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Identification of phantom movements with an ensemble learning approach

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ABSTRACT

Phantom limb pain after amputation is a debilitating condition that negatively affects activities of daily life and the quality of life of amputees. Most amputees are able to control the movement of the missing limb, which is called the phantom limb movement. Recognition of these movements is crucial for both technology-based amputee rehabilitation and prosthetic control. The aim of the current study is to classify and recognize the phantom movements in four different amputation levels of the upper and lower extremities. In the current study, we utilized ensemble learning algorithms for the recognition and classification of phantom movements of the different amputation levels of the upper and lower extremity. In this context, sEMG signals obtained from 38 amputees and 25 healthy individuals were collected and the dataset was created. Studies of processing sEMG signals in amputees are rather limited, and studies are generally on the classification of upper extremity and hand movements. Our study demonstrated that the ensemble learning-based models resulted in higher accuracy in the detection of phantom movements. The ensemble learning-based approaches outperformed the SVM, Decision tree, and kNN methods. The accuracy of the movement pattern recognition in healthy people was up to 96.33%, this was at most 79.16% in amputees.

1. Introduction

Phantom limb sensation is a sense that the amputated limb is still present after amputation. Many individuals experience phantom sensations, including pressure, itching, and temperature changes in the missing limb [1]. The phantom sensation may be so realistic that they sometimes get out of bed and try to walk with the phantom foot. The majority of people with phantom limb sensation also have extremity pain, which causes a very disturbing and debilitating effect. Phantom limb pain (PLP) is a common symptom seen in individuals who undergo this process [2]. Moreover, 80%–85% of these individuals experience severe continuous or intermittent pain attacks lasting up to 1 min and characterized by throbbing, burning, stabbing, electric shock, tingling, and cramping along the amputated limb. PLP is usually early-onset but may occur weeks or even years later [3]. Jensen et al. stated that the incidence of PLP was 72% after one week of amputation and 59% after 2 years [4]. PLP is less frequent in young children and children with congenital absence of limb [5].

The incidence of PLP is more frequent in patients with chronic vascular disease prior to amputation and chronic pain due to tumors. It is also mentioned that the severity of pre-amputation pain and the severity of PLP are directly proportional [6]. Other factors that affect the occurrence or exacerbation of PLP include seasonal changes, stress, sadness, coughing, micturition, defecation, anxiety, depression, sexual activity, tight dressing, or prosthesis on the stump [5].

The underlying mechanism of the PLP has been extensively debated but still not totally elucidated. Although it was widely believed that psychogenic factors were the reason for PLP, it was focused on changes that the amputation induces in the central nervous system (CNS) and peripheral nervous system (PNS) over time [3].

Many theories about peripheral causes of PLP are focused on the presence of neuroma, the inability of the interrupted nerves to repair previous connections, ectopic firing in the residual limb or dorsal root ganglion, and the role of pre-amputation pain [7].

Although more than 60 different therapies to alleviate PLP have been described in the literature, none of them have proven their

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effectiveness yet [8]. As more information is obtained about the formation mechanism of PLP and its predisposing factors, the number of studies focusing on the prevention or reduction of pain has increased. Research in literature has demonstrated that the primary somatosensory cortex receives signals from missing limbs and the primary motor cortex sends motor commands despite cortical reorganization [9]. Performing phantom motor execution (PME) may reduce PLP as it will cause activation in the motor cortex and normalize cortical representation of the amputated limb [10].

PME is the phantom movement of the amputated limb that patients are able to voluntarily control. The muscle activation patterns of the residual limb during PME are different from the intact limb due to the lack of skeletal muscles and motor responses of the amputated limb cannot be observed because of the absence of a limb. Recognition and classification of the PME are significant for utilizing it in the treatment of PLP. Surface electromyography (sEMG) can be used for recording signals received from amputated limbs during PME. Electrodes are connected to the stump of the patient to receive the electrical signals generated during phantom movements. The electrical signals from the amputated limb are recognized and classified by myoelectric pattern recognition, are transformed into virtual limb movements in real-time by artificial intelligence algorithms, and are used in virtual and augmented reality-based rehabilitation systems to reduce PLP.

The aim of the current study is to classify and recognize the phantom movements in four different amputation levels of the upper and lower extremities by using ensemble approaches. Ensemble learning approaches are capable of automatically distinguishing features from large amounts of data. Ensemble learning can be used to achieve better prediction performance for the recognition and classification of PME.

The main contributions of this research are two-fold, as follows:

– We created a genuine dataset of sEMG signals from 38 amputees and 25 healthy individuals.
– We performed an empirical study on phantom movement recognition using ensemble learning approaches compared with SVM, Decision tree, and kNN algorithms.

The rest of the paper is structured as follows: A summary of the literature review on phantom movement recognition is introduced in Section 2. In Section 3 the dataset, research methodology, and all methods employed are explained. Section 4 details the valuation of results. Section 5 interpret the finding and finally, conclusions are summarized in Section 6.

2. Related work

In order to improve the precision of the dynamic characteristics of the sEMG signal, it is necessary to construct a mathematical model of the signal. The deep learning approach consists of multiple abstraction structures and multiple processing layers combined to learn the representations of data. Studies about phantom movement recognition by using deep learning and other machine learning approaches have aimed to reduce PLP and control the myoelectric prosthesis. The success of myoelectric control depends to a large extent on the accuracy of classification.

