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sEMG based Real-Time Motion Classification using Virtual Reality and Artificial Neural Networks

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Abstract

The work presented in this paper addresses the enhancement of upper body rehabilitation and training methods for stroke victims and upper body amputees. One of the primary aims is to develop a tool that utilizes augmented reality to facilitate the rehabilitation of impaired human hand and forearm movements by employing mirror neurons and virtual reality. The second objective of the proposed tool is to allow for evaluation and specification of prostheses prior to acquisition and fitting of such devices to upper limb amputees. The proposed system involves the development of real–time surface Electromyography (sEMG) signal classification methods, Artificial Neural Network training, and implementation and the development of identification algorithms for inferring motion intend. The results of the proposed approach indicate preferences of specific classifiers used in the processing of sEMG data. The proposed methods are implemented in a virtual reality environment allowing for potential selection and training of prosthetic device usage as well as for physical therapy rehabilitation sessions of stroke victims.

Keywords: Artificial neural network, motion identification, rehabilitation, prosthesis hand, real – time model, surface electromyography classification, virtual reality

1. Introduction

Recent advances in rehabilitation robotics propose that their natural control can be performed in real life. These naturally controlled robotic prostheses can become a reality in everyday life. In 2015, Atzori et al., [1] presented an overview of the advancements, both in commercial and scientific domains, to outline the current and future changes in this field. In

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particular, it is worth pointing out that for upper limb amputees, prosthesis control training is suggested to be conducted before and after fitting of the prosthetic device. For functional monitoring, there are many different tests available. However, none can be used in the early phase of training. In 2015, Sturma et al., [2] proposed a tool for pre-evaluation of trainable voluntary muscle–activation skills before prosthetic fitting. The proposed tool supported the planning of rehabilitation procedures for further monitoring where essential considerations for system development and the main features of the developed prototype were presented.

There are also some structured rehabilitation methods for training new prosthetic device usage, which includes imitation, repetition, and reinforcement learning to improve multifunctional prosthetic control. For this purpose, in 2015, Roche et al., [3] suggested a structured training protocol to control a new prosthetic hand. While considering the repetitive movements for rehabilitation, video game-based therapies can increase patient motivation, effort, and performance. For this purpose, a clinically feasible and entertaining virtual rehabilitation intervention was established and evaluated for short–term improvement of Electromyography (EMG) control engaging gameplay elements [4].

Furthermore, to mitigate upper–limb deficiency for independence and quality of life, surface Electromyography (sEMG) based control systems have been widely researched for several decades [5,6]. However, advanced myoelectric prosthetic hands are limited due to the lack of real–time control performance and weak signal sources from residual muscles. A novel human–machine interface was presented in [7] for prosthesis manipulation that combined the advantages of surface electromyography and Near–Infrared Spectroscopy (NIRS) to conquer the limitations of myoelectric control. Guo et al., [7] evaluated both offline Classification Accuracy (CA) and online performance of the forearm motion recognition system based on three types of sensors: EMG, NIRS, and hybrid EMG – NIRS, where the result shows that combining EMG and NIRS signals give better real–time performance. Considering sEMG signals are extensively studied and applied in clinics and engineering, the major drawback of sEMG based prosthetic control is the poor recognition results due to the presence of noise and crosstalk. Thus, methods of reducing the noise influence are significant in EMG signal analysis research. In 2009, Phinyomark et al., [8] presented a novel feature that can tolerate the contamination with White Gaussian Noise (WGN) without using a noise removal algorithm. As a consequence, the experimental results showed better recognition outcomes in a noisy environment than in other success feature candidates. The robustness in terms of control offered by the referenced methods is still not sufficient for many real–life applications.

Upper extremity impairment is a common outcome after a stroke incident. The research shows that additional movement training can improve motor function even in years following a stroke or spinal cord injury. This leads naturally to the concept of “functional potential.” For stroke patients, the upper extremity motor recovery reaches an apparent plateau in the first year after the initial incident, using clinical and biomechanical measures. There is evidence that the time course of recovery is not fixed, rather than additional practice that can enhance movement ability in both the sub-acute and chronic phases following a stroke [9]. The additional recovery is statistically significant and provides a baseline effect with which to work. However, the effect of additional movement practice is often small, leaving patients short of a full recovery. Given the limitations of recovery for post-stroke patients, it seems necessary to find better tools and methods for retraining stroke patients.

