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Deep Learning Approaches for Phantom Movement Recognition

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***Abstract*—Phantom limb pain has a negative effect on the life of individuals as a frequent consequence of limb amputation. The movement ability on the lost extremity can still be maintained after the amputation or deafferentation, which is called the phantom movement. The detection of these movements makes sense for cybertherapy and prosthetic control for amputees. In this paper, we employed several deep learning approaches to recognize phantom movements of the three different amputation regions including above-elbow, below-knee and above-knee. We created a dataset that contains 25 healthy and 16 amputee participants' surface electromyography (sEMG) readings via a wearable device with 2-channel EMG sensors. We compared the results of three different deep learning methods, respectively, Multilayer Perceptron, Convolutional Neural Network, and Recurrent Neural Network with the accuracies of two well-known shallow methods, k Nearest Neighbor and Random Forest. Our experiments indicate, Convolutional Neural Network-based model achieved an accuracy of 74.48% in recognizing phantom movements of amputees.**

***Index Terms*—Phantom Limb Pain, Phantom Movement, Deep Learning, EMG, Movement Recognition**

I. INTRODUCTION

Phantom limb sensation (PLS) is the perception that the missing limb still exists and its orientation in space continues after amputation [1]. The majority of amputees experience PLS which includes the sensation of pressure, itchiness and warmth changes in the phantom extremity [2]. Furthermore, a significant majority of individuals with PLS experience severe phantom limb pain (PLP), particularly in the early period after amputation [3].

The most accepted theory about the underlying mechanism of PLP is the cortical remapping theory of the central nervous system, involving neuroplastic changes in the somatosensory cortex and motor cortex after amputation [2], [4]. It is suggested that deprivation of the sensory input of the primary somatosensory cortex after amputation leads to cortical reorganization, where the deprived cortex becomes susceptible to the input from the cortical neighbors and inputs displayed toward the cortical area that represents the missing limb also induce painful representations of the amputated limb [4].

Several studies demonstrated that the primary somatosensory cortex processes signals from the amputated extremity and primary motor cortex continues to send motor responses despite cortical reorganization [5], [6]. Thus, most of the patients can control phantom movements, also called phantom motor execution (PME), such as moving their toes, opening and closing their hands after surgery. These motor responses are unable to reflect the muscles in the amputated limb, resulting in activation of the residual limb muscle and generate a new muscle activation pattern specific to phantom movement [7].

PME is voluntarily control of performing phantom movements and provides the appropriate input and output component of the muscle activation circuit. Utilizing the PME would reduce PLP by activating the original motor area of the amputated extremity and normalizing the cortical representation. Also increasing in motor control of muscles at the residual limb would expand cortical representation. To facilitate PME, mirror therapy has been utilized [8]. However, the real motor execution of the patient remains uncertain due to motor responses cannot be measured. For efficient rehabilitation to reduce PLP and increase the ability of amputees to control the myoelectric prosthesis, it is essential to ensure PME. Myoelectric conversion of voluntary phantom movement at the stump as pattern recognition provides PME to be performed [9].

Recent researches have used muscle-computer interface for the recognition of phantom movements. Surface Electromyography (sEMG) is used by placing electrodes on the motor unite of the target muscle to record skeletal muscle activation signals during contraction. However, recognizing and classifying the phantom movements of the amputees is different from the movement of an existing joint. The signals recorded with sEMG during the phantom movements of the individual are received from remaining muscles that would not be ordinarily activated.

Myoelectric pattern recognition (MPR) that is commonly represented by a virtual extremity and provides appropriate

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visual feedback is utilized for prediction of the PME. MPR empowers to be performed of phantom movements in therapeutic tasks based on motor execution of the missing limb. This study aims to recognize and classify the signals obtained from sEMG that measure neuromuscular activity in the four different amputation region by using deep learning algorithms.

