A Subject-Transfer Framework Based on Single-Trial EMG Analysis Using Convolutional Neural Networks

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***Abstract*—In recent years, electromyography (EMG)-based practical myoelectric interfaces have been developed to improve the quality of daily life for people with physical disabilities. With these interfaces, it is very important to decode a user's movement intention, to properly control the external devices. However, improving the performance of these interfaces is difficult due to the high variations in the EMG signal patterns caused by intra-user variability. Therefore, this paper proposes a novel subject-transfer framework for decoding hand movements, which is robust in terms of intra-user variability. In the proposed framework, supportive convolutional neural network (CNN) classifiers, which are pre-trained using the EMG data of several subjects, are selected and fine-tuned for the target subject via single-trial analysis. Then, the target subject's hand movements are classified by voting the outputs of the supportive CNN classifiers. The feasibility of the proposed framework is validated with NinaPro databases 2 and 3, which comprise 49 hand movements of 40 healthy and 11 amputee subjects, respectively. The experimental results indicate that, when compared to the self-decoding framework, which uses only the target subject's data, the proposed framework can successfully decode hand movements with improved performance in both healthy and amputee subjects. From the experimental results, the proposed subject-transfer framework can be seen to represent a useful tool for EMG-based practical myoelectric interfaces controlling external devices.**

***Index Terms*—Subject-transfer framework, myoelectric interfaces, electromyography, convolutional neural networks.**

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I. INTRODUCTION

RECENT advances in pattern recognition and machine learning techniques within the field of signal processing have allowed a user's movement intentions to be recognized through analysis of their bio-signals. In particular, electromyography (EMG)-based intention recognition, also known as myoelectric interface, has become a useful technology due to its ease of use and noninvasiveness [1], [2]. Myoelectric interfaces have the advantage of being able to interact with both the user and external devices. From this, rehabilitation devices controlled by myoelectric interfaces have emerged as a new technology, one that allows a more efficient interaction with the environment for both able-bodied and disabled people as they perform everyday activities. Examples of these external devices include arm prosthetics [3]–[8], teleoperation robots for extreme environments [9] and gaming interfaces [10]. These techniques are capable of recreating the natural intention of actual movements.

The overall architecture of the myoelectric interface for a control device is illustrated in Fig. 1. The acquired EMG signals are preprocessed to remove noise or artifacts. Then, suitable features are extracted and classified using pattern recognition and machine learning techniques. Based on the output of the classifier, the user's movement intentions are recognized for interfacing with external devices. Various features within the time and frequency domains as well as numerous types of optimal classifier have been extensively investigated in attempts to improve the performance of movement intention classification techniques, with varying degrees of success [11]–[15].

However, most of the research efforts looking at advancing the practical applications of myoelectric control have revealed a gap between the research findings and clinically viable implementations [8]. This gap is mainly formed by the intra-user variability problem present in EMG characteristics. Intra-user variability means that the EMG characteristics show a nonstationary distribution over long-term usage, caused by physiological changes. It is attributable to several factors, such as electrode displacement, signal crosstalk, and the EMG signal recording environment system [15], [16]. Variations in EMG signal distributions can occur even between trials for the same subject. This variation can limit the long-term uses of EMG-based external device control. The classifier can

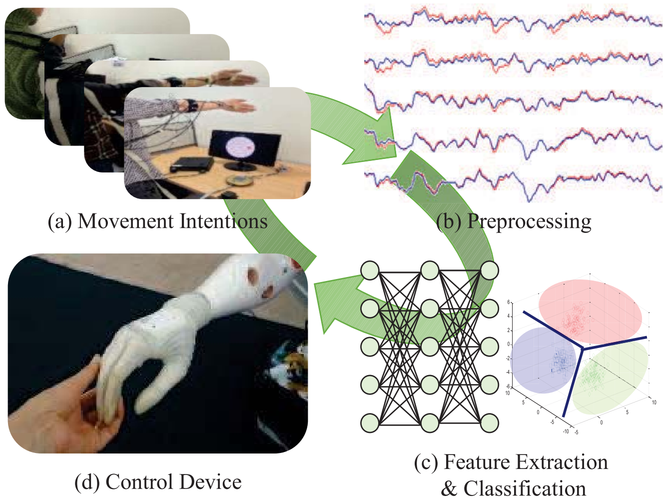


Fig. 1. Overview of myoelectric interface for control devices, using pattern recognition and machine learning.

be trained by asking users to repeat a calibration protocol, though this is inefficient and inconvenient, as the number of movements required of the user is increased considerably, even when the calibration time is only few minutes.

Various approaches based on pattern recognition and machine learning techniques have been applied to the task of eliminating the burden of calibration protocols. Notably, a self-adaptation system that can recalibrate using only the predicted intention of the user has been developed, to enhance the robustness of EMG-based user intention recognition [17]–[21]. Sensinger *et al.* [17] proposed supervised and unsupervised adaptive paradigms, to expand the training dataset by including online data along with their predictions. The experimental results showed that all the adaptative paradigms were able to reduce the error margins present in the non-adapting classifier. However, because of this additional data, the performance of the classifier could, in fact, degrade. Obtaining the adaptive paradigm which best reduces this degradation remains an open question. Tommasi *et al.* [18] proposed an adaptation approach based on multiple pre-trained models, which utilized a support vector machine (SVM). However, the proposed method was evaluated using only 7 classes of small hand movement. Therefore, experiments with more classes are required before control of various external devices is possible. Matsubara and Morimoto [19] devised a bilinear model of EMG signals consisting of user- and motion-dependent features. They separated the user-dependent EMG signals from the signals associated with movements, using a training step. A multiclass SVM was then trained with the motion-dependent data. Subsequently, the user-dependent features were extracted by providing new data, which was then inputted to the existing model after observing one trained movement modeled by the SVM. However, the dimensions of the user- and motion-dependent features were selected experimentally, something which remains a persistent limitation. Liu *et al.* [20], [21] used an adaptive linear discriminant analysis approach to compensate for the non-stationarity in EMG signals. The pre-trained classifiers were adapted using a new short-labeled dataset that was collected daily. They demonstrated an improved accuracy over the non-adapting classifier, but used the prediction results directly, which may have included data that was incorrectly classified.

