Bio-Medical Materials and Engineering 8 (1998) 241–251
IOS Press

Control of FES in paraplegia: modeling voluntary arm forces

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Abstract. Skilled behavior is difficult or impossible to articulate explicitly by the performers. Likewise biomechanical models of skilled motor actions are often limited by the lack of knowledge of the underlying mechanisms. A 'behavioral cloning' technique is described, based on a trained artificial neural network (ANN), that precisely mimics an individual's learned skill. In this paper the motor skill considered is that of paraplegics using their upper limbs whilst standing-up with FES. In a group of eight paraplegics with complete spinal injuries, it was possible to develop clones that followed closely the observed behavior of the subjects. Each subject used a unique and consistent voluntary control strategy. Subjects with more experience in using FES were more consistent in the use of their arms from trial to trial. Comparison of the clones revealed features suggestive of some common underlying voluntary control strategies.

1. Introduction

Functional electrical stimulation (FES) has been used to assist locomotion after spinal injury [9,18, 25]. The restored functions usually involve two fundamentally different kinds of controls; artificial FES control of the paralyzed extremities and the voluntary control of the intact muscles above the lesion. As an example, both of these controllers are important in a procedure usually used for FES assisted standing-up where the subject's arms are used along with the electrical stimulation of the paralyzed lower extremity muscles (Fig. 1). The voluntarily controlled arms not only help to balance the body during the maneuver but also carry a considerable amount of the body weight. According to [5,12], up to two-thirds of the body weight could be carried by the arms. Therefore, the quality of the resulting motion depends strongly on how the arms musculature are controlled and if there is an appropriate coordination between the voluntary control of the arms and the artificial control of the lower extremity muscles.

Researchers from different fields have been interested in modeling human behavior in man–machine systems. Early models during the World War II were developed to improve the performance of the pilots, gunners and bombardiers in the human-in-the-loop systems [10]. They were linear and inherently incapable of modeling nonlinear aspects of the human control behavior. Optimal control models were based on the assumption that the human operator seeks to optimize some objective function of the task at hand [17,29]. Models based on the actual input–output data of the human measured during the control of an actual or simulated process ranged from parametric system identification procedures [2] to nonlinear expert systems based on rule-based systems [1,26], fuzzy logic models [4,19,21] and neural network models [8].

The first application of machine learning to FES control was reported by Kirkwood et al. [14]. This form of supervised machine learning is now known in AI as 'behavioral cloning' following the original work of Donald Michie, WWII code-breaker and computer pioneer ([22] and

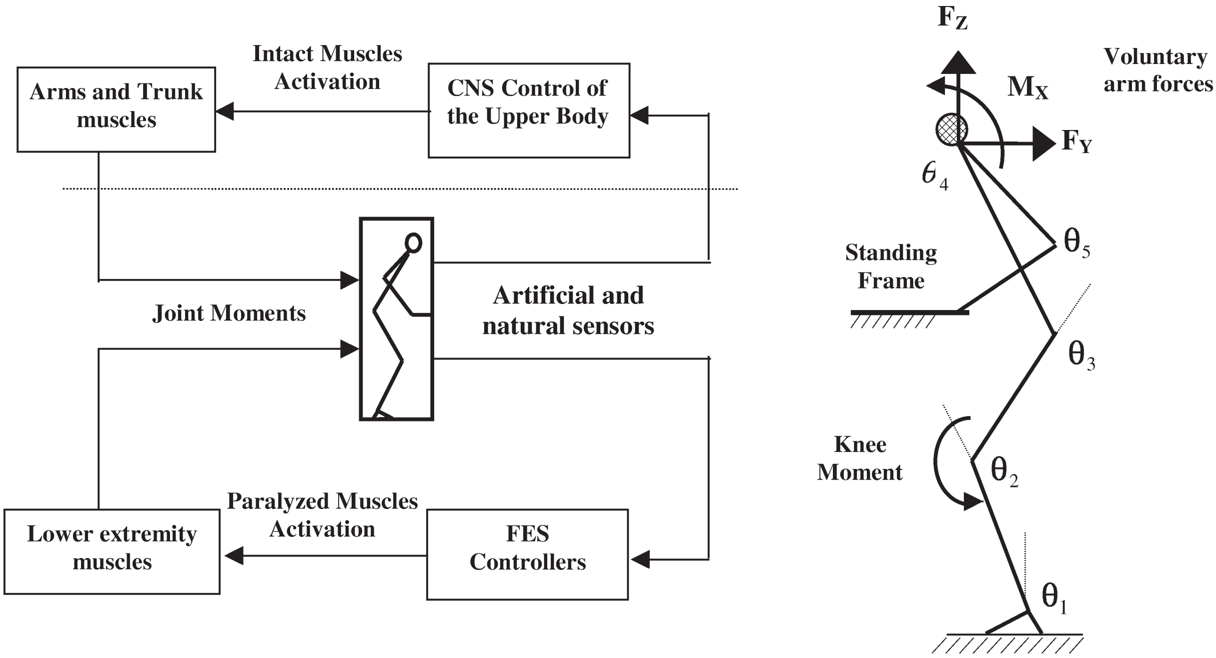

Fig. 1. FES assisted standing-up in paraplegia. A sagittal view of the subject is shown on the right. In addition to the electrical stimulation of the knee joint extensors, the voluntary arm forces help in lifting the body and keeping the balance. The equivalent forces and moments at the shoulder joint F_Y, F_Z and M_X represent the overall force actions of the arms musculature at the shoulder joint. Dashed lines represent the reference line for measuring the ankle, knee and hip joints. Two control loops affecting the FES standing-up in paraplegia are shown on the left.

http: //www.aiai.ed.ac.uk/˜dm/dm.html). Michie was in turn inspired by the seminal work of Peter Donaldson who is also well known for his work on FES. Donaldson was the first to show that a human motor skill, a pole balancing task, could be learned and mimicked by an electro-mechanical computing machine in a technique he called ‘error decorrelation’ [7]. In the FES application a motor skill, learned by a paraplegic subject whilst operating the manual control switch of the Kralj and Bajd FES walking system, was ‘cloned’ as a set of rules using rule induction based on Quinlan’s ID3 algorithm. Once cloned, this rule based could thereafter be used to automate the operation of the FES system. This basic cloning technique has since been more extensively investigated in [15]. Here we extend behavioral cloning to model the voluntary use of the upper limbs and body by paraplegics during sit–stand maneuvers assisted by FES, i.e., the two blocks above the dashed line in Fig. 1.

