Proceedings of the
7th Graz Brain-Computer Interface Conference 2017 DOI: 10.3217/978-3-85125-533-1-24

TOWARDS A NON-INVASIVE SYSTEM FOR TRANS-HUMERAL AMPUTEE MOTION RESTORATION

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ABSTRACT: There are very few studies that try to solve the motion reconstruction problem, and those few studies focused on rehabilitation of amputee patients. In this paper, we will discuss the major problems in the field and propose possible solutions for them using a rehabilitation perspective considering long-term, real-world applications. In addition, we performed a preliminary study with five subjects using electroencephalography and electromyography, a virtual avatar to obtain the position of the hand, and a set of motions containing a wide range of motions. Among the participants, we obtained a mean correlation value between the real and reconstructed motion that was equal to 0.834. This result exceeds the average in the field, suggesting that our solutions are appropriate to solve the current problems.

INTRODUCTION

Brain Computer Interfaces (BCI) have been used for amputee rehabilitation for many years. It has been especially useful for motion reconstruction problems. Motion reconstruction is the problem of reconstructing or predicting the dynamics of an extremity using bio-signals. Motion reconstruction is important for motion analysis and motor function assessment. In the case of amputees, motion reconstruction can be used to build a prosthetic device that substitutes the original limb using intuitive motions. The motion reconstruction problem can be classified by the extremity reconstructed by the system. In general, the distal part of the extremity (hand or foot) is comparatively easier to reconstruct than the proximally amputated part (arm or leg), because most of the motion related muscles are still present in the distal amputation. This makes it possible to use electromyography (EMG) signals for the reconstruction. There is also a large difference between reconstructing upper limb or lower limb movements. In the case of the leg, the dynamics are well known, and the prostheses are simpler since they reconstruct fewer degrees of freedom. For these reasons, motion reconstruction of the proximally amputated upper limb is the most complex reconstruction. There are two different types of upper limb proximal amputations: trans-humeral and shoulder disarticulation. We focused our study on trans-humeral amputations that, by definition, demonstrate conservation of the *deltoidus* muscle. A full prosthesis is needed to reconstruct every degree of freedom in the arm, including the elbow, wrist, and fingers. Since the shoulder has a few motion-related muscles that help control the hand, it is not possible to reconstruct the hand’s position using only EMG. Thus, BCI is also needed. Concerning the aforementioned limitations, we need to add the limitations that are produced from using the system for rehabilitation. For instance, the system must be able to work in real time, including preprocessing of bio-signals. Also, the accuracy required to build a prosthetic device that is needed for daily life is higher than the accuracy required for normal applications.

Due to the complexity of the task, a simplification is used most of the time. Most commonly, only the position of the hand is reconstructed [1], [2]. We used this simplification as well in this study. Most of the studies that try to solve this problem use a neuroscientific approach, i.e., the main purpose is to determine the brain’s function during motion execution using electroencephalography (EEG). For this reason, we considered it necessary to create a roadmap regarding the problems and the challenges that we must confront to solve it, always keeping in mind the rehabilitation perspective.

In this paper, we present the major problems that the motion reconstruction field faces when applied to rehabilitation, providing possible solutions that can be applied to real-world environments. We divided the system into six parts that are necessary to implement a rehabilitation system. These parts are very similar to those that compose any BCI system. For each part, we provide our analysis of how important the changes are to make the technology available under real-world conditions for trans-humeral amputees.

1. Acquisition system: which signals are used as input for the predictor. The changes needed are not important.
2. Training signal: which signal is used as output for the predictor. The changes needed are critical.
3. Evaluation: the fitness value used for evaluating the system. The changes needed are of high importance.
4. Task: which motion is performed during the training session. The changes needed are of medium importance.
5. Preprocessing: the filters and transformations applied to the signals and the features extracted from them. There are no changes needed.
6. Predictor: the architecture used for reconstructing the signal. There are no changes needed.

 DOI: 10.3217/978-3-85125-533-1-24

We excluded from our analysis the preprocessing and the predictor parts for two reasons. First, both parts are too complex to analyse in just one paper, even individually. The second and more important reason, is that they do not present problems as important as the other parts. Furthermore, these two parts have been revised the most in the literature.