Recently, the convolutional neural network (CNN) has emerged as one of the most powerful machine learning approaches [22]. Following the advances in computing power obtained via the development of graphics processing units (GPUs), the CNN has now been applied to the recognition of user intention in several myoelectric interface studies [23], [24]. Zhai *et al.* [24] proposed a CNN-based framework for hand movement classification based on reduced-dimension EMG spectrograms using principal component analysis (PCA). In addition, by combining a CNN with a median-based label updating mechanism, the proposed framework provided an effective self-recalibration procedure to maintain stable performance.

In this study, we aim to develop a CNN-based subject-transfer framework that can improve the classification accuracy for hand movements within non-stationary EMG signals. The main hypothesis of the subject-transfer strategy is that the characteristic patterns of the EMG signal between the target subject and other subjects may be similar for the same task. Therefore, the data of other subjects can help in the intention recognition of the target subject. This hypothesis has shown great success in another field of research, namely electroencephalography-based brain-computer interface studies [25]–[27].

In the proposed subject-transfer framework, the supportive CNN classifier for other subjects' EMG data is used instead of using other subjects' data directly. First, effective pre-trained CNN classifiers are selected as supportive classifiers using the first trial of the target subject. Then, the selected CNN classifiers are fine-tuned from the first trial of the target subject. Finally, the classification for subsequent trials of the target subject is determined by voting the outputs of the fine-tuned supportive CNN classifiers. To validate the proposed framework, we compare its classification performances with the self-decoding framework using the time domain and auto-regressive (TDAR) features and SVM which were widely used in EMG studies, and the self-decoding framework with CNN [24] which has shown good performance on the NinaPro databases 2 and 3 [28], [29].

The remainder of this paper is organized as follows. Section II presents the benchmark database and details the proposed subject-framework. Section III presents the experimental results, which are then discussed, along with the proposed framework, in Section IV. Finally, our conclusions and future plans are presented in Section V.

II. Materials and Methods

A. Benchmark Database

In this study, the NinaPro databases 2 and 3, which contain tasks relating to upper-limb movement, are used for the experiments [28], [29]. NinaPro is a publicly accessible database that has been previously used in myoelectric interfaces for decoding hand movements. In database 2 (DB2), the EMG data

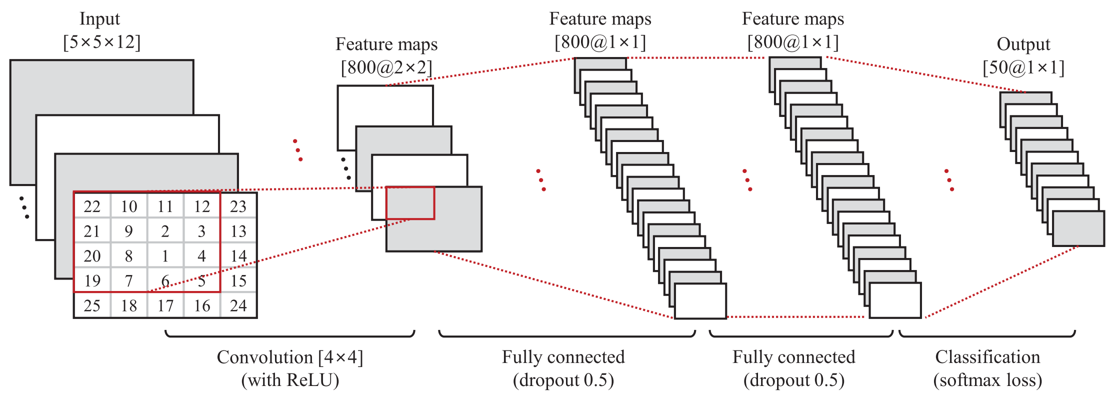


Fig. 2. The 25 principal components (PCs) were extracted and reshaped into a 2D matrix, then rearranged in such a way that the most significant PC sits at the center of the matrix. Then, 800 filters of size 4 × 4 convolved with the PCs, and fully connected the feature maps for classification.

from 40 healthy subjects (12 females, 6 left handed and aged 29.9 ± 3.4 years)who performed 49 movements (8 isometric and isotonic hand configurations, 9 basic wrist movements, 23 grasping and functional movements and 9 force patterns) relevant to the activities of daily living are present in the database. Database 3 (DB3) comprises data from 11 transradial amputees with disabilities of the arm, shoulder, and hand, containing a score ranging from 1.67 to 86.67 (on a scale of 0-100) for each subject's ability to perform the same hand movements as in DB2 [24]. In the experimental set-up, each movement was repeated 6 times with a 3-s rest period between. The EMG signal was recorded using 12 electrodes of a Delsys Trigno Wireless system, which provides a sampling rate of 2,000 Hz. Then, the recorded signal was filtered with a Hampel filter to remove the 50 Hz power line interference. The electrodes were positioned to combine a dense sampling approach [30]–[32] with a precise anatomical positioning strategy [2], [32]. Eight electrodes were positioned around the forearm at the height of the radiohumeral joint, a constant distance from each other. Two electrodes were placed on the main activity spots of the flexor and extensor digitorum superficialis [29]. The last two electrodes were placed on the main activity spots of the biceps and triceps brachii. More details about the acquisition setup are provided in the official database [28].

