Movement identification based on exoskeleton sensor data for event marking of electroencephalogram

N. Eckardt [1], A. Seeland [2], M. Tabie [3] and P. Rostalski [4]
[1] Medizinische Ingenieurwissenschaft, Universität zu Lübeck, nils.eckardt@student.uni-luebeck.de
[2] German Research Center for Artificial Intelligence - Robotics Innovation Center, Bremen, anett.seeland@dfki.de
[3] German Research Center for Artificial Intelligence - Robotics Innovation Center, Bremen, marc.tabie@dfki.de
[4] Institute for Electrical Engineering in Medicine, Universität zu Lübeck, philipp.rostalski@uni-luebeck.de

Abstract

In this paper, the development of an algorithm for movement identification based on exoskeleton sensor data is described. The exoskeleton is part of a project on post stroke rehabilitation. The algorithm shall be used to mark movement events in a simultaneously recorded electroencephalography stream as a replacement for external motion tracking. The angular values for each joint of the exoskeleton are utilized by the algorithm to calculate a threshold and decide, if a movement was done or not. The quality of the algorithm is evaluated with an experiment, where the subject has to do specific movements while wearing the exoskeleton. During the experiment, data from exoskeleton sensors, electroencephalography and motion tracking is recorded. The provisional results show, that the algorithm is able to detect the movements, but the threshold needs to be adapted to the status of the bearer. Subsequently, the algorithm gets embedded in a signal processing framework.

1 Introduction

Worldwide stroke is the most frequent cause for middle and heavy acquired impediments [1]. In 30% to 66% of the cases, the paretic limb of the stroke patient, who suffers from paralysis, remains hindered 6 months after stroke, whereas only 5% to 20% of the patients recover to full functionality [2]. One concept for stroke rehabilitation is motor learning, which is based on repetitive, task-specific training. This makes it convenient for robotic systems to assist. The functionality and strength of the patient's impaired limb may improve through robot assisted therapy and training [3], so this approach has become an important technology applied in rehabilitation engineering [4]. The aim of the *Recupera-Reha* project at the German Research Center for Artificial Intelligence (Deutsche Forschungszentrum für Künstliche Intelligenz, DFKI) is the development of a mobile whole body exoskeleton, for robot-supported rehabilitation of neurological illnesses like stroke. By the development of the robot system most different aspects must be considered, as for example suitable kinematics, the choice of fitting joints and a correct actuator strength. In addition, especially for the use case of rehabilitation, appropriate, assistive control methods must be developed. The mechatronic attempts for actuation and control of the system get combined with methods of online evaluation of electroencephalogram (EEG) as well as electromyogram (EMG)[5]. The purpose of the algorithm proposed in this paper is to identify the movements of the bearer just by using internal data of exoskeleton.This offers the advantage to no longer be dependent on external systems and devices, like motion tracking systems or push buttons, which have to be build up before use. This limits the mobility and flexibility of experiments and application scenarios, which have to be adaptable, especially in the context of rehabilitation. A similar comparison with the same intention of more freedom and independency between a motion sensing suit and a motion tracking system was done in [6]. The information about the movements is on the one hand used to get a feedback, if the intended movement was absolved right or not and on the other hand it is needed for marking the EEG data of the bearer, to evaluate intention recognition methods and to adapt learning algorithms for context recognition. As a basis for the development of the exoskeleton in the *Recupera-Reha* project and as a base and test system of the algorithm described in this paper, the active exoskeleton of the project *CAPIO* is used, which was also developed at the DFKI before. This two-armed upper body exoskeleton is connected with the human body by eight contact points and the kinematic structure covers eight active degrees of freedom at the arms and four active degrees of freedom in the back [7].

2 Material and Methods

The algorithm and all additional scripts, which are related to the algorithm were developed in the language Python 2.7. For later use, the algorithm will be embedded in the open-source software *pySPACE* (Signal Processing And Classification Environment in Python) [8].