II. BACKGROUND

Deep learning is mainly based on learning multiple levels or representations of data. Deep learning algorithms have the ability to learn distinctive features from large amounts of data automatically [10]. Traditional machine learning is based on shallow networks consisting of an input and an output layer and no more than one hidden layer between the input and output layers. Compared to shallow learning, deep learning as a subfield of machine learning has the advantage of creating deep architectures to learn more intangible information [11].

Researches about MPR and classification of the phantom movement have included controlling myoelectric prosthesis and management of PLP. Powell et al. (2014) assessed the ability of four transradial amputees to control a pattern recognition-based myoelectric prostheses capable of nine classes of movement and used Linear Discriminant Analysis (LDA) as classifier [12]. Jarrasse et al. (2016) classified phantom finger, hand, wrist and elbow voluntary gestures based on the analysis of sEMG signals measured by multiple electrodes placed on the residual upper arm of 5 transhumeral amputees with a controllable phantom limb used LDA as classifier [13]. Ghazaei1 et al. (2017) developed a deep learning-based artificial vision system to augment the grasp functionality of a commercial prosthesis and used Convolutional Neural Network (CNN) as classifier [14].

Ortiz-Catalan et al. (2013), developped an open access research platform called BioPatRec for the development and evaluation of MPR algorithms in prosthetic control [15]. Then, they utilized MPR to predict simultaneous phantom movements and as input for augmented reality (AR) environment to relieve chronic PLP [16]. They also compared offline and real time classification accuracy and all the studied offline metrics failed to predict real-time decoding [17]. After that, they used machine learning to restore neuromuscular activity in the residual limb while the patient executes phantom limb movements in a virtual environment. It was reported that phantom limb motor applications significantly reduce phantom pain [9]. Lendaro et al. (2017), classified non-weight bearing lower-limb movements using sEMG to facilitate PME and used BioPatRec algorithms for the MPR [18]. Also, they used MPR for the treatment of PLP but clinical trial is currently in the participant enrolment phase [19].

Considering previous studies, our research have been distinct in terms of recognizing phantom movements from the four different amputation area, using deep learning approach for the maximal accuracy of the recognition.

III. MATERIALS AND METHODS

The aim of this study is to provide an efficient classifier in the use of phantom movement recognition. Previously Akbulut et. al. [20] proposed a cybertherapy system that aims to reduce the PLP with creating virtual environments for amputee people. Such system needs to be fed by accurate movement identification which will be used in interactive therapy games. Proposed system consists of 4 main parts; a wearable sensor to collect sEMG data, real-time classifier to recognize phantom movements, virtual reality-based therapy games and web services to communicate different modules of the system.

With the spread of deep learning methods, their use in machine learning problems has increased. We aimed to show the effectiveness of these approaches by employing in our classifier. To train these models, a preliminary data had to be collected and evaluated for its accuracies. 4 different limps (hand, forearm, foot, leg) are considered to be recognized by the classifier and the moves for these limbs are listed below. Since each amputated limb requires different environment, data is collected for each body section separately.

1) **Transradial Amputation and Wrist Disarticulation (TAWD)**: Extension, Flexion, Grip, Release
2) **Transhumeral Amputation and Elbow Disarticulation (TAED)**: Extension, Flexion
3) **Transtibial Amputation and Ankle Disarticulation (TAAD)**: Extension, Flexion
4) **Transfemoral Amputation and Knee Disarticulation (TAKD)**: Extension, Flexion

To build the dataset in training the classifier, signals were recorded via a 2-channel sEMG sensor during the phantom movement of the amputees through electrodes placed around the residual limb. Amputations from 8 regions were found suitable for measurement. In the case of wrist disarticulation and transradial amputation, we aimed to obtain sEMG signals from the flexor and extensor muscles of the wrist and finger. In order to recognize phantom movement in elbow disarticulation and transhumeral amputation, electrodes were placed on the residual part of the biceps brachii for elbow flexion and triceps muscle for elbow extension. During phantom dorsiflexion and plantar flexion of the ankle, signals were obtained from tibialis anterior and gastrocnemius muscles respectively. sEMG signals were obtained for knee flexion and extension in knee disarticulation and transfemoral amputation. Electrodes were placed on residual part of the quadriceps muscle for phantom knee extension and the hamstring muscle for phantom knee flexion. A number was given to each joint region and to the movement performed in that joint. Below-elbow was named as first region (1), above-elbow as second (2), below-knee as third (3) and above-knee as fourth (4). Finger grip were coded as 1, finger release as 2, wrist flexion as 3 and extension as 4. In all other regions, flexion was coded as 1 and extension was coded as 2.