B. Data Preprocessing

The data preprocessing followed the method used in the studies already published [24], [33]. The EMG signals were sectioned into 200-ms (400 samples) segments with a 100-ms (200 samples) overlap. Because the delay is less than 300 ms, it is considered sufficient for continuous classification in real-world applications [34]. Additionally, a number of segments for all movement types (including rest) were balanced in this study to minimize the bias in accuracy calculations [24]. Then, each segment (with each channel) is processed independently for extraction of the spectrogram and for normalization. The spectrogram of each segment is extracted using a 256-point fast Fourier transform with a Hamming window and 184-point overlap. Hence, the spectrogram is calculated at 129 different frequencies (0-1,000 Hz) with three time bins. Only the first 95 frequencies of the spectrogram are used, as the major energy of the EMG is observed within a frequency range of 0-700 Hz. Therefore, the size of each spectrogram is 95 × 3 × 12 (frequency × time bins × channels). Then, before performing the PCA, the spectrograms are converted into a range of 0-1 via maximum-minimum normalization [33].

To apply PCA, the normalized spectrograms are vectorized at the channel to improve computational efficiency and performance. PCA is applied to the spectrogram to reduce the dimensionality whilst retaining the useful information from the EMG signals. Then, because the first 100-500 principal components (PCs) are sufficient to achieve good performance [33], only the scores of the first 25 PCs of each channel are used as an input to the classifier. As a result, each spectrogram is reduced to a dimension of 25 × 12 (PCs × channels).

C. CNN Architecture

Fig. 2 shows a schematic for the CNN architecture used in the proposed framework. The CNN is composed of the following four parts. The first part is a convolutional layer with 800 filters of size 4 × 4. The second part is a rectified linear unit (ReLU), which acts as a non-linear activation function. The ReLU is used to avoid the vanishing gradient problem [35]. The third part contains two fully connected layers with a size of 800 (dropout rate of 0.5). The fourth part is a softmax loss layer used for classification. The softmax loss layer computes the cost function using the normalized exponential function. It also outputs the probabilities of all the movement types considered in the current prediction. After several tests, the CNN was trained using a stochastic gradient descent method with a momentum of 0.9; the learning rate was set to 0.001; and the batch size was fixed at 256. An open-source MATLAB toolbox (MatConvNet) was used to implement the CNN classifier [36]. Computations using the CNN were performed with the NVIDIA CUDA Deep Neural Network library, which was trained on two NVIDIA Titan Xp GPUs [37].

D. Subject-Transfer Framework

Fig. 3 shows a schematic for our subject-transfer framework. This framework is proposed for applying existing CNN models from other subjects to a target subject. The main hypothesis

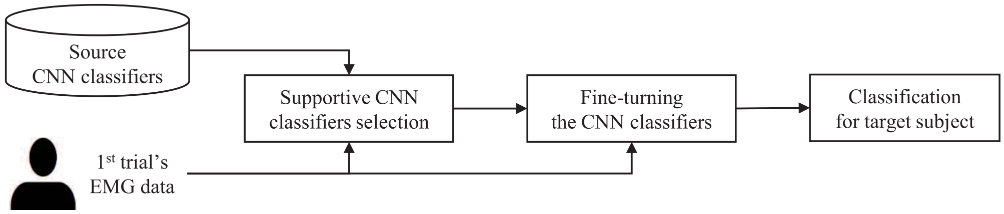


Fig. 3. Block diagram of the proposed subject-transfer framework. The supportive CNN classifiers are selected using the first trial of the target subject. Then, the supportive CNN classifiers are fine-tuned for to classify a subsequent trial the target subject.

of the proposed framework is that the characteristic patterns of the EMG signal between the target subject and the other subjects may be similar for the same tasks. Therefore, when sufficient pre-trained CNN classifiers from other subjects are available, it is possible to achieve high decoding performance by transferring multiple existing CNN models to the target subject. In addition, the decoding performance obtained using the subject-transfer approach could be high compared to that obtained using a self-decoding model trained using only EMG data from the first trial of the target subject.

1) Source CNN Classifiers: First, the source CNN classifiers are pre-trained using the EMG data of all the trials (6 repetitions in each hand movement) from all other subjects (excluding the target subject).

2) Supportive CNN Classifiers Selection: The pre-trained source CNN classifiers are ranked according to the classification accuracy for the first trial of the target subject's hand movements. Then, several CNN classifiers that show better performance are selected as the supportive CNN classifiers for decoding the hand movements of the target subject (10 supportive CNN classifiers were used in our experiments).

3) Fine-Turning the CNN Classifiers: All the selected supportive CNN classifiers are fine-tuned using the first trial of the target subject's hand movements, to adapt them to the characteristics of the target subject.

4) Classification for Target Subject: For classifying the new trial (each test trial) of the target subject, all the fine-tuned supportive CNN classifiers decode the new trial and assign it to one of the hand movements. Then, the outputs of the fine-tuned classifiers are voted for final classification. Assume that L^{new} denotes the predicted label for a new trial of the target subject. The label is predicted based on the output that was most commonly classified by the supportive CNN classifiers.

$$L^{new} \leftarrow mode(L^1, L^2, \ldots, L^{i-1}, L^i) \tag{1}$$

where L^i denode the output of i^{th} supportive CNN classifiers (in our experiments, $i = 10$).

E. Performance Evaluation

1) Classification Accuracy: The classification accuracy is defined as the ratio between the number of correctly classified segments and the total number of testing segments, in each trial. The accuracy, Acc_k for the target subject k is calculated as,

$$Acc_k = \frac{1}{M}\sum_{n=1}^{M}\left[\frac{\#\ of\ correct\ segments}{\#\ of\ total\ segments}\right]_n \tag{2}$$

where M is the total number of movement types. The class-specific accuracy is understood to be a preferred metric over global accuracy, for quantifying the performance of the classifier [38], [39].