Positron-emission tomography and functional Magnetic Resonance Imaging or functional MRI (fMRI) have indicated a mirror-neuron network (pre-motor cortex, parietal lobe, temporal lobe) that facilitates learning through action imitation and action observation [10,11]. Research over the past decade has been focusing on how the mirror neuron system may benefit the recovery of stroke patients after a stroke has occurred and enhance clinical training protocols [12]. Based on the current state of sEMG research detailed above, the aim of the present work is to develop a real–time Artificial Neural Network (ANN) based system for motion identification, incorporating a visual feedback system that facilitates rehabilitation and training of stroke victims and upper body amputees. The visual feedback system is implemented by the use of a Virtual Reality (VR) environment using commercially available VR technology. Such a system may serve rehabilitation efforts where a patient uses the unaffected side during therapy exercises while seeing the affected side move in the VR environment. Alternatively, the proposed system allows for simulating, adjusting, and practicing an upper body prosthetic device prior to being build or purchased. The simulation incorporates a virtual prosthetic device that integrates the sensing and control of the physical device, and hence allows for modification, adaptation, optimization, and training.

2. Methods

For sEMG signal acquisition circuitry, a bipolar configuration is used in this work. This configuration is utilized in order to acquire sEMG signal using two EMG detecting surfaces with the support of a reference electrode. The two-sEMG surfaces are placed only 1 to 2 cm from each other, and they are connected to a differential amplifier. The differential amplifier reduces the common noise signals to both inputs and amplifies the difference.

For acquiring sEMG signals, a circuit board consisting of three different stages was developed. The first stage feeds the sEMG signal to the non–inverting terminal of an LM324 instrumentation amplifier. It compares two inputs and amplifies the difference by a factor of 100. The second stage consists of a notch filter, which reduces the influence of interference caused by the environment, i.e., 60 Hz components. For this, a UAF42 [13] based circuit is utilized in order to define a notch filter with a corresponding set of resistors. The calculation of the resistor values is given by Equation (1), where ALP represents the gain from the input to the low – pass filter, AHP indicates the gain from the input to the high – pass filter and f_o is the fundamental frequency.

$$f_{notch} = \sqrt{\frac{A_{LP}}{A_{HP}} \cdot \frac{R_{Z2}}{R_{Z1}}} \times f_o \quad (1)$$

R_{Z1} and R_{Z2} are the resistor values which are each 2 KΩ. Consistently, the product of $(\frac{A_{LP}}{A_{HP}} \cdot \frac{R_{Z2}}{R_{Z1}})$ value is one, thus the notch filter frequency is equal to the fundamental frequency. The -3dB drop-off occurs at the cut off frequency of the filter which correlates to the half power level and the attenuation. The -3dB drop-off is estimated as:

$$BW_{-3dB} = \frac{f_{notch}}{Q} \quad (2)$$

Here, Q represents the quality factor which can be adjusted by

$$R_Q = \frac{R}{Q - 1} \quad (3)$$

A Chebyshev type II 0.1dB passband is implemented in the third stage of the analog signal conditioning/acquisition unit. It is an active filter for roll off used to describe the steepness of a transmission function with the frequency. This filter has a unique feature in eliminating the error between the idealized and the actual filter. The Chebyshev type II filter is represented by the stopband ripple which consists of a low-pass and a high-pass filter. The output from the high-pass filter is fed through a 4 Hz low-pass filter. The output magnitude of this low pass filter ranges from $\pm 0.01V\ to \pm 0.09V$. The output voltage from the low-pass filter is the signal conditioned sEMG data. However, a final step to accommodate the specific microcontroller input limitation is required. The utilized microcontroller (an Arduino Mega

2560) is limited to read only positive voltages. Therefore, amplification and shifting of the signal is accomplished by a buffer amplifier in combination with a voltage shift circuit to match the input range of the microcontroller.