2.1 The algorithm

Before the grading of movements begins, the joint values are separated into two groups (left and right arm) by their designations. While identifying movements it became apparent that voluntary movements needs to be distinguish from involuntary, as for example short twitching or smaller, passive co-movements of an arm while moving other body parts. At the same time, it is important to detect the correct movements precisely in time. To recognize whether a joint moves at the time point i, you can compare the current position x of the joint with the one t samples before, which represents a determined time span related to the sampling frequency. The difference of both values represent the average speed of change of the joint angle in the period of time. If this speed exceeds a certain threshold θ, a voluntary movement of the joint is assumed (the output of the algorithm $f_{t,\theta}(x_i)$ will be the value 1), otherwise, it is not counted as a movement (marked by the value -1):

$$f_{t,\theta}(x_i) = \begin{cases} 1, & \text{if } x_i - x_{i-t} \geq \theta \\ -1, & \text{otherwise} \end{cases} \tag{1}$$

As a initial value for the threshold the standard deviation of the activity in rest for each joint was chosen. In contrast to the difference of minimum and maximum value during rest, which could also be a possible threshold, the standard deviation was more robust against peaks caused by artifacts, but was to small, which made an additional multiplying factor for the threshold necessary. In this context it can be seen as a kind of noise, which is not assignable to any voluntary movement and can result from different causes. Now, using the outcome of the single joints, it had to be decided, whether the motions of the single joints were enough to be counted as a voluntary movement of the whole arm itself. The first attempt was to examine, which joint of each arm moved currently the most and then just focus on and compare the two for both arms. By this, the decision whether the respective arm moved was reduced to the value of this joint. Indeed, this version was able to lead to precise detection in time, with a delay minimum between the starting of the motion of one joint and movement detection of 0,1 seconds, but on the other hand produced a delay maximum at other movements of 0,7 seconds. Especially in case more complex movements this delay fluctuated and it was difficult to find a threshold, which delivered good results for the whole sequence. The next idea was to take the sum of the differences of each joint j out of n joints for each arm and according to this choose the sum of thresholds as the threshold for each arm to compare it with:

$$F_{t,\theta}(x_i) = \begin{cases} 1, & \text{if } \sum_{j=1}^{n} (x_{j,i} - x_{j,i-t}) \geq \sum_{j=1}^{n} \theta_n \\ -1, & \text{otherwise} \end{cases} \tag{2}$$

This resulted in a more robust detection of the decision function $F_{t,\theta}(x_i)$, which also seemed to be easier to adjust, so preferably only relevant movements were detected.

2.2 Data

As a basis for the development of the algorithm data from the exoskeleton were recorded, where the bearer lifted and lowered the left and right arm alternately. The record contained values of all joints of the exoskeleton with regard to the deflection of the respective joint to its ground position, the strength currently working on the joint and values of the inverse dynamics. At the same time the movements of the bearer were recorded by a motion tracking system (Oqus, Qualisys AB, Gothenburg, Sweden) using six infrared cameras and two infrared markers affixed to the wrists of the bearer. However, the data of both records had not been captured synchronously so a synchronization had to be carried out afterwards manually by using events, which could be identified in both records. This was further complicated by the unregulated and undocumented movement sequence, which later made it more difficult to assign the data and to synchronize it with the motion tracking record. For the preparation of the data of the exoskeleton it was checked, which joints did not moved during the recording or were switched off respectively. These joints (the four in the back of the exoskeleton) were sorted out, because they were not relevant for the recognition and differentiation of the arm movements. In addition, among all available parameters only the current joint angulars were used for the classification of the movements. To avoid the disadvantages of the test data set, the movement sequence for the evaluation data sets was planned concretely and was controlled during recording. In addition, the different data streams of the exoskeleton, the motion tracking system (with six markers affixed to the exoskeleton and three markers on each object) and, for further evaluation and testing for the actual use case of event marking, EEG were recorded with synchronized timestamps. The EEG was captured with a 32 electrodes system (actiCap, Brain Products GmbH, Munich, Germany).