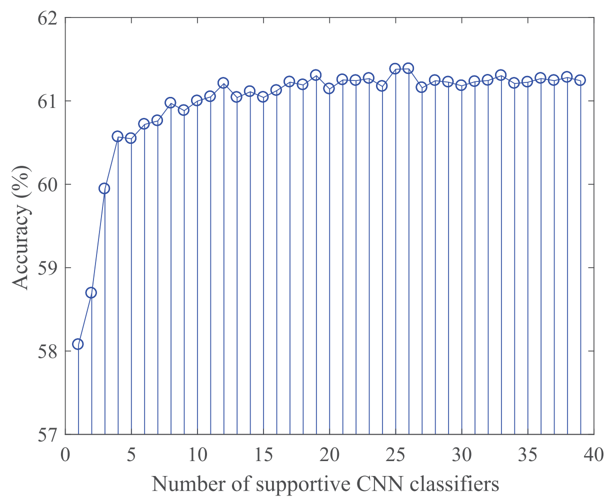


Fig. 4. Averaged classification accuracy across different numbers of supportive CNN classifiers in the randomly selected 20 healthy subjects (DB2).

2) Statistical Analysis: For better quantitative comparison between the proposed subject-transfer and self-decoding frameworks, we performed statistical analysis via the t-test and the Wilcoxon rank sum test. In each figure, $*$ means $p < 0.05$ and $**$ means $p < 0.01$. Unless specified, all the results are presented as $p < 0.05$.

III. Experimental Results

A. Performance Evaluation With Healthy Subjects (DB2)

To investigate the effects of the number of supportive CNN classifiers employed, we first implemented an experiment that could confirm the accuracies in terms of this number. In this experiment, 1-39 CNN classifiers trained by other subjects (1-39 subjects excluding the target subject) were used as supportive classifiers. Fig. 4 shows the average accuracy of a test trial of 20 subjects who were selected randomly from DB2. Of the six repetitive hand movement trials administered to each subject, the first was used for selecting the supportive

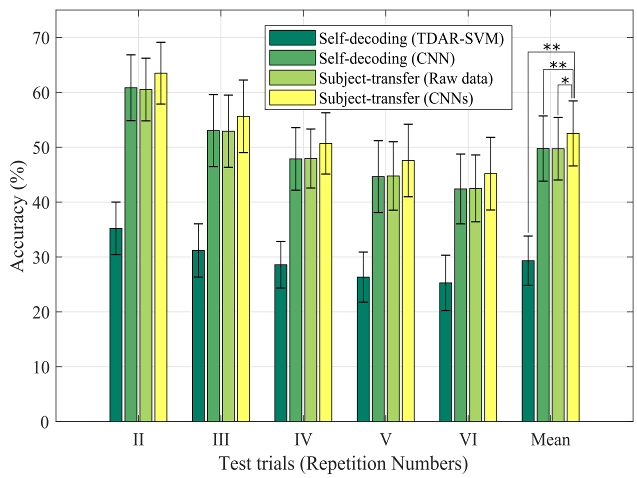


Fig. 5. Classification restults within the self-decoding (TDAR-SVM), self-decoding (CNN), subject-transfer (Raw data), and subject-transfer (CNNs) frameworks in the DB2 ($*$ means $p < 0.05$ and $**$ means $p < 0.01$).

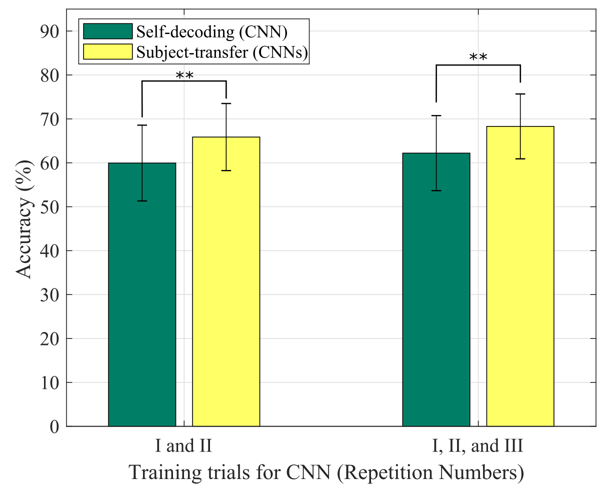


Fig. 6. Classification restults of the self-decoding (CNN) and subject-transfer framework (CNNs) within two and three training trials.

CNN classifiers and fine-tuning those selected, and the second trial was used as the test trial. Consequently, using 10 supportive classifiers showed good performance, while using more than 10 classifiers did not lead to any significant improvement. Therefore, for the proposed subject-transfer framework, we used 10 CNN classifiers as supportive classifiers in all experiments for healthy (DB2) and amputee subjects (DB3).

Fig. 5 shows the classification results obtained with two self-decoding frameworks and the two subject-transfer frameworks:

- Self-decoding (TDAR-SVM): In general, the TDAR features are widely used in the EMG analysis [15]. In this framework, the mean absolute value, zero crossings, slope sign change, waveform length, and auto-regressive feature were used as the TDAR features. Then, the SVM was used as a classifier. The SVM classifier was trained only from the TDAR features of the first trial (repetition 1) of the target subject's hand movements.
- Self-decoding (CNN): The self-decoding framework was proposed in [24] by Zhai *et al.* In this framework, a randomly initialized CNN classifier was also trained only by the first trial of the target subject's hand movements.
- Subject-transfer (Raw data): In this framework, subject-transferal took as raw data the selected supportive subjects instead of the trained CNN classifier. This framework was implemented for a performance comparison between the use of raw data from the supportive subjects and that of a CNN trained with the data of the supportive subjects. In the subject-transfer (Raw data) framework, a CNN classifier was trained by all the raw data from 10 subjects who were selected as supportive subjects. The trained CNN classifier was then fine-tuned to the first trial of the target subject.
- Subject-transfer (CNNs): In the proposed framework, 10 supportive CNN classifiers, which were pre-trained by each supportive subject's raw data, were selected and fine-tuned to the first trial of the target subject.

