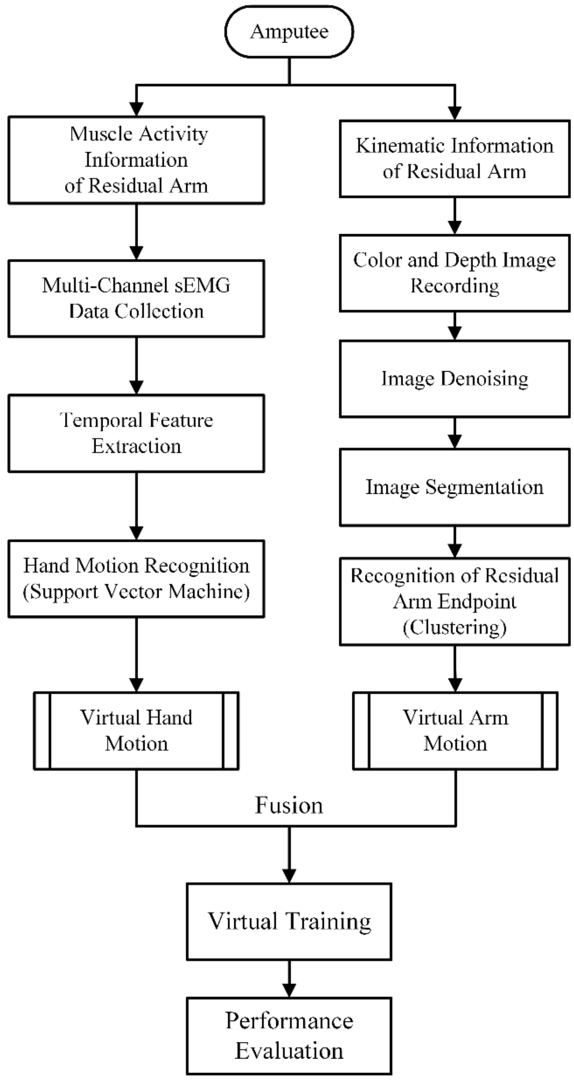

Fig. 2 Flow chart of virtual reality rehabilitation program.

Then by applying support vector machine (SVM) algorithm to analyze the sEMG feature data, two functional motion classes (hand-close and hand-open) were classified and recognized so as to grasp or drop down the target object.

For control of virtual arm, the color and depth images were processed to recognize the location and orientation information of the residual arm. The detailed processing steps were image preprocessing, image segmentation, object thinning, and recognition of residual arm endpoint. Firstly, the background objects in the color image were subtracted by using the depth information from depth image. Then, in order to segment the area of human skin, we decomposed the RGB image into YCbCr planes and set the thresholds for Cr and Cb to extract the skin area. The threshold range of Cr was between 133 and 173, while the threshold range of Cb was between 77 and 127. This processed RGB image can clearly showed skin area. After grey processing and binary processing, the skin area displayed as white color when other area was black color. In this binary image, the edge of the residual arm was picked up by using mathematics morphological methods such as dilation and erosion. Through Zhang-Suen thinning algorithm [11] and clustering algorithm, the skeleton of the residual arm and the endpoints of this arm skeleton could be obtained. By combining the depth image and color image, we could attain the coordinate of the distal end of the residual arm. Finally, by projecting the coordinate of the distal end of the residual arm in the image to the coordinate of the virtual arm in the virtual reality space, the virtual arm can be controlled to move to the target position.

2.4. Experimental Design and Performance Evaluation

The common-used training program for amputees to use the prostheses is to ask them to practice moving the prostheses to grasp and move target object anywhere. It required to recognize at least the hand-open and hand-close intention classes. Because the position of arm was a factor that influence the recognition result of sEMG signal from arm muscles, we decided to design two different programs to recognize the classes of virtual hand motion from sEMG data. Firstly, we set three positions (A, B, C) in the screen as the target positions for participant to move the virtual object. Then, in the first program for hand motion classification (Fig. 3), the sEMG data of two motion classes (hand-close and hand-open) at position A was collected as the training data to calculate the SVM classifier. The sEMG data at all three positions was used to evaluate this classifier. In the second program (Fig. 4), sEMG data of six classes (hand-close at position A, hand-open at position A, hand-close at position B, hand-open at position B, hand-close at position C, hand-open at position C) was collected as the training data, while the same type of data was recollected as the testing data.

In this study, we asked the participants to attend a grasp-move training program. They grasped and moved a virtual object, which randomly appeared 60 times anywhere in the screen, to the target position (A, B, or C). A virtual hand appeared at the end of the residual arm in the screen and moved as the arm moved. The total time to finish the whole grasp-move program was recorded to evaluate the training performance. Meanwhile, the classification accuracy for hand motion was also calculated.