In addition, we performed an experiment implementing the proposed solutions for the acquisition system, the training system, and the task. The preliminary results are presented and discussed to analyse each one of the parts.

MATERALS AND METHODS

In each subsection, we present one of the mentioned parts along with our proposed solution and their implementation.

Subjects

Five healthy right-handed subjects (3 males, 2 females, mean age 28, range 22-40) participated in the experiment. Permission from the Ethics Committee of the Graduate School of Engineering, Chiba University was obtained. All subjects participated voluntarily and gave informed consent without receiving any incentives. Participants were informed that they could stop the experiment at any time.

Acquisition Systems

The first decision we made was which system we used for acquiring the data. When applied to prosthetics, there are two main constraints: the system must be non-invasive and it must be portable. The most common solution, taking into consideration the constraints, is to use EEG. The use of EEG itself does not present a problem. In the BCI community, it is considered one of the best non-invasive methods to read brain signals. Additionally, near-infrared spectroscopy is becoming more common in BCI studies due to its higher spatial resolution and robustness against artefacts [3]. The major drawback of this technology is the lower resolution time compared to that of EEG. Both technologies can be used together to complement each other [4]. Nevertheless, EEG has rarely been combined with other technologies in motion reconstruction studies. Usually, EMG is not used for motion reconstruction. In the cases that used EMG [5], the goal was to control wearable systems and the electrodes were positioned all along the arm to get better results. In the case of trans-humeral amputees, this would be impossible. Nonetheless, EMG provides a signal highly correlated with motion, is more localised than EEG, and is also less noisy. We also recognise that both systems complement each other.

In our experiment, we used an EEG cap (BioSemi ActiveTwo) with 16 active electrodes at 2048 Hz. We decided to place the electrodes in an asymmetric setup to better cover the contralateral motor area. The locations for the electrodes were Fz, F2, F4, FC2, FC4, FC6, Cz, C2, C4, C6, CPz, CP6, Pz, and P2. We covered a wide area since there is no consensus regarding which areas (other than the motor area) contribute to reconstruction of motion [1], [6]–[9].

In addition, we included four surface EMG electrodes (Delsys Trigno Wireless EMG) with a sample rate of 2000 Hz. We placed two on the *trapezius*, one on the *deltoidus*, and one on the *pectoralis major*. The locations were identical to our previous study [9]. We placed the electrodes in the shoulder area to consider the rehabilitation goals.

Training Signal

To train the systems, we paired the acquired bio-signals with the desired position of the hand. Most studies use a motion tracking system. Motion tracking systems use cameras to detect the position of the hand by using, for example, reflective devices. This kind of system tracks the position of the subject's hand precisely in a 3D space. However, this approach cannot be used with amputee patients since there is no hand to track.

There are two possible solutions: either use a virtual avatar, i.e. the subject looks at a virtual avatar moving the arm while he/she repeats the motion; or use a surrogate system in which the motion tracking device is placed in the trainer's hand and the subject repeats the motion of the trainer.

We decided to use the first approach, since this method confirms that the motion is always the same, since the position data comes from a virtual avatar that has a predefined motion compared to a human that may slightly vary the position for each iteration. In addition, implementing a system such as this would be easier, since there is no need for a specialized trainer and it can be used whenever the subject wants. The drawback of this approach is that it adds inherent error, because the position of the avatar and the real position cannot be the same. Thus, the subject's motion cannot achieve a perfect correlation with the avatar's motion.

Task

Regarding which motion the subject should perform to train the system, there was little discussion as it is not considered an important part of the experimental design. The most common task used is the centre-out motion, which consists of moving the hand between a centre position to a set of surrounding positions, because it is easy to perform for the subject and has been used in neuroscience experiments for many years. We considered that these motions were not the best for a rehabilitation approach, so we decided to create a new set of motions. We thought that the motions should cover two aspects: wide variation of motions and *useful* motions that are required for daily life.

