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Predicting manual wheelchair initiation movement with EMG activity during over ground propulsion

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Context/Objective: This is a preliminary study of movement finalities prediction in manual wheelchairs (MWCs) from electromyography (EMG) data. MWC users suffer from musculoskeletal disorders and need assistance while moving. The purpose of this work is to predict the direction and speed of movement in MWCs from EMG data prior to movement initiation. This prediction could be used by MWC to assist users in their displacement by doing a smart electrical assistance based on displacement prediction. Design: Experimental study.

Setting: Trained Subject LAMIH Laboratory.

Participants: Eight healthy subjects trained to move in manual wheelchairs.

Interventions: Subjects initiated the movement in three directions (front, right and left) and with two speeds (maximum speed and spontaneous speed) from two hand positions (on the thighs or on the handrim). A total of 96 movements was studied. Activation of 14 muscles was recorded bilaterally at the deltoid anterior, deltoid posterior, biceps brachii, pectoralis major, rectus abdominis, obliquus externus and erector spinae. **Outcome Measures:** Prior amplitude, prior time and anticipatory postural adjustments were measured. A hierarchical multi-class classification using logistic regression was used to create a cascade of prediction models. We performed a stepwise (forward-backward) selection of variables using the Bayesian information criterion. Percentages of well-classified movements have been measured through the means of a cross-validation.

Results: Prediction is possible using the EMG parameters and allows to discriminate the direction / speed combination with 95% correct classification on the 6 possible classes (3 directions * 2 speeds). **Conclusion:** Action planning in the static position showed significant adaptability to the forthcoming parameters displacement. The percentages of prediction presented in this work make it possible to envision an intuitive assistance to the initiation of the MWC displacement adapted to the user's intentions.

Keywords: Prediction, EMG, Logistic regression, Manual wheelchairs, Initiation

Introduction

A manual wheelchair (MWC) is a highly used technical assistance device used to increase the mobility of people with a wide range of disabilities in a variety of situations and activities.¹ However, it is often the

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cause of musculoskeletal disorders, including those affecting the upper limbs, with a prevalence of 19% to 61%.²

Several researchers have been interested in improving human locomotion (with or without MWCs) by studying the prediction of the forthcoming displacement. Potential applications of these predictions include activation of electrical assistance on the MWC based on user's intentions. Some of them based their investigations on brain-computer interfaces. When central and peripheral nervous system level activations precede the movement, electroencephalogram (EEG) changes can be observed, for example, 1.5 s before the execution of a slow movement.^{3,4} In addition, these activations are related to the movement parameters which probably imply a specificity and an adaptability. The study by Bai *et al.*⁴ aimed to determine if, and when, it is possible to predict with certainty the voluntary human movement before it occurs, from EEG signals, online and in real-time. The main result is that prediction, based on EEG signals, is possible 0.62 s \pm 0.25 s before the real movement controlled by EEG signals. Under certain conditions, human voluntary movement can be predicted before any segmental displacement.

More recently, the study by Wentink *et al.*⁵ aimed to study the feasibility of detecting the intention to gait initiation in real-time in tibial amputee subjects. In this study, the EMG activity of 9 muscles was analyzed for 10 healthy subjects. Inertial sensor data were also collected by placing a sensor in the middle of the heel and the first metacarpal head of each foot. Only data available in amputees were used to determine whether gait initiation can be predicted within a compatible delay with the control of a transfemoral prosthesis and to generate "push-off" while ensuring stability. The results show that the "toe-off" and the "heel-strike" can be predicted using the EMG signal and kinematic data in non-amputees around 130–260 ms in advance. The authors hypothesize that similar results can be found in transtibial amputees, which would allow a satisfactory control of the prosthesis during the gait initiation. Other authors have also hypothesized that EMG signals contain information to detect the user's intention.^{6–8} However, despite the advantage of indicating the intention of movement early, brain-computer interfaces generally offer poor performance if based only on surface EEGs.⁸