The implemented Printed Circuit Board (PCB) design requires $\pm 5V$ of battery supply to power the circuit. As a battery supply provides a Direct Current (DC) signal with little noise compared to an outlet based powered supply (switching circuit), a battery sourced power supply is designed. The power supply circuit diagram and connection are shown in Figure 1. The power supply employed uses three regulators, U3 is a 10V regulator, U1 and U2 are +/-5V regulators. The battery supplies approximately 23V.

The Arduino microcontroller is utilized as a data acquisition system, while the ANN resides with the PC in the form of a Simulink™ code. Usually, Arduino microcontrollers do not have sufficient AVR memory, and because of its lower processor speed, the processing of large data volume and high computational loads are limited. An alternative and economical approach is employed in this work, where the microcontroller is connected to a PC using the serial port. In this fashion, the microcontroller acts as the data acquisition system, and the PC processes the data and computes the control commands. This method allows for sufficient fast processing time in order to create a real-time implementation of the proposed approach.

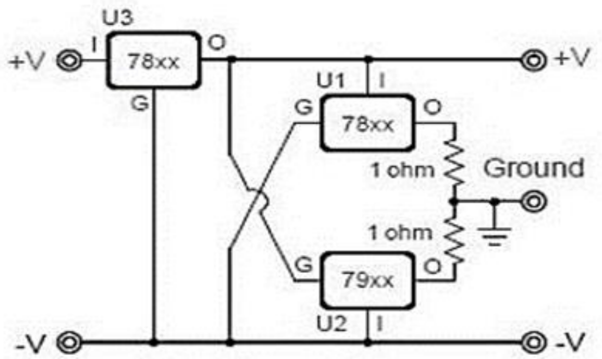

Figure 1. Implementation of a PCB model [14]

An ANN based algorithm is used for both objectives of this work, i.e., controlling a prosthetic device and for real-time hand motion depiction in a VR environment. ANNs are generally capable of capturing and modeling complex dynamical system characteristics based on training data. While training of ANNs data and computational expensive, a trained ANN can execute input data rather fast and hence is well suited for the real-time application proposed in this work. For this purpose, the ANN implementation using Simulink™ models is structured in three parts: 1. Implementation of real–time classification Simulink™ model,

2. Training of the ANN model based on real–time classification, and 3. Development of the identification algorithm for identifying motion intend using real–time ANN models.

Figure 2 represents the real–time classification Simulink™ (MATLAB 2018a) block diagram model. The first part contains the connection for receiving the signal from the microcontroller to the computer running Simulink™ over the serial port. The second part in Figure 2 shows the buffer blocks for the calculation of the overlapping data sequences using a sliding window. The third part in the Simulink™ block diagram represents the different classification algorithms and their final outputs.