As shown in Fig. 5, the proposed framework (subject-transfer (CNNs)) exhibits the highest accuracy for each test trial (repetitions 2-6). The averaged accuracies (50 classes) showed 29.32%, 49.76%, 49.73%, and 52.52%. The proposed framework shows a substantial performance improvement of 23.2% than the self-decoding (TDAR-SVM) framework. The proposed framework also shows performance improvements about 3% over compared to the self-decoding (CNN) and the subject-transfer (Raw data) frameworks. Furthermore, the statistical analysis revealed statistical significances between the proposed framework and other frameworks. Subsequently, using the CNN classifier, which was pre-trained using other subjects' data, yielded a better performance than that of using the raw data of other subjects. Based on these experimental results, we can conclude that the proposed framework can help improve the decoding accuracy of the hand movements in healthy subjects.

Fig. 6 shows the classification results with two training trials (repetitions 1-2) and three training trials (repetitions 1-3). In practice it would not be difficult to implement two or three repetitions. Consequently, the self-decoding (CNN) and proposed subject-transfer (CNNs) frameworks were implemented with two and three training trials in these experiments, to investigate the decoding performance. As a result, the proposed framework performs better in each training set. These results demonstrate that the proposed framework is more effective than the self-decoding framework, even for two or more training trial sets.

Fig. 7 shows the decoding accuracies within various electrode sets, to validate the effectiveness of the proposed subject-transfer framework (CNNs). In practice it is difficult to attach the electrodes to general and specific places, such as the main activity spots of extensor digitorum supercialis, depending on the user's type. Therefore, to consider the various user types we also investigated the decoding performance within three electrode sets. In the NinaPro dataset, the electrodes were attached at generic placements (eight around the forearm) and specific placements (the two main activity spots of the exor and

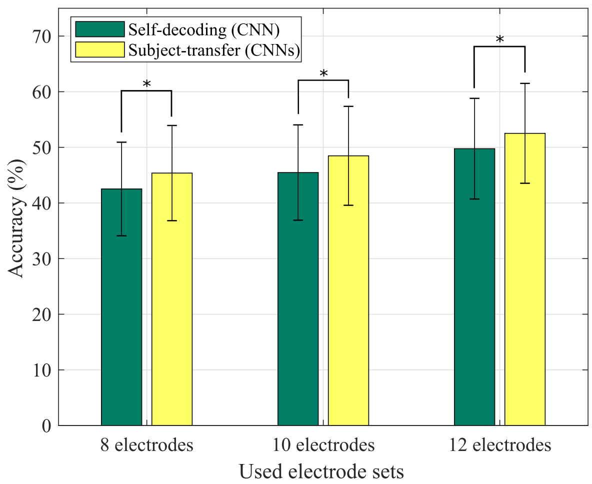


Fig. 7. Classification results with three electrode sets (eight around the forearm, two at the two main activity spots of the exor and extensor digitorum supercialis, and two at the two main activity spots of the biceps and triceps brachii).

extensor digitorum supercialis, and the 2 main activity spots of the biceps and triceps brachii). Therefore, the electrode sets comprised the following:

- 8 electrodes: 8 electrodes around the forearm.
- 10 electrodes: The 8 electrodes set plus the 2 main activity spots of exor and extensor digitorum supercialis.
- 12 electrodes: The 10 electrodes set plus the 2 main activity spots of the biceps and triceps brachii.

In Fig. 7, the proposed subject-transfer framework (CNNs) shows better performance in all electrode sets. The results were calculated as the average of all the test trials (repetitions 2-6 in all healthy subjects). Based on these experimental results, we confirmed that the accuracies of hand movement decoding methods are higher when a higher number of electrodes are attached. Furthermore, we can conclude that the proposed subject-transfer framework (CNNs) has better performance in all electrode sets.

B. Performance Evaluation With Amputated Subjects (DB3)

We also tested the proposed subject-transfer framework (CNNs) on the amputee subjects in NinaPro database 3 (DB3). In the aforementioned experiments with DB2, all subjects were able-bodied, implying that they are far more anatomically similar to each another than to the amputee subjects. Because of the similarity, the proposed subject-transfer framework may show better performances than the self-decoding framework. Therefore, the objective of these additional experiments was to confirm that the proposed framework shows better performance than self-decoding frameworks, even for amputee subjects.

Fig. 8 shows the classification results with two self-decoding frameworks and three subject-transfer frameworks:

- Self-decoding (TDAR-SVM) and Self-decoding (CNN): The same framework as previously mentioned for DB2.
- Subject-transfer (Healthy): In this framework, the subject-transferal used supportive CNN classifiers from only healthy subjects. This framework was implemented to confirm that the CNN classifiers from healthy subjects can be used for amputee subjects.
- Subject-transfer (Amputee): In this framework, the subject-transferal used supportive CNN classifiers from only amputee subjects.
- Subject-transfer (All): In this framework, subject-transferal was conducted using supportive CNN classifiers from healthy and amputee subjects. The objective of this framework was to confirm how many CNN classifiers from healthy subjects to select when classifying hand movement decoding for amputee subjects.

For Fig. 8, we omitted two amputee subjects (Sub7 and Sub8) from the database, as they had only 10 electrodes owing to insufficient space on their stump. The results show that the subject-transfer framework has better performance than other frameworks. Specifically, the subject-transfer (Amputee) framework shows the best performance for each test trial. These results prove that the subject-transfer strategy can help decode the hand movements of amputee subjects via EMG signals.