Recent advances in electric wheelchair control based on EMG signals can satisfy the needs of users with limited limb movements and provide a high-performance control. Therefore, electric wheelchairs controlled by EMG signals may be appropriate for elderly and

disabled users.^{9,10} EMG signals at the biceps brachii and triceps brachii levels,¹¹ as well as in the neck muscles,¹² have been used to assist people who do not have sufficient power to propel using the handrim. The signals have also been used to detect how much power is applied and predict the forthcoming displacement. These predictive elements are sensitive to or influenced by the parameters of the movement, and thus are likely to be flexible and adaptable.¹³

While past studies indicate that EMG can provide a useful signal for drive control of power wheelchairs, its usefulness as a tool to assist the propulsion of manual wheelchairs has not been explored. The objective of this study is to investigate whether EMG data obtained in a static position is predictive of the speed and direction of manual wheelchair displacement. Based on prior observations of the level of adaptability and arm-trunk coordination observed during the displacement initiation in MWCs,¹⁴ the hypothesis is that it is possible to use EMG data collected in the static position to predict the speed and direction of the forthcoming displacement in MWCs. To assess this, we will develop a hierarchical multi-class classification model using logistic regression to predict movements among 6 possibilities (3 directions: front / left / right * 2 speeds: spontaneous / maximum).

Materials and methods

Participants

Eight right-handed healthy male subjects volunteered to participate in the study. Mean and standard deviations for age, weight, height and BMI were, respectively, 21.3 \pm 1.8 years, 73.8 \pm 8 kg, 180 \pm 10 cm and 22.3 \pm 1.3 kg/m². All subjects are students in the Bachelor of Sport Science program at Valenciennes University, France. All subjects were familiar with MWC displacement and signed an informed consent approved by the university's institutional review board. The experiments were conducted following the principles of the Declaration of Helsinki.¹⁵

Sensors

EMG

The electrodes were placed bilaterally on the following muscles: postural component; rectus abdominis (RA), obliquus externus (OE), and erector spinae (ES); focal component; deltoid anterior (DA), deltoid posterior (DP), biceps brachii (BB), and pectoralis major (PM). This step was carried out in accordance with the recommendations of Hermens *et al.*¹⁶ A Bipolar Zero Wire 16-channel Aurion amplifier was used to record muscle activity with 1000 Hz data sampling.

Video sequences

A camcorder was used for video recording at 25 Hz and synchronized with the EMG system. The videos allow the identification of the moment of MWC movement initiation named T0. The sequence T0 was visually identified by observation of the images every 40 ms.

Variables and measures

Prior time

The time ranged from the onset to the T0. Onset is the moment of muscle activation.

Prior amplitude

The amplitude ranged from the onset to the T0.

The level of muscle contraction was calculated according to the method of Clancy *et al.*,¹⁷ consisting of: (a) high pass signal filtering at 35 Hz to remove most part of the artefact from ECG^{18,19} (the filter used was an IIR Butterworth order 4 with the forward-backward process); (b) removal of the sector artefact by a notch filter between 48 and 52 Hz (IIR Butterworth order 8 with the forward-backward process); (c) rectification of the signal by computing the absolute value and application of a low pass filter at 12 Hz, in order to get an estimate of the instantaneous power (IIR Butterworth order 4 with the forward backward process); (d) amplitude normalization using a maximal voluntary contraction previously recorded. Each treatment was performed on MATLAB.²⁰

Onset instants were calculated in two steps. First, the derivative of the instantaneous power was calculated. Second, the onset of muscle activation was fixed to a local maximum of this derivative. The first local maximum was taken, and those whose value was greater than the threshold fixed at the 93rd percentile

of the signal allow a better adaptation to the current signal.