Considering this, we included six motions in our training set. The first three were generic motions that covered motions in both shoulder and elbow joints. They included shoulder flexion-extension, shoulder abduction-adduction and elbow flexion-extension. The other three motions included reaching motions at three different positions: right middle height, centre upper height, and left lower height. In our experiment, the motion was

 DOI: 10.3217/978-3-85125-533-1-24

performed with the left arm.

For each motion, there were two phases: training and execution. During the training phase, the subjects could watch an animation as many times as they wanted. They could change the perspective freely to obtain a clear view of the motion. Also, they were asked to practice the motion and not only to watch the motion. The execution phase started when the subjects indicated that they were ready. During this phase, they had to perform the trained motion 10 times. They could also start each of the 10 repetitions by pressing a button on a handheld controller.

Preprocessing

During EEG recordings, movement of muscles can generate noise in the electrodes [10]. If the preprocessing is not performed correctly, this can result in poor results. Here, we have decided not to discuss this issue.

In this experiment, the EEG signal was divided into windows of 1 s with 93.75% overlap. This resulted in 16 different windows per second. Then we downsampled the signal to 10 Hz, using each of the points as a feature. This is similar to a process proposed by Bradberry et al. [1] and followed by Ofner et al. [2]. There is, however, discrepancy in the field about the validity of this method. The main argument against it is that the arm motion creates artefacts in the low frequency band, and the system uses those artefacts for reconstruction and not EEG data [10]. Still, there is an important argument against this statement. In every study that has analysed the relevance of each electrode for reconstruction, those located in the contralateral area have shown (especially in the motor area) better results. If the artefacts from the arm movements were so strong (or important for the reconstruction), a larger effect would be shown on the lateral area (since it is closer to the source of the artefact) or a uniform distribution over the scalp would be observed (compared to a more focused distribution on the motor cortex area). Nevertheless, these concerns are important and should be addressed in depth.

For EMG, we also divided the signal in 1 s windows with 93.75% overlap. Then, we calculated seven features from the time domain. The seven features were integrated EMG, modified mean absolute value 2, mean absolute value slope, simple square integral, zero crossing, slope sign change, and Wilson amplitude. For more information regarding the features, please refer to Phinyomark et al. [11] Please also see Fernandez-Vargas et al., [9] in which we provide an analysis on why these features were selected with additional information about them. Finally, for calculating the output for each window, we took the mean for each of the three position coordinates (x, y, and z) used a sliding window of 0.0625 s (1/16 s) without overlapping. This position corresponded to the avatar’s hand and was acquired at a variable rate of ~60 Hz.

Predictor

Excluding the preprocessing, the predictor is probably the component with the highest variability across studies. The most common predictor is the linear regression [1], [2], [12], [13]. This predictor creates a linear regression model using features of EEG as input and the position of the hand as output. One of the advantages of this method is that it is easy to interpret the results. Other options include the particle filter model [12], the kernel ridge regression method [13], or artificial neural networks [9]. For this study, we decided to use the linear regression approach for the EEG data because of its wide use, simplicity, and overall accuracy. For the EMG data, an artificial neural network was selected as previously published [9]. Then, the result of both predictors was used as input for a second linear regression. Additionally, to this second linear regression we used the previous two reconstructed points as input, and we refer to these two points in this report as temporal data.

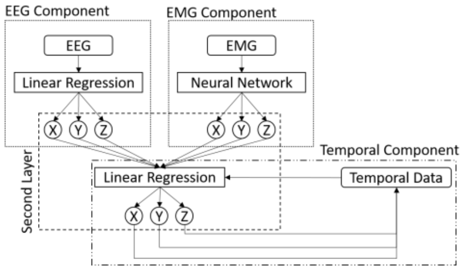

Figure 1 Schematic representation of the predictor. Each component is marked with a rectangular shape to indicate the data that belong to that component.

With this configuration, we divided the predictor into four different components: EEG, EMG, second layer, and temporal. EEG and EMG components correspond to the predictors that used only the EEG and EMG data, respectively. The second layer is the predictor that used the output of both previous components as input. Finally, the temporal component uses the previously reconstructed points. The actual predictor, represented in Figure **1**, uses as input for the second layer the output of the EEG component, the EMG component, and the temporal data at the same time. Nonetheless, the *second layer* term refers to the result obtained when using only the data from the EEG and EMG components, whereas the “temporal” term refers to the result when the temporal data was added.