Fig. 9 shows the decoding accuracies within the three electrode sets that were previously used for DB2. In healthy subjects, we are generally able to attach the EMG electrodes to their standard positions; however, this may not be possible for an amputee. Therefore, we investigated the performances of the proposed subject-transfer framework within three electrode sets for the amputee subjects. Because it is very difficult to attach the electrode to the same place for each amputee subject, we wanted to explore the possibility of solving these electrode placement issues. The results were calculated as the average of all test trials (repetitions 2-6 in all amputee subjects), similar to DB2. In the results, the proposed subject-transfer framework (CNNs) shows better performance in each electrode set than the self-decoding framework (CNN), even with amputee subjects. Based on these results, we confirm that the proposed framework can help amputee subjects despite the issue of electrode placement.

IV. Discussions

A. Decoding of Hand Movements With the Subject-Transferring

In our experiments, we applied a subject-transferal method to improve the decoding accuracy for the hand movements of healthy and amputee subjects. In Fig 5, the averaged classification results show that the proposed subject-transfer framework (CNNs) can classify hand movements more effectively in each trial (DB2). Fig. 10 illustrates in detail the differences in classification performance between the self-decoding and subject-transfer frameworks for all subjects. The largest difference in each test trial was observed in Sub35 with 6.77%, and the smallest difference was observed in Sub10 with 0.03%. These results mean that the proposed method might not be effective for some subjects, but subject-transferal can help to improve accuracy in general. Fig. 11 also shows the same results for the amputee subjects (DB3) with 10 electrode sets. The largest difference in each test trial was observed in Sub3 with 6.68%,and the smallest difference was observed in Sub10 with 0.66%.

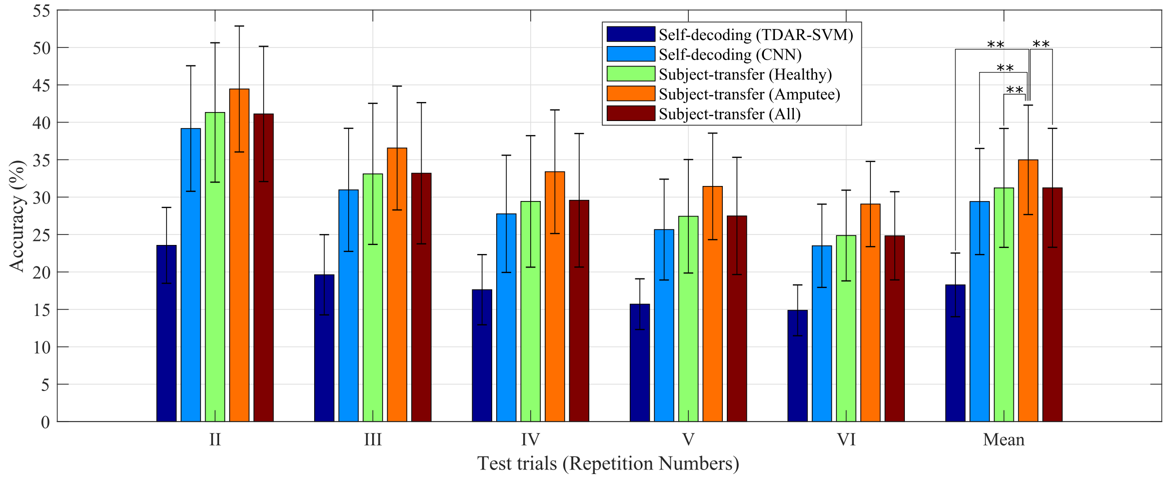


Fig. 8. Classification results within the two types of self-decoding (TDAR-SVM and CNN) and three types (healthy, amputee, and all) of subject-transfer framework (CNNs). In each subject-transfer framework, supportive subjects were selected in healthy subjects only, amputee subjects only and all subjects, respectively.

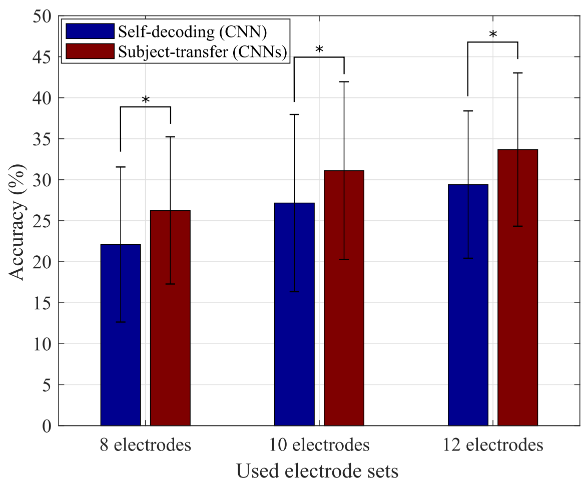


Fig. 9. Classification results with three electrode sets (same sets as in DB2). For the classification accuracy within the 12 electrode sets, only 9 subjects' data was used because Sub7 and Sub8 attached only 10 EMG electrodes.

Based on these results, we conclude that the proposed subject-transfer framework did not always improve the accuracy for all subjects, including amputee subjects. We also concluded that additional experiments are required to address this issue, and these will be conducted with more subjects (healthy and amputee) in future work. In this study, we focused on the validation of the effectiveness of the proposed framework. Therefore, the scope was limited to offline data and experiment. Additionally, the EMG data in Ninapro dataset was collected ideally within a conditioned environment. This is a limitation of our experiments. For an online scenario, the proposed framework has to be validated for effectiveness in real-world environments.

B. Supportive CNN Classifiers for the Target Subjects

Regarding the subject-transfer approach, recent work [40] showed that subject-transferal is not effective for healthy subjects. Specifically, the experimental results showed that the subject-transfer method can be ineffective, via hyper-parameter optimization of the SVM classifier. However, more experiments are required to confirm the ineffectiveness, because the experiments were conducted using only the SVM classifier. Additionally, experiments validating effectiveness with healthy subjects were not conducted in this study because the CNN classifier showed better decoding performance than the SVM classifier in recent work [24]. However, to be clear about this issue, we plan to analyze the effectiveness of the proposed subject-transfer framework for healthy subjects via another database.