3 seconds determined as sufficient to identify a move and the data collection module is capable to get 20 samples for each sensors in a second. An additional amplifier is used for collection module to get more clear data. Dataset contains 25 healthy and 16 amputee people data together. The distribution

of the collected samples are given in Table I. Since TAWD amputee participant couldn't be found, therefore this section is excluded for amputees.

TABLE I
MOVE COUNTS UP TO CLASSES

	Below Elbow	Above Elbow	Below Knee	Above Knee
Healthy	1679	1000	1000	1000
Amputee	-	80	452	120

As the classification approach of our model, initially we worked with shallow models such as; kNN (k Nearest Neighbor) and Decision Tree that did not produce satisfied results. Thus, we employed more complicated methods to increase movement recognition accuracy. MLP (Multilayer perceptron), CNN (Convolutional Neural Network) and RNN (Recurrent Neural Network) are the ones implemented so far.

kNN (k Nearest Neighbor): With kNN, the input data is compared with the others in the dataset. Whichever data is the most similar to a cluster is considered in the same class. In this model, according to closest 3 neighbors, a class is defined for the input data.

Decision Tree: The purpose of this well-known algorithm is to determine the properties that have the most effect on the results and to create trees according to these features. The entropy equation is used to find out which sample is most effective in the results. Then other entropies are calculated according to this first number and sub-branches of the tree are started to be formed.

Multilayer Perceptron (MLP): MLP model based on the method workings of the human brain and by using artificial neural cells in layers, artificial neural networks are formed. These networks have an input layer, a hidden layer and an output layer. In our model, we have 120 data input layers at one time. After passing 60 artificial nerve cells in the hidden layer, they are divided into 2 or 4 classes in the output layer (Figure 1).

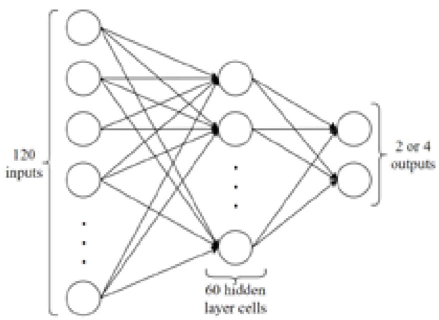

Fig. 1. 3 Layer MLP Network Architecture

Convolutional Neural Network (CNN): In order to achieve more accurate movement recognition in amputated patients, CNN network was also utilized in our experiments. This network is mostly utilized for image classification and so, our approach here is to preprocess the data as making it a 2-dimensional array. A movement in our dataset consists of 120 samples. In the algorithm, we include a "0" to the end of this data to form a 11x11 matrice, following that this 121 data sequence was processed with multiple layers. Our model consists of 2 convolutional and one hidden layers. The general view of our model is shown in Figure 2.

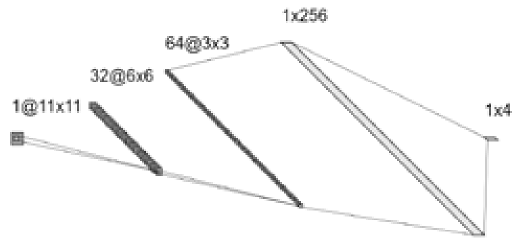

Fig. 2. CNN model Architecture

Recurrent Neural Network (RNN): RNN is a typical MLP except it has an extra weight that called as hidden state for each cell of hidden layer. Previous weight values are stored and then being used as inputs for neurons with new inputs. Each RNN cell processes old and new input together and that is why RNN is a good way of fusing current and past data. Eventually, it is very suitable for interpretation of repetitive sequential data. The RNN model for this study (Figure 3) uses 3 layers of 128, 64 and 32 cells and 1 dense layer of 16 cells.