The summary of the sEMG studies that have motion classification are shown in Table 1. Lucas et al. proposed a method for classifying multi-channel sEMG signals to control myoelectric prostheses. The classification was accomplished by a Support Vector Machine (SVM) approach in a multi-channel representation area. In order to classify six different hand movements, sEMG signals were recorded by means of superficial electrodes placed at eight sites on the forearm. The method was found to be suitable for real-time classification due to its low rate of misclassification and its ability to be implemented with fast algorithms [11]. Ahmad and Chappell classified the sEMG signal to detect the regularity of the movements. Twenty subjects performed wrist flexion/extension, isometric contraction, and co-contraction while EMG signals were recorded with surface electrodes. The results demonstrated that the sEMG signal had regularity at the beginning and end of the muscle contraction, with a low regularity in the middle [12]. Khezri et al. used superficial EMG signals to describe movement models of the hand prosthesis. For the control of a prosthetic hand, a fuzzy logic inference system has been proposed to determine motion commands. The myoelectric signals used in the classification consist of six hand movements. The fuzzy-logic systems designed and used in this study have been tested independently in a mixed manner for both time and time–frequency characteristics [13].

Jarrasse et al. classified the phantom movements of fingers, hands, wrist, and elbow using sEMG signals measured by multiple electrodes placed on the residual limb in five participants with transhumeral amputations. LDA was used for classification [14]. Also, they used myoelectric pattern recognition and classification of voluntarily phantom movements to control prosthesis without surgical reinnervation in patients with transhumeral amputation. Their aim was to evaluate the possibility of using a PME based control approach to perform more realistic functional grip tasks. Results indicated that transhumeral amputees successfully achieved grasping activities with a prosthesis by using PME [15]. Resnik et al. compared the usability and efficacy of sEMG based pattern recognition and inertial measurement units on DEKA arm prosthesis control. Transradial amputees reported usability of pattern recognition less satisfactory than inertial measurement units while transhumeral amputees rated both methods similarly [16]. They also compared pattern recognition and direct myoelectric control in terms of manual dexterity, function, satisfaction of prosthesis, and a performance of activities [17]. Patients using pattern recognition reported that manual dexterity and satisfaction decreased in a week. Al-Timemy et al. aimed to develop a method for improving the performance of multi-functional upper extremity prostheses controlled with sEMG against force variation for individuals with trans-radial amputation. Results demonstrated that the proposed features can lead to significant reductions in classification error rates compared to other known pattern recognition methods [18]. Akbulut et al. compared the accuracy rate of different deep learning approaches in decoding PME and found that Convolutional Neural Network-based had the highest accuracy rate [19]. Powell et al. used Linear Discriminant Analysis (LDA) to assess the ability of four participants with trans-radial amputation to control pattern recognition-based myoelectric prostheses with nine motion classes [20]. Ghazaei et al. developed an artificial vision system based on deep learning to enhance the grip functionality of a commercial prosthesis and used the Convolutional Neural Network (CNN) as a classifier [21].

Ortiz-Catalan et al. conducted a series of pattern recognition studies both for use in prosthetic control and technology-based rehabilitation systems developed to reduce PLP. First, they developed an open-access research platform called BioPatRec for the development and evaluation of myoelectric pattern recognition algorithms in prosthetic control [22]. Then, they used myoelectric pattern recognition as input for augmented reality-based rehabilitation systems for the prediction of simultaneous phantom movements and alleviating chronic PLP [23]. They also compared the accuracy of offline and real-time classification, and not all offline metrics studied could predict real-time decoding. They then used machine learning to restore neuromuscular activity in the remaining limb while performing the patient's phantom limb movements in a virtual environment. PME has been reported to significantly reduce phantom pain [24]. To facilitate PME, Lendaro et al. classified non-weight bearing lower extremity movements using sEMG and used BioPatRec algorithms for myoelectric pattern recognition [25]. Izonin et al. aimed to develop a new ensemble-based prediction method using stacking approach based on the several GRNN's and one SGTM neural-like structure and described a prediction method using a new, stacking-based GRNN ensemble model. A comparison of its efficient with a number of classical regression methods, as well as neural network-based methods was done. The highest accuracy of

Table 1
Summary of sEMG studies that have motion classification.