Evaluation

In each study, the correlation value (CV) between the real position and the reconstructed position was used as the fitness value. In general, this approach is well accepted, despite its possible problems.

The main problem is that the CV is calculated only with data obtained during the training session. Even if the task contains a wide range of motions, those motions will be repeated several times. Thus, the training, test, and validation sets will be similar, which could result in a lack of generalisation of the system. This is usually intended since, in general, we want to train the system with data that is similar to the data that we are going to use in the future. However, in this specific case, the problem is that the set of motions that the arm can perform is too large to train them all. If we were to use those systems in a real environment, the result would be

 DOI: 10.3217/978-3-85125-533-1-24

worse than what we would expect by only considering the CV. In brief, any system excels at reconstructing motions similar to those that were used for training it. However, we cannot know how the system behaves with radically different movements. Since we cannot train the system with all possible arm motions, we need to calculate the quality of the system when presented with unexpected motions.

As a solution, we propose to use a time related feature, which can be calculated after training the system. For example, the subject uses the trained system to move a virtual avatar or prosthetic device to perform a set of motions different from those included in the training task. The time to complete those motions would be used as the fitness value. Unfortunately, we were not able to implement this approach in our study; consequently, we used the CV as the fitness value.

For training the system, we used a 10-fold leave-one-out cross validation procedure, and 9 out of the 10 repetitions of each motion then used the remaining motion as validation. This process was repeated 10 times, rotating which repetition was left for validation. The final CV was calculated as the mean of the obtained CV for each repetition.

RESULTS

Table 1 shows the results obtained during the experiment for every component of the system. In addition, we performed a permutation test to calculate the chance level, i.e., we calculated the obtained CV for the EEG component using random EEG data from the motion task. As a result, we obtained a CV <0.001.

In three cases, the EMG component obtained better results than the EEG component. Nonetheless, in every case, the second layer was better than any of the other two components. In addition, the temporal component was also always better than the second layer.

The correlations between the second layer and each component were EMG-second layer 0.905, *p-value* 0.035; EEG-second layer -0.75, *p-value* 0.145; temporal-second layer 0.687, *p-value* 0.2.

Finally, Figure 2 presents the reconstruction of the system for subject #3. Note that the CV for this reconstruction was 0.789, which was below the mean CV for subject #3. As was explained before, the mean CV for every subject was obtained through a 10-fold validation process. This means that there were 10 different reconstructions with slightly different CVs among them.

Table 1 Component CV and the mean CV of all subjects.

#	*EMG*	*EEG*	*2nd Layer*	*Temporal*
1	0.672	0.584	0.747	0.870
2	0.125	0.676	0.679	0.810
3	0.350	0.693	0.716	0.794
4	0.784	0.576	0.811	0.856
5	0.621	0.586	0.732	0.838
Mean	***0.510***	***0.623***	***0.737***	***0.834***

DISCUSSION

Acquisition System

The results obtained in this study show that the combined use of EEG and EMG provides an improved result in terms of CV compared to using only one of the systems. This also indicates that EEG and EMG contain different information regarding the position of the hand. Notably, the variation of the CV of the EMG component is much larger than the CV of the EEG component. This suggests that the EEG component is more robust than the EMG component. This result is counterintuitive, since EEGs signal are noisier than EMG signals. In addition to the fact that the overall CV appears to correlate with EMG accuracy, it would be very important to study the reason for this. Also, results obtained in this study using only the EEG component are above average in the field, even using only 16 electrodes compared to the common 32-64 used in most studies.