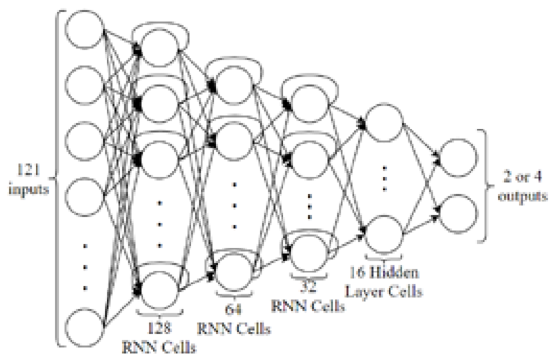

Fig. 3. RNN model Architecture

When all the models are compared (Table II), kNN model is only successful for healthy TAAD with 87.5%. However, TAWD classification which has 4 classes was not sufficient with accuracy 65.93%. That's why general accuracy is not high for healthy people. For amputee patients, it has 65.2% average accuracy which is not sufficient for the virtual environment. Decision Tree has less accuracy except for amputee TAKD, so it can not be used as a classification model either. MLP's achievement is the TAWD accuracy (73.85%), so we can say that MLP has more accuracy for multi-class classification. Other than that, MLP couldn't get the best result for any region. CNN algorithm is examined as the most successful model with 86.76% accuracy for healthy people and 74.48% for amputee patients. The lack of CNN accuracies according

TABLE II
COMPARISON OF OVERALL ACCURACY

	Below-Elbow		Above-Elbow		Below-Knee		Above-Knee		General Accuracy	
	Healty	**Amputee**	**Healty**	**Amputee**	**Healty**	**Amputee**	**Healty**	**Amputee**	**Healty**	**Amputee**
kNN	65.9321%	-	92.6%	66.25%	87.5%	67.6991%	92.4%	61.6667%	84.608%	65.2053%
Decision Tree	60.6909%	-	84.9%	62.5%	80.4%	63.2743%	82.9%	65.8333%	77.2227%	63.8692%
MLP	73.8535%	-	90.7%	67.5%	87.1%	63.2743%	91.6%	63.3333%	85.8134%	64.7025%
CNN	72.0238%	-	94.5%	79.1667%	86.5%	72.0588%	94%	72.2222%	86.7560%	74.4826%
RNN	75%	-	79.67%	66.67%	82.33%	61.76%	90%	63.89%	81.7500%	64.1067%

to MLP algorithm is TAWD and healthy TAAD but, even for these regions, it is not far behind. RNN is, like MLP, only have good results for TAWD while other region successes are far behind other algorithms. For machine learning algorithms, cross validation (k=10) is used to split the data, while CNN and RNN data are splitted as 70% for training.

IV. CONCLUSION

The proposed deep learning-based movement recognition method achieves 86.75% accuracy for healthy people and 74.48% for amputated people on average. When we examine the sEMG signals of our dataset we observed that neuromuscular activity of the muscles is different in healthy and amputated people due to signals recieved from remaining muscles of the residual limb depending on amputation level. A new muscle activation pattern specific to phantom motor execution appears because the mass, structure and insertion of the muscles changes after amputation. Therefore, the performance of classifiers on amputated data has resulted in 14% - 22% less than that of healthy participants. Another major finding of our experiments reveals that the deep models achieve higher accuracies than the shallow models. However, the primary disadvantage of the classifiers using deep models is that they need higher capacity enabled hosts such as cloud environments. As a result of our classification scores, PLP patients can be able to participate in cybertherapy as attending in virtual reality and augmented reality sessions as an alternative to traditional mirror therapy.

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