Study	Aim	MVMT	PTP	Method	Acc	Results	Limitations
Lucas et al. [11]	Classification of multi-channel sEMG signals to control myoelectric prostheses	Hand	H n = 6	Support vector machines (SVM)	NA	Suitable for real-time classification due to its low rate of misclassification and its ability to be implemented with fast algorithms	Limited number of participants, not compared with other classification methods, only one body part and healthy subjects but not amputees
Ahmad and Chappell [12]	Classified the sEMG signal to detect the regularity of the movement	Wrist	H n = 20	Moving Approximate Entropy	NA	sEMG signal had regularity at the beginning and end of the muscle contraction, with a low regularity in the middle	Not compared with other classification methods, only one body part and healthy participants
Khezri and Jahed [13]	Use an intelligent approach integrated with a real-time learning scheme to identify hand motion commands	Hand	H n = 4	Adaptive neuro-fuzzy inference system (ANFIS)	96.7%	ANFIS coupled with mixed time and time frequency features can provide acceptable results for designing sEMG pattern recognition suitable for hand prosthesis control	Limited number of participants, not compared with other classification methods, only one body part and healthy participants but not amputees
Jarrasse et al. [15]	To recognize the muscle activity of the residual limb associated with the execution of phantom movements	Hand Wrist Elbow	TA n = 5	Linear discriminant analysis (LDA)	>80%	it seems possible in transhumeral amputees to recognize phantom hand, wrist and elbow actions from the sEMG signals measured on the residual limb.	Limited number of participants, not compared with other classification methods, only one body part
Jarrasse et al. [14]	To evaluate the possibility for transhumeral amputees to use a PLM-based control approach to perform more functional grasping tasks	Finger Hand Wrist Elbow	TA n = 2	Linear discriminant analysis (LDA)	87.70%	Transhumeral amputees successfully achieved grasping activities with a prosthesis by using PME.	Limited number of participants, not compared with other classification methods, only one body part
Al-Timemy et al. [18]	To develop a method for improving the performance of multi-functional upper extremity prostheses controlled with sEMG against force variation	Finger Hand	TA n = 9	Linear discriminant analysis (LDA), Naive Bayes (NB), Random Forest (RF), k-Nearest Neighbor (kNN)	73.93–99.15%	The proposed features can lead to significant reductions in classification error rates compared to other known pattern recognition methods	Limited number of participants and only one body part, average accuracy of other classification systems is unclear
Ghazaei et al. [21]	To enable to use a simple, yet efficient, computer vision system to grasp and move common household objects with a two-channel myoelectric prosthetic hand	Finger Hand Wrist	TA n = 2	Convolutional Neural Network (CNN)	88%	Deep-learning based computer vision systems can enhance the grip functionality of myoelectric hands considerably	Limited number of participants, not compared with other classification methods, only one body part
Ortiz-Catalan et al. [28]	To develop an open-access research platform for the development and evaluation of myoelectric pattern recognition algorithms in prosthetic control	Hand Wrist	H n = 17	Multi-layer Perceptron (MLP), Linear discriminant analysis (LDA), Regulatory Feedback Networks (RFN)	91.2% (MLP) 92.1% (LDA) 83.8% (RFN)	BioPatRec provides a publicly available repository of myoelectric signals that allow algorithms benchmarking on common datasets.	Limited number of participants, only one body part, healthy subjects but not amputees
Lendaro et al. [25]	To investigate the performance of two alternative electrode configurations to conventional bipolar targeted recordings in terms of real-time metrics.	Knee Ankle	H n = 6 LLA n = 2	Linear discriminant analysis (LDA)	81.7–86.9% (Amputee) 81.4–84.7% (Healthy)	Monopolar recordings using a circumferential electrode of conductive fabric, performed similarly to classical bipolar recordings, but were easier to use in a clinical setting	Limited number of participants, limited body part, not compared with other classification methods

Types of Participants: H: Healthy, TA: Transhumeral amputees, LLA: Lower Limb Amputees.

the developed method based on Root Mean Square Error (RMSE) in comparison with existing methods is experimentally established [26]. Izonin et al. also proposed a prediction method for probable recovery of partially missing or completely lost data based on the improvement of an ensemble of two GRNNs by the additional use of extended-input SGTM neural-like structure. They have improved the ensemble of two GRNN networks, where the first predicts the value of the desired quantity and the second the error of the first network of the ensemble [27].

3. Materials and methods

Our study aims to recognize and classify phantom movements to reduce PLP by performing phantom motor executions with a virtual limb in virtual and augmented reality-based rehabilitation systems. In these systems, patients receive visual inputs about their ability to perform PME, and motor and sensory feedback obtained from PME of the virtual limb induce activation of the somatosensory and motor representation areas. Phantom movements must be decoded in order

Fig. 1. Amputee sEMG setup.

for amputees to see their PME in a virtual environment simultaneously. Therefore, by recognizing the activation of the muscles in the remaining limb during the phantom movement of the amputee, we process the sEMG signals to allow the same movement to occur in the virtual limb (Fig. 1).

Our study does not include every movement the patient can try to make for his/her phantom limb, instead, it considers some specific movements. Therefore, the model makes decisions between a certain number of movements and provides less complexity for the algorithm. This study includes 4 different limbs (hand, forearm, foot, leg), and movements for these limbs are listed below.

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

The data taken from healthy people is used for testing. The data showed that it is not appropriate to classify data points with rule-based methods. Therefore, machine learning algorithms are used for efficient classification. A data set obtained from sEMG is needed to classify PME by using the ensemble learning technique. Therefore, 2-channel sEMG was developed to obtain the dataset while training in the classifier. 8 different amputation regions from 4 extremities were determined to perform PME. The sEMG electrodes were placed in the remaining muscles around the residual limb. Muscle activation signals were collected from the muscles responsible for flexion and extension of the wrist and fingers in the below-elbow amputations. This amputation level was labeled as the first region (1). In order to recognize PME in above-elbow amputations, electrodes were placed in the remaining parts of the biceps and triceps muscles. This amputation level was labeled as the second region (2). The sEMG signal was received from the remaining parts of the tibialis anterior and gastrocnemius muscles for phantom movement recognition and classification of the below-knee amputations, while the electrodes were placed on the remaining parts of the hamstring muscles and quadriceps to record muscle activation of the above-knee amputations. These regions were numbered as third (3) and fourth regions (4), respectively. Handgrip was numbered 1, finger release 2, wrist flexion 3, and extension 4. In all other regions, flexion was coded 1, and extension was coded 2.

Table 2
Move counts per regions.

	TAWD	TAED	TAAD	TAKD
Healthy	1679	1000	1000	1000
Amputee	–	80	1138	280

sEMG Sensors are available to take 20 samples per second. In the study, 3 s are considered enough to get the movement. Therefore, each movement consists of 60 samples. Because we have 2 sEMG sensor channels, we get 120 samples at the end. Data is collected from 25 healthy and 38 amputee people, and movement counts for each region are shown in Table 2.

After data are collected, machine learning algorithms have been implemented to recognize movement from sEMG signals. We randomly ordered the dataset and split the first 80% of it into a training set and the last 20% into a test set.