Anticipatory postural adjustment (APA)

The amplitude of the APA was calculated between 100 and 50 ms respecting T. T is the first onset activation of all focal muscle. The set of details is mentioned in the studies by Clancy *et al.*¹⁷ and Chikh *et al.*¹⁴

Task

The subjects were informed of all steps of the experiment and provided their informed consent before the experiment began. The electrodes were placed bilaterally on the muscles mentioned above (2.2. sensors). A standardized warm up was carried out by each subject for 5 min; each subject then performed three passages without recording. Maximal voluntary contractions were measured for focal component muscles. All experimental displacements were then set up in a counterbalanced order. The rear wheels were positioned according to the direction of displacement requested (front, right or left). Subjects then received information about the hand position (thighs vs handrim) and the speed (spontaneous vs maximum) while sitting in the MWC in a static position. After that, recording was initiated (Figure 1). After a random period (2–5 s), a verbal start signal (“Go”) was given by the experimenter. The subjects had to then initiate the movement and make a displacement over a distance of 5 m with spontaneous push recovery cycle. A total of 12 different displacements (2 speeds * 3 directions * 2 hand positions) was performed by each subject. Each condition was repeated three times, for a total of 36 displacements per subject. Finally, only one repetition of each condition was retained for further analysis. The repetition

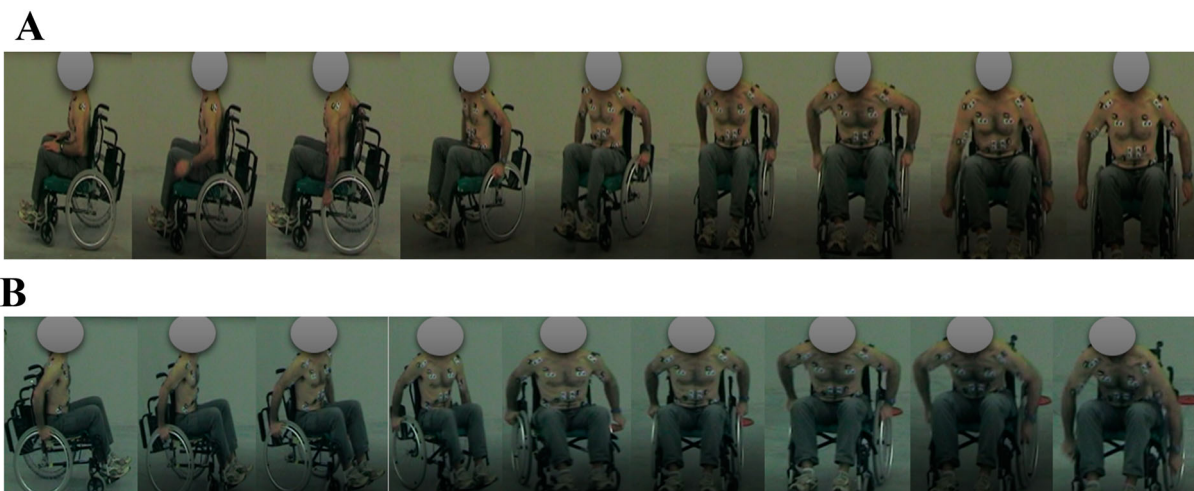


Figure 1 Example of left displacement (A: hands on the thighs) and right displacement (B: hand on the hand rim).

selected was the one closest to the average test of the three repetitions. A total of 96 movements (8 subjects * 3 directions * 2 speeds * 2 hand positions) was studied.

Predictive modeling

The objective was to predict the forthcoming movement among the 6 possibilities (3 directions: front / left / right * 2 speeds: spontaneous and maximum) using EMG variables (APA, prior time and prior amplitude). A total of 22 possible explanatory variables was studied. Six variables for the postural component muscles were: RA, OE, and ES bilaterally (measurement of APA). Sixteen variables for the focal component muscles were: BB, DA, DP, and PM bilaterally (measurement of prior time, prior amplitude).

Seven binary classifiers using logistic regression were performed: (1) lateral vs. front movement (all speeds combined); (2) right vs. left (all speed combined, only lateral movements); (3) maximum speed vs. spontaneous speed (all directions combined); (4) maximum speed vs. spontaneous speed (front movement only); (5) maximum speed vs. spontaneous speed (left movement only); (6) maximum speed vs. spontaneous speed (right movement only); and (7) maximum speed vs. spontaneous speed (lateral movement only). For each of these binary classifiers, a stepwise (forward-backward) variables selection was performed using the Bayesian information criterion (BIC) to avoid overfitting of the model.²⁹ Once the variable was selected, a cross-validation (leave-one-out) was used to measure the best classified percentage for each classifier.²¹ The

threshold probability for being in one class or another was set to 0.5 for all 7 classifiers. Ultimately, a hierarchical multi-class classifier was built using a cascade of the previously computed binary classifiers²² (Figure 2).