2.3 Comparison

To examine if the movement detection performed by the algorithm is able to replace the identifying of movements by using the motion tracking data, both methods should be compared. In addition, by observing the motion tracking record will help to check, how the movements were actually carried out or if there are any unexpected motions, which will may be detected by the algorithm. Further, it was checked, how the algorithm is reacting to smaller movements, which are not counted as a real movement of one arm. The comparison allowed to adapt the parameters of the algorithm (time window t, factor for threshold adjustment) to an optimum (500 ms, 15 times the standard deviation of the activity in rest) for the present data by increasing the values from 50 ms in 50 ms steps in the first case and from 1 in 0.5 steps in the case of the threshold factor. In both cases, a further raise would lead to a increased detection delay or even to more missed movements. Then again, to small parameter values would lead to more detection, then expected, caused by wrong detection when no movement is actually

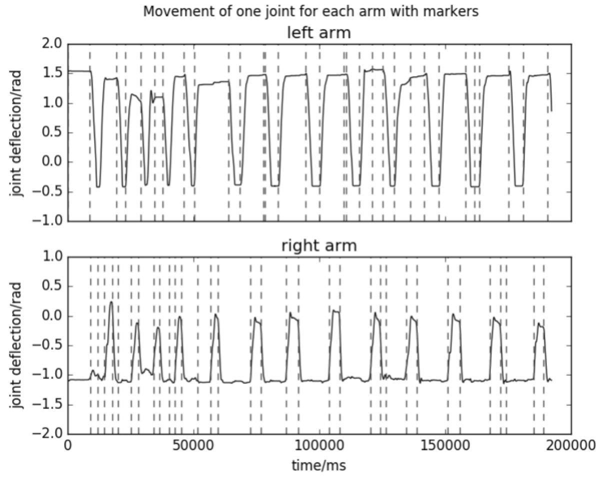

Figure 1: Illustration of the movement marking on the test data by the algorithm with adjusted threshold after comparison with the motion tracking data. The vertical, dashed lines mark the beginning of the detected movements, the solid lines the values of the current deflection of the first shoulder joint of the left (top) and right (bottom) arm over time. These joints were chosen as a optical reference because of their wide and clear shift during movements. A missed movement can be seen in top graph at around 12000 ms, a split at around 110000 ms and an unexpected detection in the bottom graph at around 50000 ms.

done or by splitting up one actually correct movement into two or more smaller ones. The results of the adapted algorithm and a differentiation of the different errors is given in Table 1. A visualization of the data with marks at the start of the movements is shown in Fig. 1 with the deflection values of one joint for each arm as a comparison.

Table 1: Differentiations of movement marking on the test data set

movement	left arm	right arm
expected	27	28
detected correctly	25	28
missed	2	0
splits	4	3
unexpected	2	2

2.4 Experiment

To evaluate the algorithm, adapted to the test data set, an experiment was set up, to obtain further data under controlled conditions. Four subjects participated, the only restriction was a suitable body shape and strength to wear the exoskeleton. After the motion tracking system was calibrated and the subject was prepared for EEG recording, he or she puts on the exoskeleton, which is additionally connected to a counterweight, which reduces the load for the subject by twenty kilogram. In front of the subject, a table was located, on which three objects lie: a cup, a bottle and a box. These objects were used for some of the following movement tasks. The tasks can be separated into easy movements, like moving an arm forth or back and more complex, more realistic movements like grabbing a cup or lift a box with both arms, like it probably will be done in the rehabilition secenario. Behind the table, a screen was built up. On the screen, the subject received commands, one by one and in an appropriate speed (5 seconds for easy movements, 8 for the more complex ones, with a 2 seconds break between each command). The commands tell the subject, which movement he or she has to do, by showing stylized pictures, as shown in Fig. 2 exemplarily. In addition, the respective meaning of the picture is written below the picture. Before the experiment starts, the subject gets an instruction on how to move with the exoskeleton and what movements are meant with the commands. The command sequence itself lasts ten minutes. To support later analysis, it is tried to document during the sequence, how the movements are performed by the subject, to know, if the they were done as expected.