ML algorithms provide a set of hyperparameters to control the gap between the training and test errors. We manually tuned the hyperparameters to determine the optimum hyperparameters. Each combination of parameters was then assessed using cross-validation, in which the accuracy score was determined to decide the performance of the models. We set the SVM by changing the parameters C = 1.1 and the kernel function as the Radial basis function (RBF) with 3 degrees. For DT, we control the size of the trees with 3 as max depth and 5 as max-leaf nodes. In kNN, we choose the optimal number of neighbors (k) as 8.

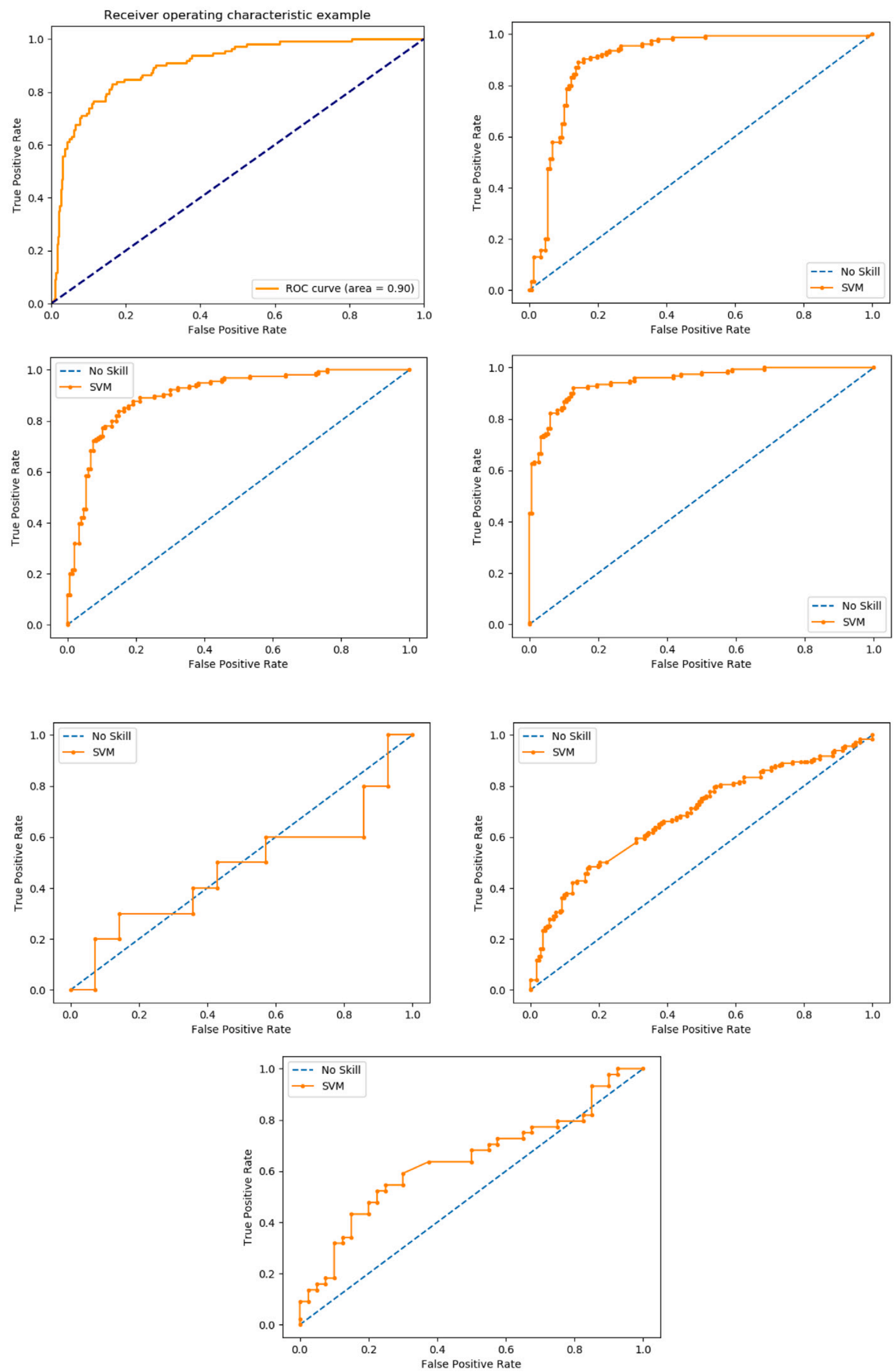

Fig. 2. SVM ROC curves.

We used Python programming language v3.9.5 to develop machine learning models over the Tensorflow v2.9.1 framework. Shallow algorithms were implemented using scikit-learn library and data visualization was performed using matplotlib library.

4. Results

We preferred the Support Vector Machine (SVM) approach as the first method of experiments. SVM is a model that discriminates classes with vectors (2 classes) or hyper-planes (multi-classes). This model has higher accuracy compared to other machine learning methods for above-knee amputee people. Table 3 shows these accuracy values. Also, ROC curves show how SVM struggles to discriminate, especially, for amputee patients (Fig. 2).

As the second approach that we employed, Decision Tree is a model that aims to find the features that have the most effect on the classification. It creates a tree based on the features. According to this trained tree, new samples are being classified. Decision Tree did not have great success, as shown in Table 3. Because the movement can be done early or late within 3 s, samples may be different even if it is the same movement. Therefore, it is also not efficient to classify the movements (Fig. 3).