Interestingly, in Fig. 8, the classification results for the 'Subject-transfer (Healthy)' and 'Subject-transfer (All)' framework were almost matched in every test trial. Therefore, we investigated the selected supportive CNN classifiers in the 'Subject-transfer (All)' framework. Fig. 12 shows the selected supportive CNN classifiers for hand movement decoding for the amputee subjects. The results show that the supportive CNN classifiers for amputee subjects were almost always selected from healthy subjects. Consequently, it can be inferred that the classification results were calculated to be similar in every test trial because the supportive CNN classifiers were primarily selected from the healthy subjects.

In fact, the highest decoding performance was exhibited when the supportive subjects were selected only from the amputee set, as shown in Fig. 8. This could imply that an incorrect supportive CNN classifier (from the healthy subject group) is selected during the 'Supportive CNN classifiers selection' step shown in Fig. 3. In the proposed framework, the supportive CNN classifiers were selected using only the classification results of the target subject's first trial, without using any advanced selection method. Therefore, in future work, we will apply the advanced selection method (such as the multiple distance measurement-based selection of [27]) to our subject-transfer framework, to solve the selection issue.

C. Self-Recalibration With Subject-Transferring

Recently, an efficient self-recalibration method was developed for real-world prosthetic applications [24]. To validate the

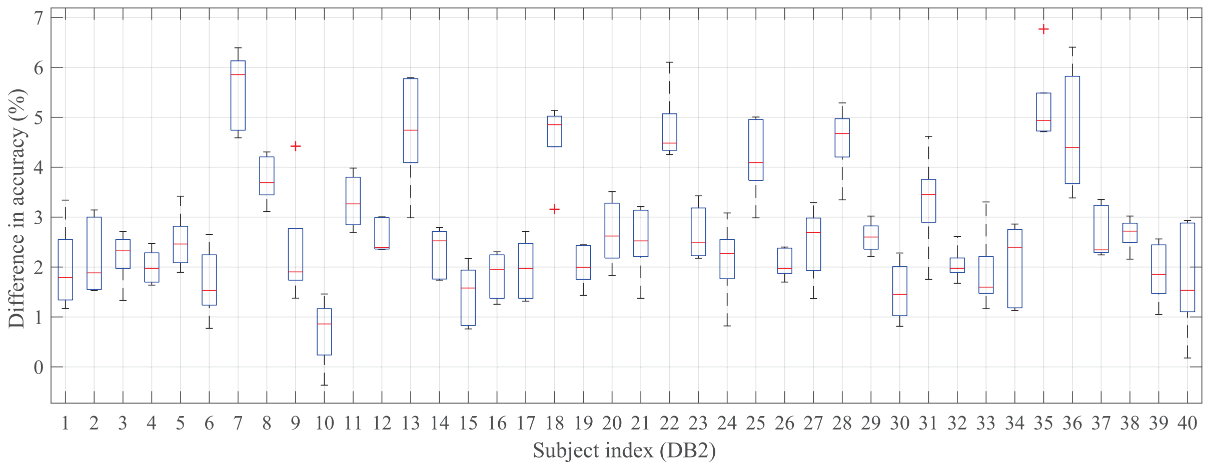


Fig. 10. The difference of classification accuracy in each healthy subject (DB2) between the proposed framework and the self-decoding framework ($p < 0.05$).

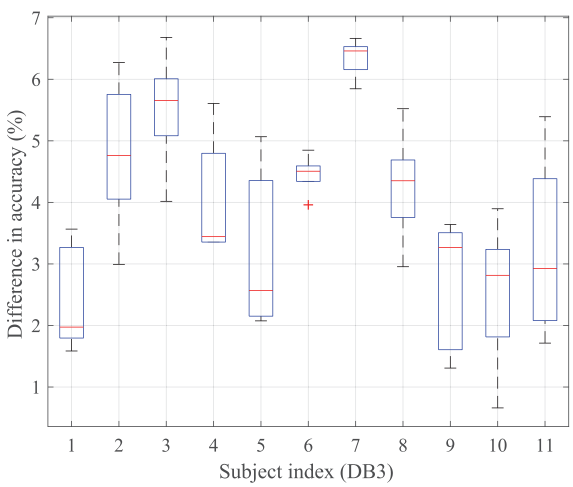


Fig. 11. The difference of classification accuracy in each amputee subject (DB3) between the proposed framework and the self-decoding framework ($p < 0.05$).

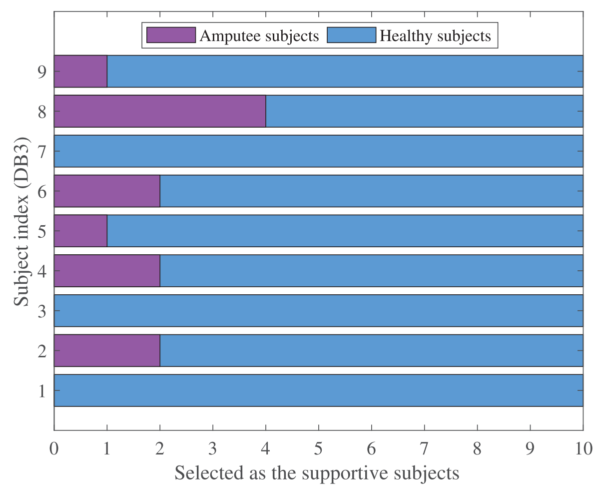


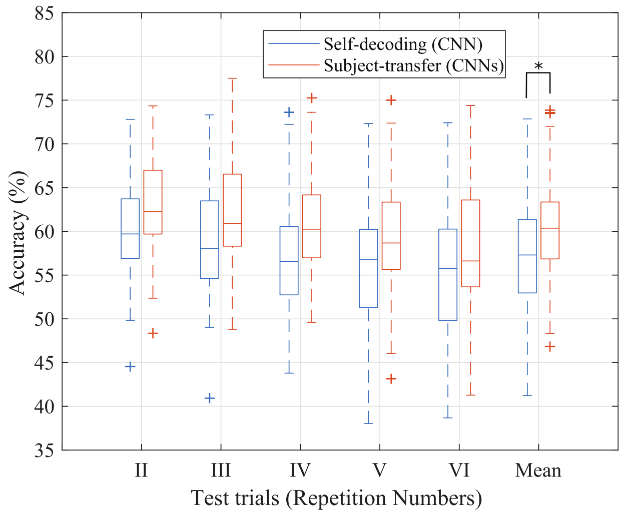
Fig. 12. Selected supportive CNN classifiers from healthy and amputee subjects for amputee subjects.