Concerning classifiers 3–7, which have the purpose of predicting the movement speed, the objective was to test if it is more efficient to train a global classifier for all directions (3) with a larger input number, but with possible non-linearity, or to train a specialized linear classifier inside each subgroup (corresponding to directions) with small input numbers but with less possible non-linearity. Three strategies were tested to predict the speed of movement using either a global classifier or specific classifiers as presented in Figure 2. Strategy 1 consists of using the same classifier for all movement directions (classifier 3). Strategy 2 consists of using a second classifier for left movement and a third classifier for right movement. Strategy 3 consists of using a first classifier for front movement and a second classifier for lateral movement (common for left and right). The strategy that provides the best classification rate was ultimately kept. The final criterion was the percentage of well-classified movement among the 6 possibilities.

Results

Results of the binary classifications

Each binary classifier distinguishes two types of displacements. Seven prediction models were used as follows.

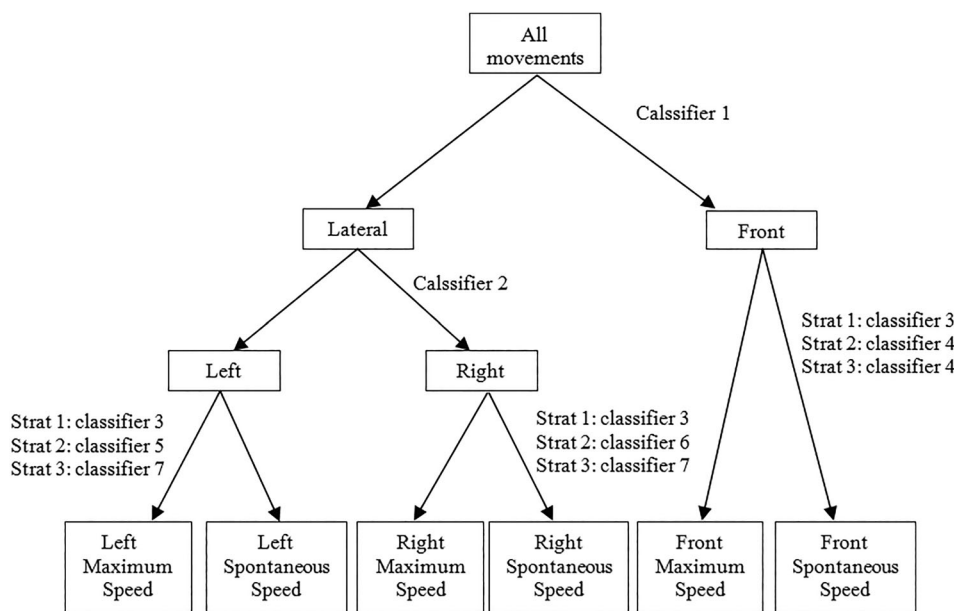


Figure 2 The hierarchical multi-class classifier used to predict the forthcoming movement with the 3 possible strategies for predicting the speed of movement.

Prediction of the direction

The purpose of classifier 1 is to perform a first dichotomy to predict whether the next movement will be performed *front* or *lateral* (all speeds combined). The percentage of accurate prediction obtained by cross-validation was 100% (Table 1). This prediction is possible from prior times of DA-Right (DA-R) and DA-Left (DA-L). This prior time observed in DA muscle is shorter for front than for lateral direction.

The purpose of classifier 2 is to perform a second dichotomy to predict whether the next movement will be realized *left* or *right* (all speeds combined). The percentage of accurate prediction obtained by cross-validation was 100% (Table 1). This prediction is possible from prior times of PM-L. This prior time is shorter for right than for left direction.

The purpose of classifier 3 is to predict whether the next movement will be realized with *spontaneous* or *maximum* speed (all direction combined). The percentage of accurate prediction obtained by cross-validation was 91% (Table 1). This prediction is possible from: BB_R_Prior Time; BB_R_Prior Amplitude; BB_L_Prior Amplitude; DP_R_Prior Amplitude; DP_L_Prior Amplitude; DA_R_Prior Amplitude;

PM_L_Prior Amplitude and OE_L_APA. Maximum speed is characterized by a great amplitude compared with spontaneous speed.