The most successful machine learning algorithm in this study is kNN. This model determines the class for each movement, according to the distance of other known movements. For our study, distance is

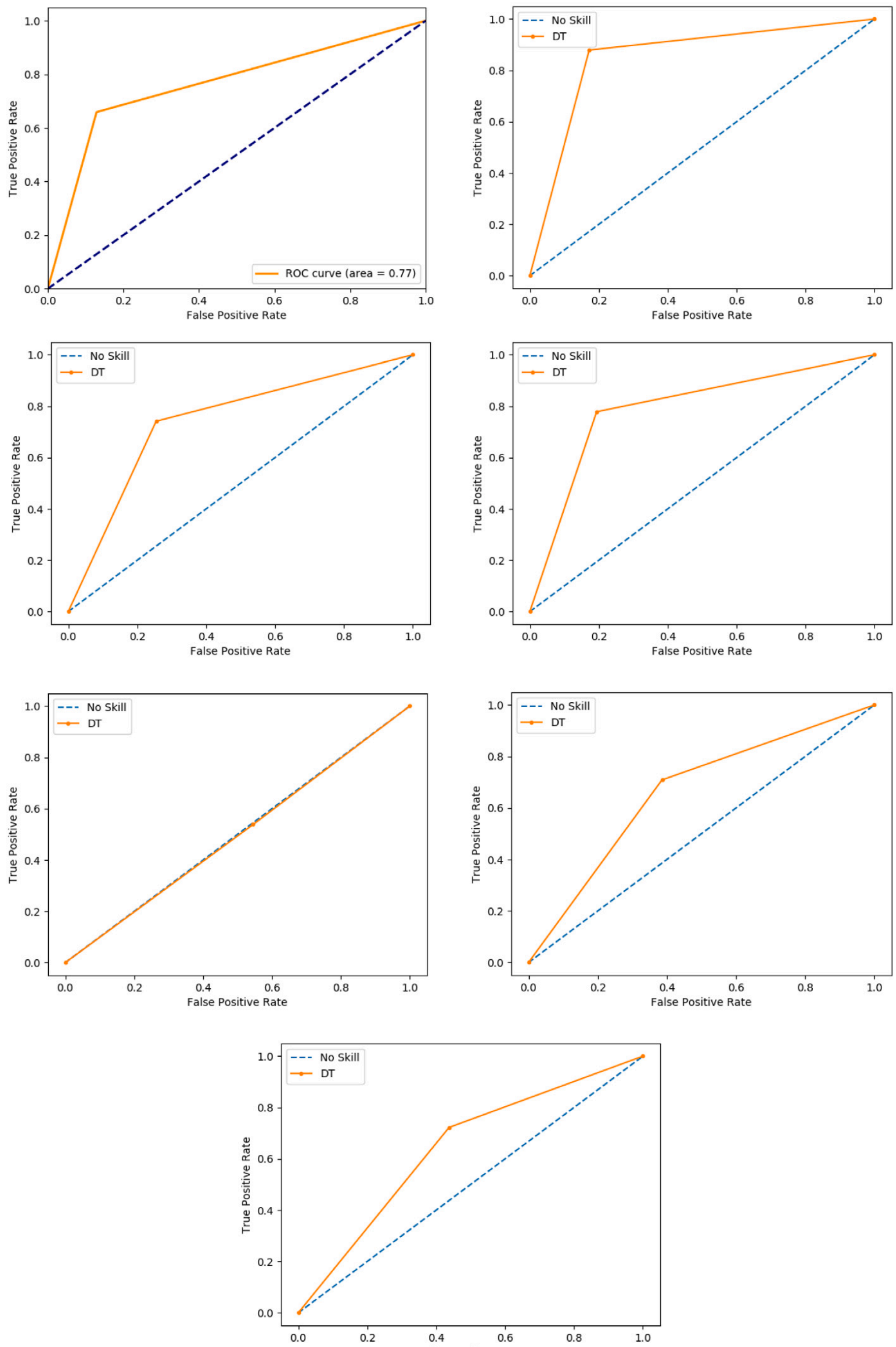

Fig. 3. Decision tree ROC curves.

being found by subtracting each sample relatively. After finding the distance with every known movement, class is defined by the closest 3 neighbors. Distance logic also removes the timing issue that the Decision Tree has. As such, it can be above 90% for healthy people. 70% accuracy for amputee patients can be accepted as a success for the lab conditions but it is not sufficient for real-life applications (Table 3). ROC curves for kNN also show the success for healthy people, but amputee accuracy is still not away from the baseline, especially for the above-knee region (Fig. 4).

Despite the fact that machine learning models achieve satisfying results for healthy people, they are not sufficient for recognizing the movements of amputee patients. Therefore, we aimed to increase the accuracy by using ensemble learning. Ensemble learning is a technique that handles data not as a whole but part by part. For each part of data, models are trained and at the end, these models are combined together. It has different methods to implement, and we implemented bagging, boosting, and voting methods in our models.

Bagging: This method divides the data into bags, and for each bag, it trains the model. After training, for each test movement, this trained model decides on a class. The class, which gets the most votes is accepted as a result (Fig. 5).

The Bagging method increased the accuracy of the Decision Tree — Healthy model at most. While the basic Decision Tree has 77% average accuracy, with bagging it reaches 84%. For amputee classification, the kNN algorithm has increased its accuracy by almost 3%(70.16–72.96)(Table 4).