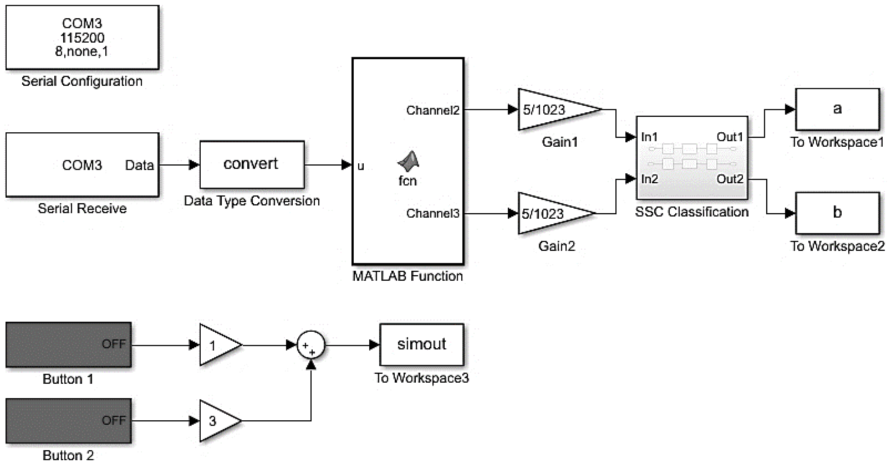

Figure 2. Simulink™ block classification model

Before the classification process is initiated, a delay of 25-time units is generated for constructing a time series with 25 past data points. This generation of a time series is updated at every time step, hence creating an overlapping sliding window process. After creating a time series with a sliding window using buffer blocks for overlapping, the collected sEMG signals are processed for classification purposes. A set number of individual classification methods is chosen based on their performance. The performance is measured by assessing the overall output accuracy in terms of predicted motion intent. Thus, waveform length, zero crossing, slope sign change, and Willison amplitude classifications showed significant output changes due to a slight change in the real – time sEMG signal. Thus, these four classifications are chosen and used to train the Artificial Neural Network for better identification results. These classifications are most popular in sEMG pattern recognition because of their computational simplicity [8]. The mentioned features can be done in real-time and normally used for muscle contraction, muscle activity detection and sometimes are used in EMG pattern recognition.

The Waveform Length (WL) classification is related to the waveform frequency, amplitude, and time. WL is the increasing length of the waveform over a time segment [8]. The Zero Crossing (ZC) represents the number of times when the amplitude value of the sEMG signal crosses the zero y–axis. For sEMG feature extraction, the threshold condition is used to refrain from the background noise or white noise. It provides an approximate estimation of frequency domain properties, [8]. The Slope Sign Change (SSC) is similar to the zero-crossing classifier. SSC is another way to represent the frequency information of the sEMG signal. This method is an indicator of the slope sign change over three consecutive segments. This classification of the sEMG signal has also been used in the previous research [8]. The Willison amplitude (WAMP) accounts for the number of times two consecutive sEMG signal amplitudes exceed some pre-defined threshold value. One of the benefits of using the WAMP is the potential reduction in the effect, noise has [8].

In this research, it is found that if sEMG data is trained for a specified period of time, for continuous different motions without placing any gap between interchanging motions, it can lead the ANN to train the random values. As a result, real – time identification will give random noise signals which are not related to the identifier of the motion executed. Thus, in this work, for training the ANN, the limb motions were randomized and each category of motion was identified by an integer value. The experiments also included random period of time without any motion initiation. This training pattern can help the ANN to become more robust in terms of the many variations of the signals as well as the associated muscle activation and joint movements.

In order to ensure that the resulting input-output data represents a causal system, the initiation of a hand motion is captured by the use of virtual a pushbutton [15]. The chosen values of the artificial pushbuttons are 'one' which is associated with the inner forearm muscle movement and 'three' which is associated with the outer forearm muscle movement values. The value "zero" is associated with the resting position of the forearm.

The implemented sampling time is 0.067 seconds and is bounded by the amount of processing assigned to the microcontroller and by the communication speed between the microcontroller and PC. For the offline training of the ANN, a Levenberg–Marquardt backpropagation algorithm is used [16]. The ANN consists of a feed–forward network comprised of two–layer backpropagation, with 40 neurons in the hidden layer. For the training, the performance ratio is set to 0.007. The learning rate is chosen to be 0.05, the number of epochs is set at 5,000, and the parameter goal is chosen as 1e-15. Training is done for four different individual classifications, such as WL, ZC, SSC, WAMP.

The bounded ANN output data is filtered and fed to a simple Simulink™ fuzzy logic reasoning block in order to generate crisp output values corresponding to the limited choices for motion numbers; for this work, the three different motions labelled are “zero”, “one”, and “three.” This crisp output is used to feed a VR based realization using a Unity3D environment to depict the identified motion on a VR device. The communication with the virtual device is accomplished using UDP protocol connections for observing the virtual reality. The VR implementation is for facilitating therapeutic intervention in rehabilitation situations (where the virtual hand is mirrored with respect to the physical hand that is used for sEMG capturing and motion inference) or for training with a virtual prosthetic device. In the case of rehabilitation, using the mirrored image of the physical forearm and hand motion, the user stimulates the corresponding brain cells associated with the mirrored forearm. Hence, therapeutic measures can be taken where stroke victims use the unaffected body part to train the affected body part; in this case, the hand and forearm. The proposed implementation is accomplished by the use of an immersive VR environment where the subject’s brain receives manipulated visionary signals. Although the subject’s other senses might not send information matching with the visual information, the brain still can get deceived due to the powerful immersing VR environment. The VR system is constructed using an Oculus Rift™, and Leap Motion™ camera to capture the user’s hand motions and gestures with its 3D model in Unity3D software. The Virtual Reality implementation using VR goggles, leap motion camera, motion sensors, and sEMG data acquisition is shown in Figure 3. The Leap Motion™ system can be used for training of the ANN in the absence of the sEMG system.