The purpose of classifier 4 is to predict whether the next movement will be realized *front with maximum* speed or *front with spontaneous* speed. The percentage of accurate prediction obtained by cross-validation was 97% (Table 1). This prediction is possible from DA_R_Prior Amplitude; PM_R_Prior Amplitude and OE_L_APA.

The purpose of classifier 5 is to predict whether the next movement will be realized *left with maximum* speed or *left with spontaneous* speed. The percentage of accurate prediction obtained by cross-validation was 75% (Table 1). This prediction is possible from PM_L_Prior Time and BB_R_Prior Amplitude.

The purpose of classifier 6 is to predict whether the next movement will be realized *right with maximum* speed or *right with spontaneous* speed. The percentage of accurate prediction obtained by cross-validation was 81% (Table 1). This prediction is possible from BB_L_Prior Amplitude and OE_R_APA.

The purpose of classifier 7 is to predict whether the next movement will be realized *lateral with maximum* speed or *lateral with spontaneous* speed. The percentage of accurate prediction obtained by cross-validation was 94% (Table 1). This prediction is possible from DA_L_Prior Time, BB_R_Prior Time, DP_L_Prior Time, BB_R_Prior Amplitude, DP_R_Prior Amplitude, DP_L_Prior Amplitude and DP_R_Prior Time.

All 7 classifiers with the percentages of correct prediction and the variables used are presented in Table 1.

Table 1 Prediction of directions (front vs. left vs. right) and speeds (maximum speed vs. spontaneous speed) with EMG signals.

Movement and % of prediction	Variables
Classifier 1 Front vs. Lateral	100% DA_R_PT; DA_L_PT
Classifier 2 Right vs. Left	100% PM_L_PT
Classifier 3 Maximum speed vs. Spontaneous speed	91% BB_R_PT; BB_R_PA; BB_L_PA DP_R_PA; DP_L_PA; DA_R_PA PM_L_PA; OE_L_APA
Classifier 4 Front-Maximum speed vs. Front-Spontaneous speed	97% DA_R_PA PM_R_PA OE_L_APA
Classifier 5 Left-Maximum speed vs. Left-Spontaneous speed	75% PM_L_PT BB_R_PA
Classifier 6 Right-Maximum speed vs. Right-Spontaneous speed	81% BB_L_PA OE_R_APA
Classifier 7 Lateral-Maximum speed vs. Lateral-Spontaneous speed	94% DA_L_PT; BB_R_PT; DP_L_PT BB_R_PA; DP_R_PA; DP_L_PA DP_R_PT

APA, anticipatory postural adjustment; BB, biceps brachii; DA, deltoid anterior; DP, deltoid posterior; L, left; OE, obliquus externus; PA, prior amplitude; PM, pectoralis major; PT, prior time; R, right.

Results of multi-class hierarchical classification

Given the results of the different binary classifiers (Table 1), it appears that the best strategy for predicting speed using our hierarchical classifier is strategy 3 (Figure 2). It consists of predicting the speed using a specific classifier (4) for the front movements and classifier 7 for the lateral movements (left or right).

Table 2 corresponds to the attached size and attached proportions. The case located at line i, column j of the table gives the number of movement type i that has been classified as movement type j by our classifier. The correctly classified elements are those on the diagonal. Thus, the percentage of correctly classified elements within the 6 possible classes with our final model is 95% (Table 2). Regarding the 5% error, the predicted direction was correct, but the speed was incorrect.

Table 2 Percentage of solutions correctly classified using classifiers 1, 2, 4 and 7.