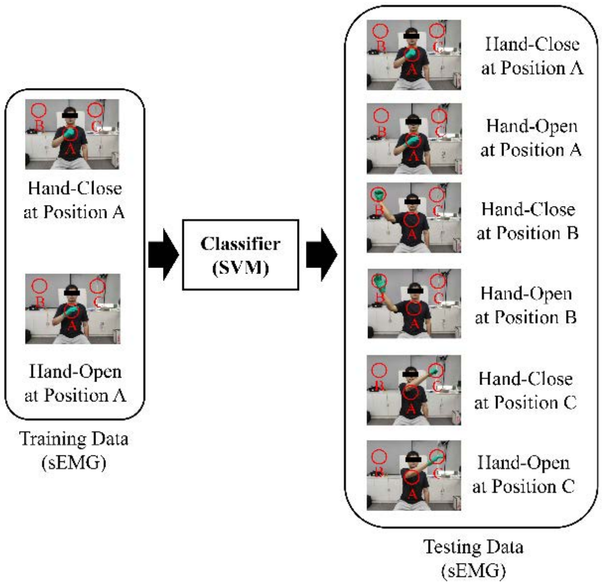

Fig. 3 Data collection and analysis procedure in the first training program.

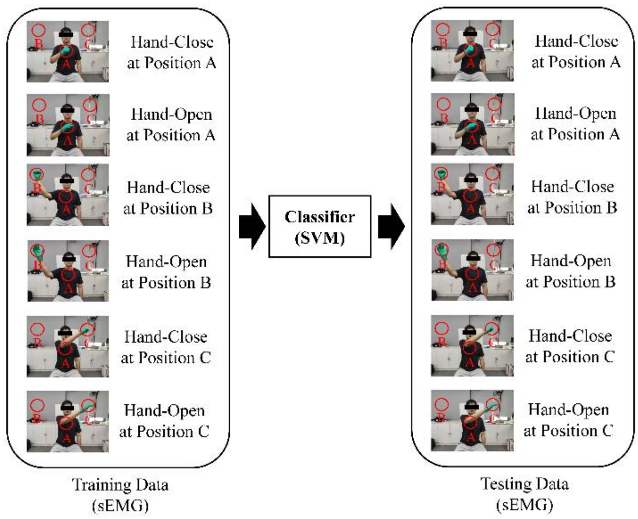

Fig. 4 Data collection and analysis procedure in the second training program.

3. RESULTS AND DISCUSSION

An interface (Fig. 5) was constructed to realize the training program for participant. The edge of the residual arm could be recognized precisely by using the depth camera. When the virtual object was grasped and moved into the target position, the number displayed in that position increased.

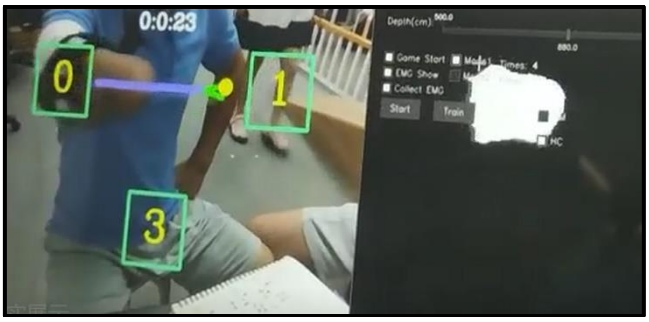

Fig. 5 Interface of virtual reality rehabilitation system.

Table. 1 Evaluation results of the first training program.

Subject	Classification Accuracy (%)	Program Finish Time (seconds)
Able-bodied subject 1	97.05	34.3
Able-bodied subject 2	100.00	37.0
Able-bodied subject 3	100.00	31.7
Amputee 1	97.05	39.0

Table. 2 Evaluation results of the second training program.

Subject	Classification Accuracy of six classes (%)	Classification Accuracy of two classes (%)	Program Finish Time of two classes (seconds)
Able-bodied subject 1	92.00	93.67	51.0
Able-bodied subject 2	82.00	92.67	60.6
Able-bodied subject 3	95.67	99.67	40.3
Amputee 1	79.66	87.33	59.3

The training performance based on the first program for hand motion classification was shown in the Table 1, while that based on the second program was shown in the Table 2. The results showed that each participant's classification accuracy in the first program was higher than that in the second program, while the program finish time in the first program was shorter than that in the second program. Especially, in the second program, the classification accuracy was higher when the classes of the testing data were two (hand-close and hand-open). Meanwhile, although the performance of the amputee was worse than that of the majority of able-bodied subjects, this amputee could finish the whole grasp-move program better if he was trained more times.

4. CONCLUSION

This study proposed a novel virtual-reality rehabilitation training system for transradial amputee by fusion analysis of sEMG data and depth image data from residual forearm. It preliminarily displayed good performance results on recognition of participant's (able-bodied subject's and amputee's) hand motion and arm motion. This rehabilitation system will help to improve the efficiency of upper-limb myoelectric prosthesis.

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