Figure 3. Virtual reality implementation

Unity3D is a popular and powerful software for creating VR environments. To have the virtual model of the hand, a leap motion camera and its SDK for Unity3D are implemented. While the proposed VR application utilizes the virtual model of Leap Motion for the hand, the angles of the hand are not edited so the user has the natural feeling of moving and relocating his/her hands.

Each ANN output signal corresponds to a predefined motion in Unity3D that represents the intended motion of the subject. Each of these motions is created for the virtual hand by changing the values of the joint angles in the wrist and finger models, as shown in Figure 4. In this figure, the top left shows the virtual model of the hand simulated in Unity by Leap Motion SDK which follows the movements of the real hand and forearm including all the fingers and the wrist. The top right part of Figure 4 illustrates the virtual model (white color) that does not follow the motions of the joints of the hand consisting of fingers and wrist at its initial state, i.e., the resting state associated with integer "0". It is noteworthy that the location of this model, however, follows that of the real hand. The bottom pictures depict the hand at state "3" and "1" from left to right, respectively.

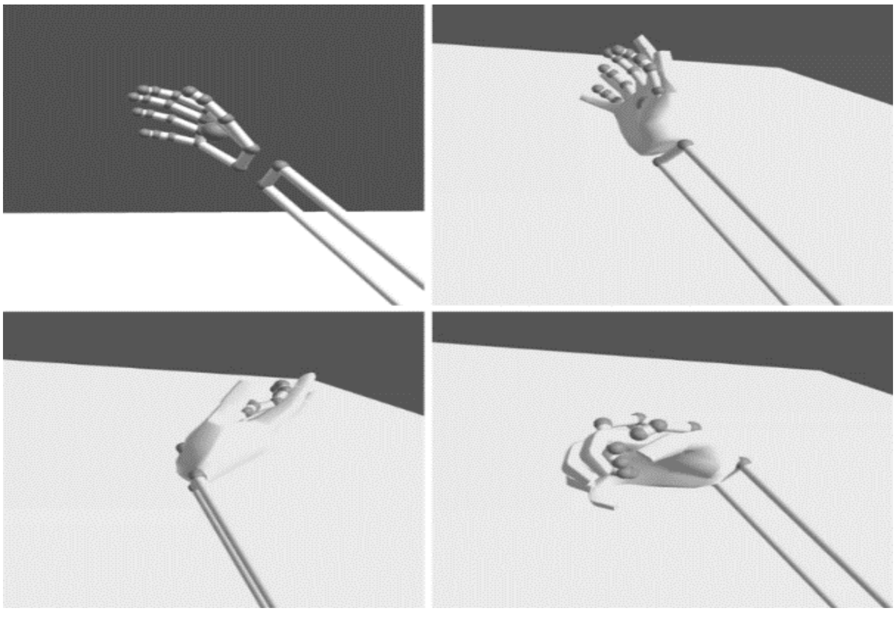

Figure 4. From top left: Virtual model following the real hand motions, virtual model following sEMG signal at state zero, virtual model following sEMG signal at state 3, virtual model following signal at state 1

By this method, as soon as the subject intends to initiate the respective hand/arm motion, the virtual hand does the intended motion in the VR environment where the subject's hand is reflected. One of the uses of this application is the training of stroke victims who have one of their upper limbs affected while the other upper limb is unaffected. With the proposed system, the subject can train the neurons of the affected side by performing hand/arm actions and motion with the unaffected side and seeing the intended motion mirrored in the VR environment. The other application for this proposed system is the facilitation of the training and fitting process of a prosthetic device. The patient can experiment with the functionality of the device, while the prosthetist can evaluate and optimize the control functions as well as the location of sEMG sensors for the prosthetic device prior to the device's construction.

3. Experimental Setup

Figure 5 demonstrates the two hand motions utilized for the proposed real-time implementation of ANN hand motion identification system.