Predicted	Solution						Total
	F-SS	F-MS	L-SS	L-MS	R-SS	R-MS	
F-SS	15 (15.6%)	1 (1.0%)	0 (0%)	0 (0%)	0 (0%)	0 (0%)	16 (16.7%)
F-MS	0 (0%)	16 (16.7%)	0 (0%)	0 (0%)	0 (0%)	0 (0%)	16 (16.7%)
L-SS	0 (0%)	0 (0%)	14 (14.6%)	2 (2.1%)	0 (0%)	0 (0%)	16 (16.7%)
L-MS	0 (0%)	0 (0%)	1 (1.0%)	15 (15.6%)	0 (0%)	0 (0%)	16 (16.7%)
R-SS	0 (0%)	0 (0%)	0 (0%)	0 (0%)	15 (15.6%)	1 (1.0%)	16 (16.7%)
R-MS	0 (0%)	0 (0%)	0 (0%)	0 (0%)	0 (0%)	16 (16.7%)	16 (16.7%)
Total	15 (15.6%)	17 (17.7%)	15 (15.6%)	17 (17.7%)	15 (15.6%)	17 (17.7%)	96 (100.0%)
Correctly classified	95%						

F, front; L, left; MS, maximum speed; R, right; SS, spontaneous speed.

Reliability of prediction models

In order to test if the model is robust and can be applied to other subjects, we have tried to realize a one-subject-out-cross correlation. More precisely, for each subject, we measured the performance of a model tested on the seven other subjects. Using this validation method, the performance of the classifier is reduced by only 2% (93% well classified versus 95% not). Moreover, 100% of subjects would be classified as good if we considered only the direction (front, left, right). These results indicate that this model seems valid for every subject who meets the inclusion criteria.

Discussion

The objective of this study was to determine if it is possible to predict speeds and directions of movement in MWCs, from EMG data prior to the displacement, in healthy subjects using a binary logistic regression. The prediction percentages confirm the initial hypothesis. Prediction is possible and consists of discriminating among 3 directions and between 2 speeds regardless of the initial position of the hands (thigh or handrim). The EMG parameters predict the speed and direction of movement in MWCs in very interesting proportions. Two possible hand positions at the start (thigh or handrim) showed the reliability of percentages and predictor variables. Despite two different starting conditions, the predictive models make it possible to predict the forthcoming movement. It seems that one advantage of using this method is that it can be applied to all subjects and the model does not need to be adapted for a new subject.

The predictor variables of the speed, chosen by the model, are different from those for the direction. Speed is predicted by amplitude variables while the direction is predicted by temporal variables. Also, more predictors were observed for speed than direction, which can be explained by a greater difficulty in differentiating speed movement than direction. Sensitivity to

speed appears to be more important than sensitivity to the direction. This result confirms the concept of adaptability to speed, also called speed sensitivity strategy.²³ The APA observations at the OE level, predictive of the speed, confirm previous explanations concerning the adaptability of the APA to the parameters of the forthcoming movement such as the speed.¹³ Another possible explanation would lie in a greater ease of speed control than direction control, or by an effect of the initial position of the hands more specifically. Because of the demand for speed to be maximal or spontaneous, it is possible that at maximum speed the absence of ‘dosage’ of the effort by the subject leads to greater reproducibility of movement. In all cases, the subjects in our study were asked to use their maximum effort at the intensity level required to be at maximum speed. In summary, to change speed, the subject must vary the amplitude of their muscular contraction (ie. they must use more amplitude if the speed increases), whereas to change direction, it is necessary to change the chronological order of the muscular contractions (for example, to go straight, the right DA and the left DA activate simultaneously, while to turn left, the right DA activates before the left DA). This principle of temporal chronology related to the direction has also been used to predict the direction in an electric wheelchair.¹¹

The researchers used a direction discrimination function which is limited to discriminate between a forward or a backward displacement. They compared the EMG signal during the grip phase at biceps brachii (BB) and triceps brachii (TB) and gave a sign as follows: when the BB signal is more important than the TB signal, the signal is positive, whereas when the BB signal is lower than the TB signal, it is negative. The shorter prior time observed in front than lateral direction could be explained by a more important arm-trunk coordination for lateral direction. Also, it has been shown a shorter prior time for right than left direction.

All subjects were right-handed which could facilitate turning to the right.