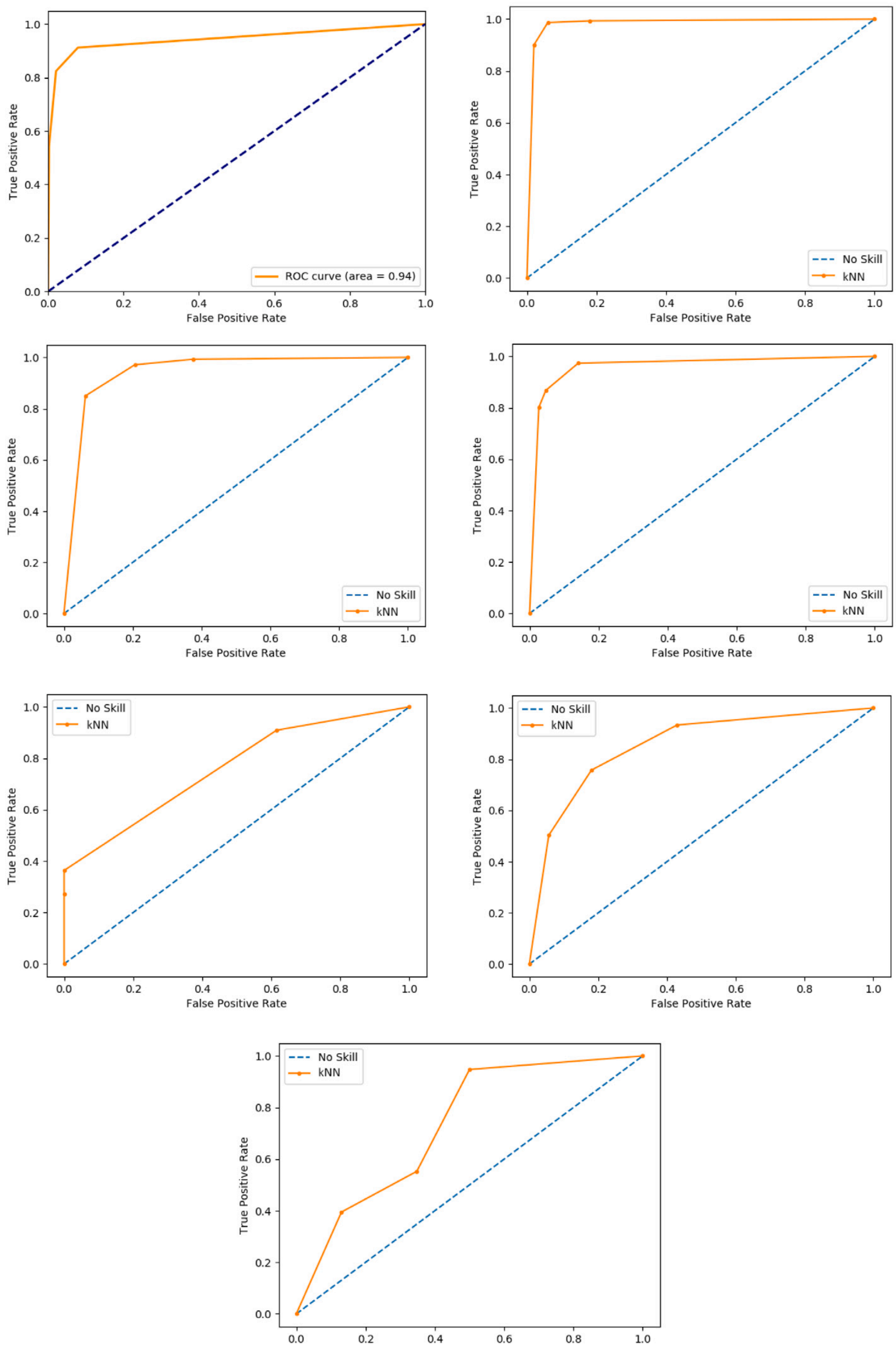

Fig. 4. kNN ROC curves.

Table 3
Comparison of machine learning accuracies (H:Healthy, A:Amputee).

	Below-Elbow		Above-Elbow		Below-Knee		Above-Knee		Average	
	H	A	H	A	H	A	H	A	H	A
SVM	68.25%	–	87.33%	58.33%	83.66%	63.15%	88.66%	63.09%	81.97%	61.52%
DT	57.93%	–	86.33%	62.5%	82%	71.63%	82.66%	61.9%	77.23%	65.34%
kNN	74.40%	–	96.33%	70.83%	87.66%	78.94%	91%	60.71%	87.34%	70.16%

Boosting: Boosting method trains the model with the whole data first. Following that, the weights for incorrectly classified moves are increased and model is trained once more. Ultimately, with each training phase, incorrectly classified samples become more important in terms of target recognition (Fig. 6).

As depicted in Table 5, boosting method could not improve the overall accuracy for all of the regions. As the initial observation, the average stayed behind the original models. The kNN model is not included in boosting because it is not a base model and it does not benefit from weights.

Table 4
Comparison of accuracy values of machine learning algorithms with bagging (H:Healthy, A:Amputee).

	TAWD		TAED		TAAD		TAKD		Average	
	H	A	H	A	H	A	H	A	H	A
SVM	67.06%	–	87%	41.66%	77.66%	61.40%	84.33%	61.90%	79.01%	54.98%
DT	68.84%	–	90.33%	54.16%	86.66%	66.66%	90.33%	76.31%	84.04%	65.65%
kNN	71.82%	–	92%	70.83%	85.66%	74.26%	94%	73.8%	85.87%	72.96%

Table 5
Comparison of accuracy values of machine learning algorithms with boosting (H:Healthy, A:Amputee).

	TAWD		TAED		TAAD		TAKD		Average	
	H	A	H	A	H	A	H	A	H	A
SVM	64.08%	–	81.66%	45.83%	77.66%	66.37%	84.33%	63.09%	76.93%	58.43%
DT	54.16%	–	85.66%	66.66%	78.33%	70.76%	81.66%	63.09%	74.95%	66.83%

Table 6
Comparison of accuracy values of machine learning algorithms with voting (H:Healthy, A:Amputee).