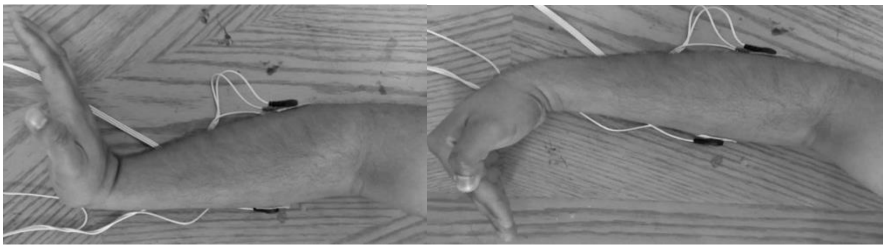

Figure 5. a) Outer forearm muscle movement position, b) inner forearm muscle movement position

Figures 6 and 7 show the output from two sEMG channels for the two different motions. Figure 6 represents the inner forearm muscle movement when the hand is open. Figure 7 represents the outer forearm muscle movement while the hand closes.

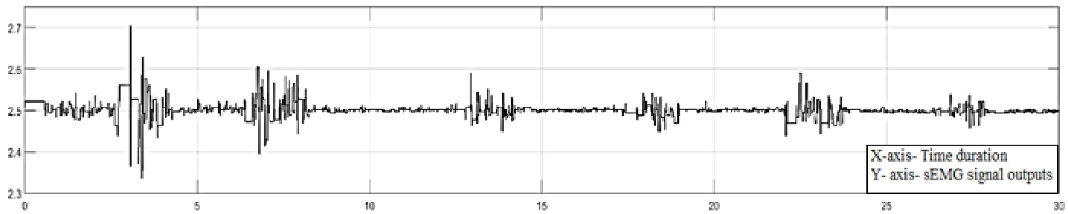

Figure 6. sEMG signal for inner forearm muscle movement

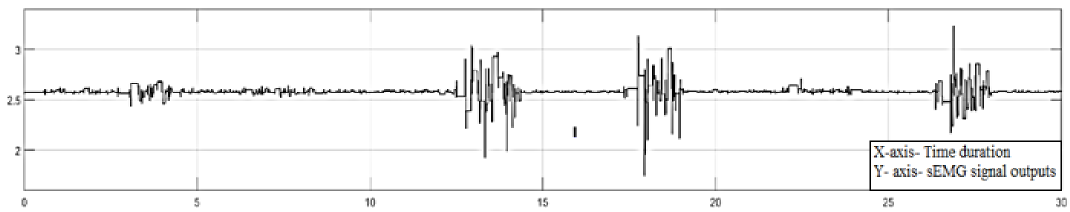

Figure 7. sEMG signal for outer forearm muscle movement

By observing Figures 6 and 7, it is noticeable that the two sEMG signals have opposite pattern. The reason for this is the spatial arrangement of the two sEMG sensors on the corresponding muscle groups. Figure 8 depicts the inner and outer muscle movement corresponding to their target values of “1”, “3” and “0” for the listed sEMG signals shown in Figure 6 and 7.

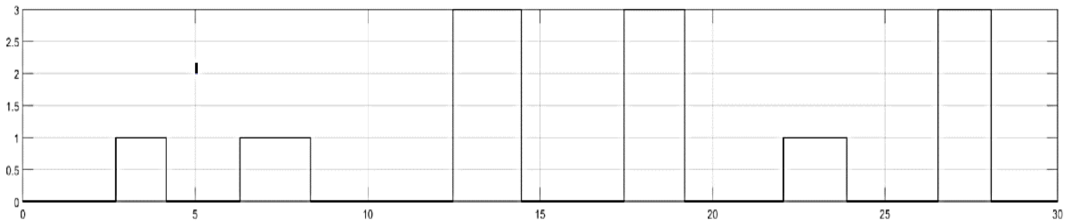

Figure 8. Real-time pushbutton output considered as a target for ANN training and testing

4. Results and Discussion

In this section, the result of the implemented identification algorithm is presented and discussed using a set of human test subjects. Figure 9 depicts a typical training set in terms of trained output values (inner forearm motion-red and outer forearm motion-green) compared to the targeted output data (blue).