In the literature, during wheelchair propulsion, it has been shown that DA and BB have a major role in the 'traction' phase. Anatomically, the BB is a flexor of the elbow and the DA is a flexor-stabilizer of the shoulder. These two muscles ensure contact with the handrim by a significant activation of the DA during the pushing phase.^{24,25} The PM shows significant participation or contraction during push phase.²⁵ The PM is an adductor of the arm, which ensures contact and pushing inward with the handrim. By its contraction, it thus indirectly ensures the stability of the trunk. Initiating movement while using an MWC requires propulsion on the handrims. This propulsion is generated by the activation of muscles with the hand on the handrim with a condition for which the APA are sufficiently specific and reproducible. This logic has been used by Wentink *et al.*⁵ in the study of the feasibility of detecting gait initiation intention in real-time in tibial amputees. The main result shows the possibility of predicting walking initiation 130–260 ms in advance. The prediction was based on activations prior to gait initiation. The analysis of the EMG activities, muscle by muscle, makes it possible to predict the initiation of the displacement in 81–95% of the tests, according to the considered muscle. By using an accelerometer or gyroscope, their prediction level increases to 95%. In our study, the prediction of the displacement initiation in an MWC was not only studied at the level prior to a simple forward movement but also with a variation of the finality in terms of speed and direction. The parameters studied allow much more accurate prediction of the displacement initiation in an MWC than in the study of Wentink *et al.*⁵ However, not all prediction percentages are at a 100% level. As a rule, the percentage of prediction depends on the adaptability of the variables to each condition. It also depends on the repeatability or the redundancy of the variables in the same condition, that is, the ability to reproduce the same behavior for the same displacement finalities.

Study limitations and future perspectives

Some limitations were present in this study. First, the determined models are from healthy subjects, all of whom are young, male and right-handed. It might not be possible to generalize this model for all MWC users, as members of the disabled population would likely perform the tests differently from healthy subjects. However, these models could be used as references for a variety of MWC users. It would be possible to involve the prediction models in a displacement assistance

system and specify it for each person via a learning program that would consider the specific characteristics of each individual and his or her MWC. Also, the sample population is healthy and small. The actual users of MWCs are very heterogeneous. Thus, it would be interesting to study the effect of the characteristics of spinal cord injuries by different injury levels on a larger population. The literature also shows that the presence of a spinal cord injury as well as the level of the spinal cord injury^{26–28} could influence muscular recruitment mode and movement execution parameters.

Secondly, the predicted type of displacement is not continuous in either speed or direction. However, at this time we do not have a quantitative numerical output, that is, we do not know how much speed and what angle of rotation in the direction were actually used. It would be interesting to measure the actual speed and direction. Our research only showed the ability to predict the initiation of movement from the static position, while the user of an MWC may have more possibilities (e.g. accelerate, brake, stop). Similarly, the data used is limited to EMG, and it would be interesting to supplement them with other types of variables such as center of pressure displacement on the MWC seat and accelerometers at the MWC and the user level.²⁹ Finally, the MWCs are very variable in terms of characteristics and setting and the displacement surface could vary in terms of angle and difficulties. So, the predictive models should be tested according to these different parameters.

Conclusions

The prediction of the speed and direction of MWC displacement is possible from the prior EMG data and the use of a logistic regression. Speed prediction, based on amplitude variables, presents more variables than direction prediction, based on temporal variables. The prediction percentage is 95%. This prediction reinforces the theory of control adapted to the characteristics of the forthcoming movement (i.e. the central nervous system adapts the motor commands to reach the intention). Nevertheless, further studies will be needed to enrich the present research. These studies should focus on studying prediction in a diverse population with other quantitative finalities of displacement and using other measurement tools to vary input variables (e.g. center of pressure, accelerometer). The results presented in this work make it possible to envision EMG-controlled, power-assist MWC designs that provide propulsion assistance adapted to the user's intentions.

Disclaimer statements


Contributors *Group name.* CASE 1: Soufien Chikh, Cyril Garnier, Rawad Elhage, Fairouz Azaiez: Article writing and achievement of experience. CASE 2: Samuel Boudet, Antonio Pinti: Statistical modeling and method writing. Eric Watelain: Project organization, author coordination and article review.

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