	TAWD		TAED		TAAD		TAKD		Average	
	H	A	H	A	H	A	H	A	H	A
Voting	64.28%	–	92%	79.16%	85%	75.43%	93.33%	71.42%	83.65%	75.33%

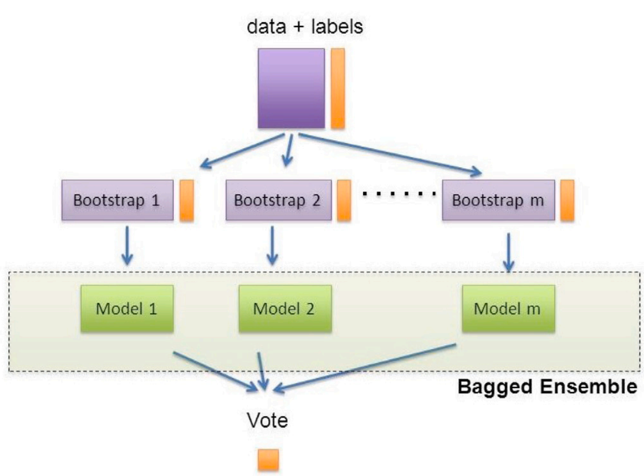

Fig. 5. Bagging structure.

Voting: In this method, different classifiers are trained with same data, then, the move class is predicted. The class that has most votes from all classifiers is determined as the final result (Fig. 7).

Voting uses all of the 3 models and makes voting for classification. With this technique, we have achieved the highest accuracy rate for amputees. Even though it is 2% less than kNN for healthy people on average, for amputee classification, above-elbow has increased from 70% to 79%(9% difference) and above-knee has increased from 60% to 71%(11% difference). In the end, we have a 5% increase for amputees according to the kNN model (Table 6).

5. Discussion

Classification results show that the accuracy of healthy participants is way higher than that of amputees. Because while data is being collected, healthy people actually do the move which resulted in the complete signal from the related body location. Contrarily, amputee people only have to imagine that they are making the move that mostly ends up with incomplete or corrupted sEMG signals. Thus, the amputated limb's nerve cells are dying over time and it makes the data more complicated. That is why for healthy people, accuracy never goes down below 80% (only for 2 class regions), while the amputee classification has 40% accuracy for some classifiers. Also, other factors like noise, depression of patients, age, the difference between sEMG pads, etc. make the classification even harder with each patient's data. In this manner, we have reached 75% of average accuracy with 38 different amputees people data.

Even though SVM is a good classifier for most studies in literature, in our case it was the weakest one among the 3 classifiers. The decision tree was more successful than SVM, however, it could not provide efficient results as well. This is because timing can be different for different data. kNN has the ability to classify even the time of movements that are different, therefore, it provides the best accuracy so far. Unlike our study, most of the studies on the classification of movements with sEMG were conducted only on healthy individuals and with a small number of participants [11–13,22]. Studies of processing sEMG signals in amputees are limited, and studies are generally on the classification of the upper extremity and hand movements [14,15,18,21]. We consider that the most important reason for this is to ensure more functional use of the upper extremity myoelectric prosthesis. Although LDA and SVM are frequently preferred methods for classification of motion signals [14,15,18,22,25], new prediction approaches have also been studied [26,27]. Our study suggests that the kNN method can also make an important contribution to the classification of PME signals.

Table 7 shows all the accuracy values with different models and methods.

Fig. 8 shows the confusion matrices for the voting ensemble, which was the model that worked most accurate. Authors note that TAWD works as a one-class classifier.

The data collection period is set to 3 s and each classifier takes 120 samples as inputs. That means 3 s are required to recognize a complete movement. However, in real-world taking action after 3 s in a virtual environment are not be satisfying for the patients. As such, sequential algorithms like CGRNN, LSTM can be considered because they provide fast results. On the other hand, new inputs can be used with old input and each time, movements can be recalculated for future applications. The developed machine learning model works person-dependent. The training process and data labeling are required for each participant who will use this system. In the future, if the dataset contains a large number of observations, it may be possible to work independently.

In order to productionize the proposed ensemble model, it can be deployed into a microservice ecosystem. In this way, a platform-independent service that a wearable sensor system can invoke is created. RESTful APIs (e.g., FastAPI) is the most preferred approach to tackle this problem. Thus, a system that performs prosthetic control can use the machine learning model.

There are several aspects that could affect the results exposed to the real-world scenarios. First, the presented system considers specific movements and does not include every possible movement of the patient. This can be a limiting factor for some movements. Second, our dataset consists of data points from 38 amputees and 25 healthy

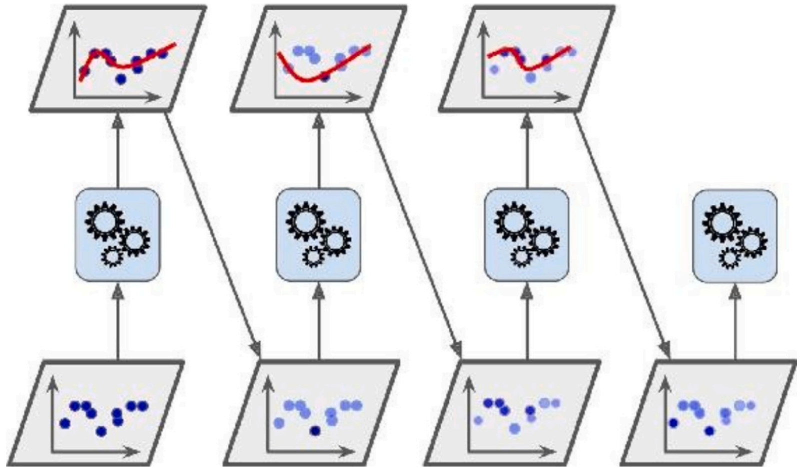

Fig. 6. Boosting structure.