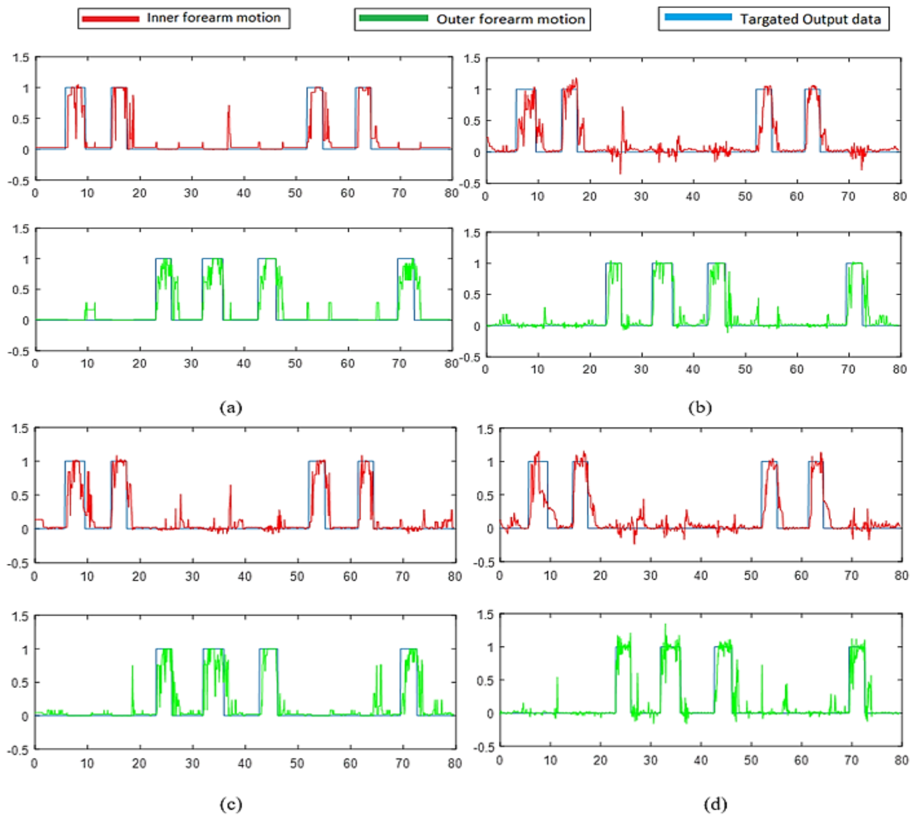

Figure 9. Four different classification (a) SSC, (b) WL, (c) ZC and (d) WAMP trained output graphs

A typical outcome plot for the real-time implementation of the proposed algorithm using the setup is shown in Figure 10, which is based on the SSC classification method. The lower plot corresponds to the ANN –FL output, i.e., the predicted motion in terms of integers, while the upper plot is the actual input, also coded by using the same integer mapping. A small time-delay is noticeable on each motion action. Some errors do occur as well, i.e., during the first one fourth of the experiment.