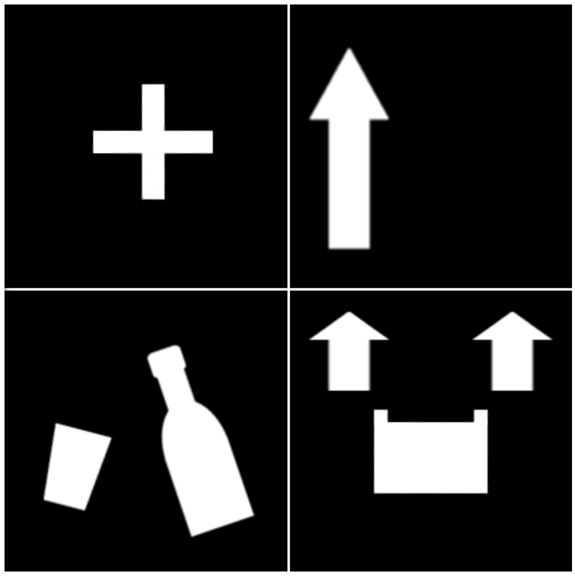

Figure 2: 4 examples out of 15 command pictures the subject get to see during the experiment: Top left: relax, top right: left arm forth, bottom left: grab bottle and cup, bottom right: pick box. These descriptions are depicted on the screen, too. The remaining command pictures are variations (reversion, change of sides, etc.) of the pictures shown here.

3 Results and Discussion

First results seem promissing that the algorithm is capable of detecting movements. As a first test, the algorithm is applied to the new data sets with the parameters adapted on the test set. The results of these runs are shown in Table 2. It can be recognized, that most of the missed movements were complex movements. On the other hand, most of the unexpected detection happened during the task times of easy movements. Both can partially be explained by the performance of the subjects. For example, subject 1 had connected the commands *put box down* with *both arms back* to one, which led to an additional movement during the first task time and a missing one during the following. Another example is given by subject 4, who one time had got the command left arm back, but additionally had moved his right arm back in three small steps. The algorithm detected one movement on the left and three on the right, so an actual correct detection. To figure out, if more errors can be explained this way, for example if some of the splits are actual separable movements during a complex task, a closer examination of the motion tracking recording is necessary. In addition, the movement marks should be applied to the EEG data to examine their accuracy. This and a more detailed analysis of the results and further steps to a more automatic threshold adjustment and embedding are currently in preparation.

Table 2: Differentiations of movement marking on the four obtained data sets

movement	left arm	right arm
type	easy / complex	easy / complex
expected	26 / 27	28 / 25
subject 1		
detected correctly	25 / 26	26 / 25
missed	1 / 1	2 / 0
splits	12 / 42	19 / 22
unexpected	9 / 1	9 / 8
subject 2		
detected correctly	26 / 19	28 / 25
missed	0 / 8	0 / 0
splits	15 / 9	13 / 28
unexpected	0 / 0	0 / 2
subject 3		
detected correctly	25 / 23	26 / 20
missed	0 / 4	2 / 5
splits	8 / 20	6 / 14
unexpected	3 / 1	0 / 1
subject 4		
detected correctly	26 / 20	28 / 19
missed	0 / 7	0 / 6
splits	10 / 13	4 / 7
unexpected	2 / 2	5 / 0

4 Conclusion

In this article, the development and evaluation of an algorithm for movement detection of an exoskeleton was presented. The algorithm, which was developed based on a test data set, was evaluated on four data sets recorded in a extra designed movement sequence experiment. The first results showed, that the parameters of the algorithm, which were optimized on the test data, are a good starting point, but have to be adjusted for every individual subject, to get the optimal outcome. Apart from a more thorough analysis and the embedding into the signal processing framework, there a few possible enhancements, which could be added to the algorithm. The use of kinematic information about the exoskeleton may allow to separate the detection to more differentiated categories, like which part of the arm is moving in which direction, which kind of movement is done etc. In addition, changes in the torque values of the joints could tell the algorithm, if the bearer is carrying something or in general, if something changed about the status of the bearer. Furthermore, a closer look to the detections during the more realistic, complex movements could be a basis to draw up characteristic sequences for these kinds of movements.

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5 References

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