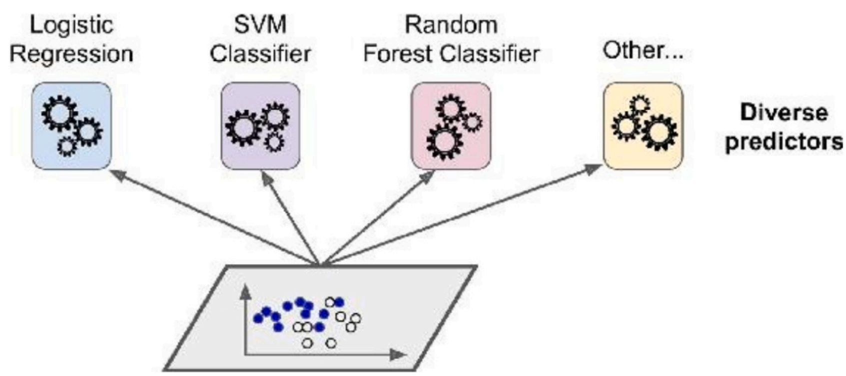

Fig. 7. Voting structure.

Table 7
Overall comparison of machine learning models (H:Healthy, A:Amputee).

SVM	TAWD		TAED		TAAD		TAKD		Average	
	H	A	H	A	H	A	H	A	H	A
Basic	68.25%	–	87.33%	58.33%	83.66%	63.15%	88.66%	63.09%	81.97%	61.52%
Bagging	67.06%	–	87%	41.66%	77.66%	61.40%	84.33%	61.90%	79.01%	54.98%
Boosting	64.08%	–	81.66%	45.83%	77.66%	66.37%	84.33%	63.09%	76.93%	58.43%
Voting	64.28%	–	92%	79.16%	85%	75.43%	93.33%	71.42%	83.65%	75.33%
DT	H	A	H	A	H	A	H	A	H	A
Basic	57.93%	–	86.33%	62.5%	82%	71.63%	82.66%	61.9%	77.23%	65.34%
Bagging	68.84%	–	90.33%	54.16%	86.66%	66.66%	90.33%	76.31%	84.04%	65.65%
Boosting	54.16%	–	85.66%	66.66%	78.33%	70.76%	81.66%	63.09%	74.95%	66.83%
Voting	64.28%	–	92%	79.16%	85%	75.43%	93.33%	71.42%	83.65%	75.33%
kNN	H	A	H	A	H	A	H	A	H	A
Basic	74.40%	–	96.33%	70.83%	87.66%	78.94%	91%	60.71%	87.34%	70.16%
Bagging	71.82%	–	92%	70.83%	85.66%	74.26%	94%	73.8%	85.87%	72.96%
Voting	64.28%	–	92%	79.16%	85%	75.43%	93.33%	71.42%	83.65%	75.33%

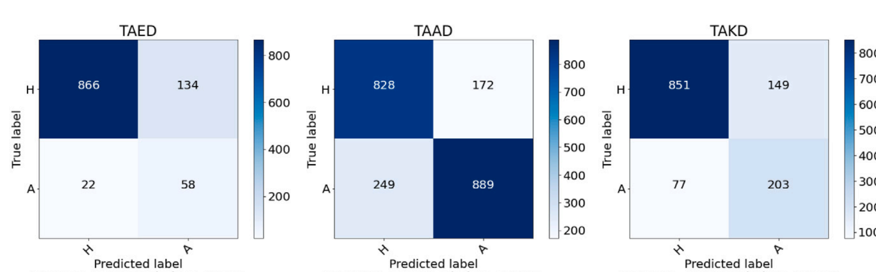

Fig. 8. Confusion matrices of (a) TAED, (b) TAAD, and (c) TAKD.

individuals. However more data points would make our system more generalizable. The system's performance might be different in some rare cases because the system did not encounter with all possible patients. Third, the complexity of the presented model might be a limiting factor. For a very large dataset, the training time and the required computing power can be too much compared to the presented system. Last but not the least is related to the data collection period, which was set to 3 s during the experiments. This might not be feasible in real-world scenarios. Therefore, faster algorithms might be required in this case.

6. Conclusion

In this study, the ensemble learning-based approach outperformed the SVM, Decision tree, and kNN methods. For amputated participants, voting employed an ensemble learning approach received an accuracy of 75% in phantom movement recognition. This result was considered sufficient for the perception of basic phantom movements and their use in cyber-therapy systems. While the accuracy of the movement pattern recognition in healthy individuals was up to 96.33%, this rate was at most 79.16% in amputees. The kNN was found to be the most successful method in recognizing and classifying PME when compared to other classification methods. In addition, the kNN method recognized the phantom movements of the below-knee and above-elbow amputees with higher accuracy compared to other regions (78.94% and 79.16%, respectively). Classification for many different amputation sites, comparison of the accuracy rates of different classification methods, and the number of samples being higher than the studies in the literature, are the strengths of our study. The limitations of our study are that the sEMG used is 2-channel and the signal regions taken from the stump are limited, and there is no sample available for trans-radial amputees. In the future, there is a need for studies with high sample size in which multi-channel sEMG is used, real-time and offline classification are evaluated and compared with different classification methods.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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