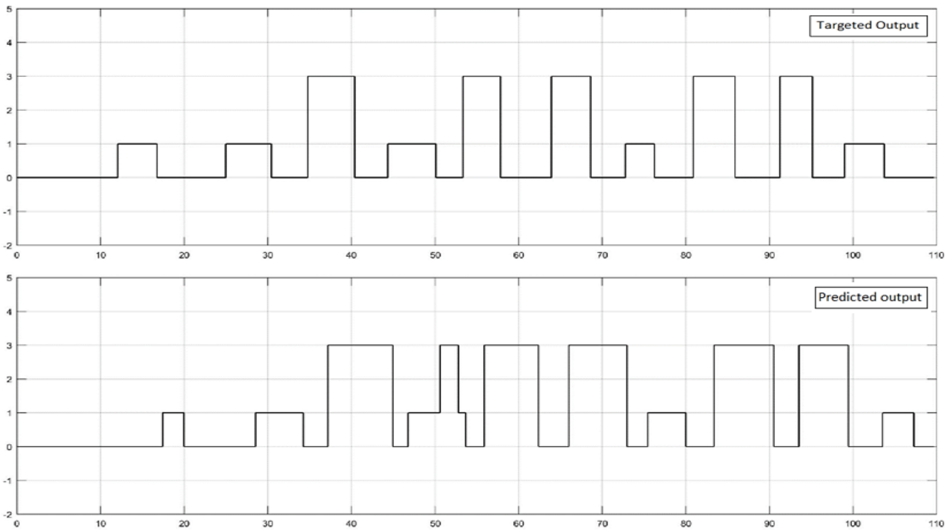

Figure 10. Identification using SCC classification

Table 1 lists the computed accuracy values for the different subjects used and the classification employed. The accuracy is measured in terms of the difference in the real–time motion prediction compared to the intended motion. By noticing the identification results from four different classifications, ZC (91%) indicates to be performing better than the other classification methods. Also, from Table 1, the WL and ZC based identification results point to a higher accuracy than the SSC and WAMP based results. SSC seems to have greater variance, while WAMP based results indicate a general worse outcome for all the subject tests.

Table 1. Identification Accuracy Results

Partic.	**Gender**	**Age**	**Dominant Hand**	**Accuracy (%)**			
				SSC	WL	ZC	WAMP
Sub. 1	Male	30	Right	99.5	95	97	85
Sub. 2	Male	26	Right	83.5	90	86	49
Sub. 3	Male	26	Right	63	85	92	55
Sub. 4	Male	27	Right	75	93	89	64
Sub. 5	Male	29	Right	97	84.5	93	57
Mean				**83.6**	**89.5**	**91.4**	**62**

An influencing factor not accounted for in this study is the variation in actual test performance by the individual subjects. In this case, the delay between the participant reaction and the targeted output values plays a role. There is some noise in the identification output which represents the error values from the trained ANN.

For the real-time implementation, an important outcome of the proposed system is the resulting delay between muscle action and identification outcome. This quantity is a function of the subjects' performance. Further studies are needed to better assess the uniformity and consistency of the subjects' performance with the testing and training procedures. In general, the real-time implementation of this proposed system resulted in delays that are well below the standard delay requirements for upper body prosthetic devices of 0.25 seconds. In addition, the virtual reality creates a plausible environment where the subject can see the motions that were intended; as a result, activating the desired neurons and cells for rehabilitation purposes or providing feedback for the prosthetic fitting and optimization process. The virtual reality can be enhanced by using different hand representations from the ones shown. Also, the proposed system can easily be adapted to depict a virtual prosthetic hand, reacting to sEMG signals. The sensor locations as well as the training of the corresponding ANN can be tailored to the individual user. The prosthetic device can be optimized using the proposed system by evaluating and adapting the underlying algorithm as well as the mechanical functioning of the device well before the device is manufactured.

5. Conclusion

The study of human apprehension through artificial intelligence has recently seen a rapid improvement due to an increase in soft computing abilities and the implementation of many concepts such as Artificial Neural Network (ANN) onto small form computational boards. There is an abundant number of researchers studying the relation of sEMG signals to human motion through the application of ANN. Most of the studies include the use of different features/classifications to help the learning process of the ANN. The present work includes the real-time implementation of a proposed ANN based classification approach with visualization option using Virtual Reality (VR) as well as all the corresponding hardware components. As this research explores the relationship between sEMG and the human forearm movement motions, considerations must be made to the fact that sEMG signals are complex signals, spatially and temporally distributed, time varying, and subject dependent. In addition, the variation in the execution of human mechanical motion shows great variability, even after applying constraints in terms of action planning and practice of joint movements. Thus, for better results, this research attempts on finding the classifications which can robustly identify the motions even if there are slight changes in the sEMG signal and motion mechanics. Also, through this work, it is shown that real–time identification through ANN training is possible with limited time delays. Moreover, VR has the potential to enable the designers to create and compare different prosthetic devices tailored to the user's needs, shortening the design process by combining the trial and comparison steps, hence increases the efficiency and decreases the development cost. The suggested system in this work can also be used for rehabilitation purposes of stroke victims by training the affected hand in a VR environment.

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