effectiveness of our proposed subject-transfer framework we used this self-recalibration method. In the method, the prediction results from the previous trial (the adjacent ± 15 segments) are re-inputted to retrain the classifiers prior to each testing trial. To investigate the effects of the proposed subject-transfer framework, we applied the self-recalibration method and conducted additional experiments using DB2 and DB3.

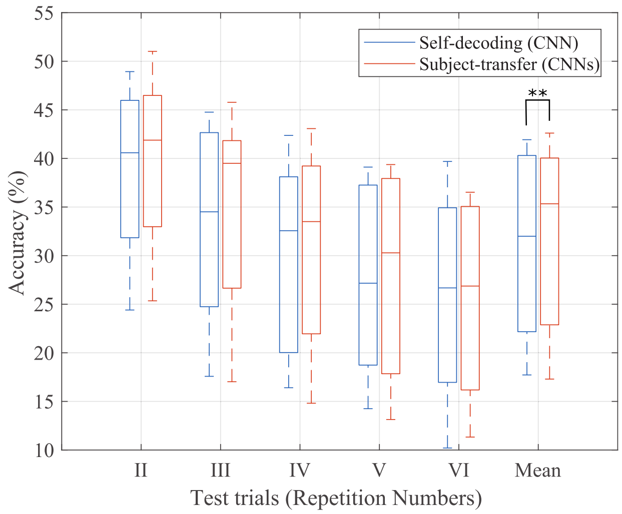
The objective of these experiments was to confirm that after subject-transferal, the supportive CNN classifiers would be well retrained and adapted, based on the predictions from previous trials. This is because in the proposed framework the supportive CNN classifiers were trained with all trials, including the trial-to-trial variability of other subjects. For each experiment, only the first repetition was used as the fine-tuning data. The first testing trial was performed on repetition 2, after which the predicted labels were updated using the prediction from the most recent testing trial. Subsequently, the supportive CNN classifiers were retrained by the updated labels. The same procedure was repeated for the other test trials (repetitions 3-6).

The average decoding performance in each database (DB2 and DB3) with the self-recalibration method is shown in Fig. 13. With healthy subjects (Fig. 13a), the average decoding performance showed that the proposed framework outperforms the self-decoding one. Furthermore, the differences between the first and last test trials were 4.22% and 4.69% in the proposed and self-decoding frameworks respectively. This means that the proposed framework showed a lower loss of accuracy than the self-decoding framework.

In the amputee subjects (Fig. 13b), the results revealed that the proposed framework is slightly better than or similar to the self-decoding framework. It can be interpreted that the proposed framework has no effect on the classification performance for amputee subjects when using the self-recalibration method. However, for DB3, all subjects (excluding the target subject) were selected as the supportive subjects because there were only 9 subjects who attached all 12 EMG electrodes. Therefore, additional experiments with more amputee subjects should be conducted, to validate the effectiveness in amputee subjects. In addition, as these



(a) Healty subjects (DB2)



(b) Amputee subjects (DB3)

Fig. 13. Comparison of classification accuracy between the proposed subject-transfer (CNNs) and the self-decoding (CNN) with self-recalibration frameworks [24].

experiments were an initial step which was conducted offline, additional online experiments are required to test a real-world environment.

Regarding online environments, we also examined training time and classification time when using only a microprocessor (Intel i7-7700K CPU) and when using only a GPU environment. On average, the training time when using the microprocessor was approximately 3 times that required when using the GPU environment. However, for the classification time in each test trial, the microprocessor averaged 3.83 s ($\pm$4.8 s) and the GPU averaged 3.73 s ($\pm$4.7 s). Thus, the training time for the proposed subject-transfer framework is long, but the classification time did not differ greatly. Therefore, if the training time can be decreased via cloud computing, distributed computing and other methods, the proposed framework can improve efficiency in the online environment, even if the self-recalibration strategy is applied.

V. Conclusion and Future Work

This paper presented a subject-transfer framework for improving the performance of hand movement classification. In the proposed framework, the supportive CNN classifiers, which are CNN classifiers pre-trained by other subjects, were ranked and selected by a single-trial EMG analysis. Then, the classifiers were fine-tuned and voted for the classification of hand movements within the target subject. In several experiments examining 50 classes (49 hand movements and rest state) of healthy and amputee subjects (DB2 and DB3), the proposed framework demonstrated better classification accuracy than the self-decoding frameworks. These experimental results validated the feasibility of applying the subject-transfer approach to myoelectric interfaces for real-world applications.

However, the performance of classifying hand movements in each subject depends on many factors, such as muscle fatigue induced by repetitions, experimental environment and signal processing methodology. In future work, we will confirm that the proposed framework can achieve stable performance for greater numbers of amputee subjects through numerous trials and sessions conducted over multiple days. Moreover, online experiments will be implemented in real-world applications, such as 3D games or robotic arms, to validate the feasibility and usability of the proposed framework. We believe that the subject-transfer framework will be more suitable than self-decoding frameworks in several real-world applications.

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