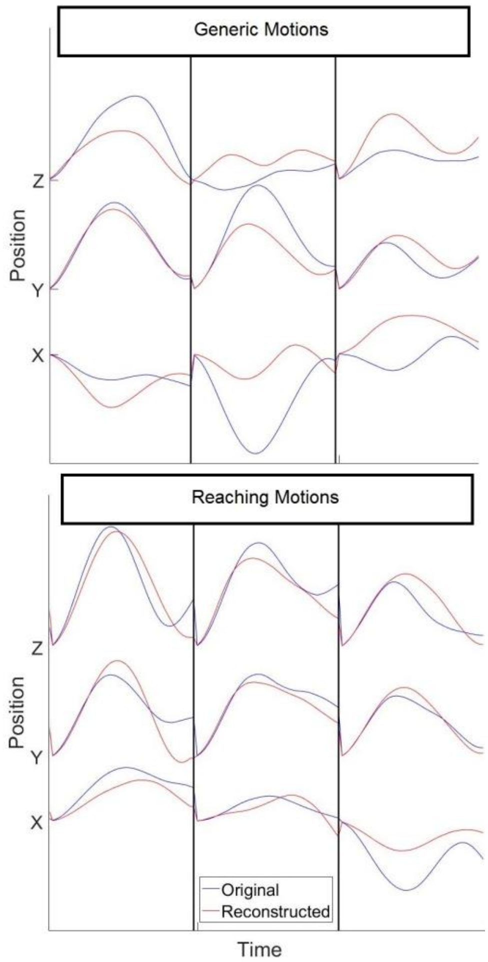

Figure 2 Motion reconstructed from subject #3. Each line corresponds to one dimension. The position has no real-world dimensions since it corresponds to the position of the avatar's hand in the virtual world. The vertical thick lines divide each one of the six reconstructed motions that correspond to the motion described in the subsection "Task".

 DOI: 10.3217/978-3-85125-533-1-24

Table 2 Problems and solutions summary

Section	Common Approach	Disadvantages	Importance	Proposed Solution	Expected Impact	Implemented
Acquisition System	Only EEG	Noisy signal, difficult to analyse	Low	Adding EMG and temporal data	Great accuracy improvement	Yes
Training Signal	Motion Tracking	Cannot be used by amputees	Critical	Using virtual avatar	Accuracy decrease	Yes
Evaluation	CV	May not represent the system's real accuracy	High	Post-training measurement	Better system evaluation	No
Task	Centre out movement	Is not a daily life movement	Medium	Using general and reaching movements	More general predictor	Yes

This means that placing the electrodes on the contralateral motor area provides results that are similar to using more electrodes over the whole scalp. This result suggests that it possible to create cheaper systems for real-world applications. An additional advantage of using fewer numbers of electrodes is that the preparation time is shorter.

Training signal

The most important solution that we implemented is the use of the virtual avatar for recording the training signal.

The results obtained from the EEG component in this study are similar to those obtained in [1], [2], [6], [12], [13]. In addition, compared with our previously published results [9], the temporal component had a better result. Nonetheless, with these preliminary results, we do not have enough evidence to properly compare with other studies. We will perform more experiments to make a proper comparison in the future.

Task

We consider that the reaching motions are the most important motions that the system should be able to reconstruct, because those motions are the most useful for amputee patients. Figure 2 shows that the reconstructions for reaching motions are more accurate than the reconstructions for the generic motions. Thus, if we only consider the accuracy of the reaching motions, the selected task is appropriate for the problem. Nonetheless, we should investigate what effect the different training sets have on the overall and specific accuracies.

Predictor

Table 1 shows that adding more layers to the predictor and temporal data increases the accuracy in every case. In short, more complex predictors increase the CV. In our opinion, the predictor should be even more complex, with different parts predicting specific movement components. As an example, Figure 2 shows that the motion for the shoulder abduction-adduction has the biggest error, especially in the "*x*" dimension. To improve the accuracy of the system, we could add an additional layer that classifies the motion into subgroups. Then, once we know the subtype of motion, we could use the EEG and EMG data as input for different specific predictors. This could also be useful if we want to reconstruct wrist motions without moving other parts of the arm.

CONCLUSION

We identified four problems that the motion reconstruction field faces from the rehabilitation perspective (Table 2). Out of the four problems, we implemented a solution for three of them and obtained preliminary results that suggest that these are valid solutions, especially for the training signal and the acquisition system. However, there are still many problems to solve. We consider the problem of the evaluation method to be one of the most important problems that the field is currently facing.

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