The importance of the voluntary control in FES assisted standing-up has also been known for some time. In a study of FES control methods Quintern et al. [27] point out the importance of the co-ordination between FES and the voluntary control for improvement of the FES standing-up. Donaldson and Yu [6] proposed a method for minimization of the arm forces by using the measurement of the arm forces in a scheme to adjust the electrical stimulation of the lower extremity. In a planar model of standing-up, however, Khang and Zajac [16] assumed that the upper extremity forces are external disturbances. Although this simplification was necessary for their approach to the design of conventional controllers to be applicable, we believe that it is not valid in reality. Veltink et al. [28] on the other hand assumed more intelligent role for the arm forces. In their three-segmental model of standing-up, the arm forces were modeled by linear proportional control laws with a vertical velocity and a horizontal position setpoints. In our previous study [3], we developed a qualitative model of the arm forces during the standing-up motion using fuzzy logic controllers. The controller was based on a set of general rules defined according to our observations and understandings of the motion objectives. The model however, was not representative of an individual subject's voluntary control actions. In this study, we individualize our models using the neural networks and the input–output data measured from paraplegic subjects in repeated standing-up trials.

The main objective of the above studies was to achieve some form of co-ordination between the artificial FES control and the voluntary control of the subject. However, two main obstacles hindered this. First, it was difficult to mathematically characterize the voluntary control behavior with acceptable accuracy. Second, the conventional control theory did not have the necessary tools to deal with systems as complex as the voluntary control. Here, we investigate the first problem and show that the accurate models of the voluntary control strategy during the FES assisted standing-up can be developed. We also discuss how these models can be used to design FES controllers that are coordinated with the voluntary controllers. Sit-to-stand maneuver was chosen because it is a prerequisite for many of the daily life activities such as walking and reaching to objects not accessible to the wheelchair. Further, the voluntary arm forces are integral part of the maneuver and contribute considerably to the quality of the resulting motion.

1.1. *The modeling task*

Figure 1 shows a planar model of FES assisted standing-up introduced by Kralj and Bajd [18] and practiced in many FES laboratories. The FES controllers activate the paralyzed muscles extending the knee joints and the voluntary control of the subject activates the arms musculature.

In this model, the sit-to-stand maneuver is viewed as a task in which the positions of the three segments including the shank, thigh and trunk must be co-ordinated to move the subject from sitting to standing position. The three-segmental system is affected by two actuators. FES actuators position the knee joint and the arms are viewed as the actuators that by applying the forces and moments position the shoulder joint and trunk to help in sit-to-stand maneuver. The modeling task is to identify this actuation strategy, i.e., to find a model that for the given state of the three segmental system could produce the shoulder forces similar to those observed in the experiments. Therefore, the model will replace the two blocks above the dashed line in Fig. 1.

To develop such a model, we need to identify the necessary inputs to the model. The actual decision making process uses different sources of sensory information [13] but we are not able to directly measure them. Therefore, we decided to use a different set of measurable variables that could partially replace the sensory information accessed by the central nervous system. The state information of the three-segmental system defined by the angular positions and angular velocities of the ankle, knee and hip joints were used to resemble the information received from the visual and vestibular systems. The forces and moments in the shoulder joint (which are correlated to the forces in the arms musculature and hand contact forces) were used to resemble the proprioceptive and exteroceptive information from the intact upper extremities.

2. Experimental procedures

2.1. *Subjects*

Eight paraplegic patients participated in the study, five men and three women. Their ages ranged from 17 to 57 years, weights from 58 to 95 kg and heights from 159 to 185 cm. Sample group included

Table 1
Paraplegic subjects participating in the study

	MK	ZB	BJ	AK	SB	MT	TM	ZJ	Mean
Sex (M/F)	M	M	M	M	M	F	F	F	–
Age (years)	23	22	23	44	31	28	19	57	32.0
Weight (kg)	58	74	85	74	64	75	59	53	70.3
Height (cm)	168	184	185	180	183	171	178	159	79.3
Injury level	T9	T10–11	T9	T10–11	T10–12	T4–5	T3–4	T11	–
FES use (months)	2.5	6	5	6	11	60	42	36	21.1

patients with different levels of spinal cord injury and different experiences of FES usage as summarized in Table 1.

2.2. Instrumentation

The measuring system used in the analysis consisted of two measuring frames, which were built as copies of a wheel chair seat and conventional walker. The seating frame was instrumented by the use of AMTI force plate providing information of the seat support forces, while the forces on the arm support frame were assessed by the six axis JR3 robot wrist sensor. Additional AMTI force plate was used for measuring the ground reaction forces under a foot. Kinematics of the body movement was assessed by the OPTOTRAK contact-less optical system measuring the 3D active markers position. The markers were attached to the ankle, knee, hip, pelvis, shoulder, elbow, wrist, and head, defining thus thirteen segments of the human body.

2.3. Protocol

Subjects were seated on the instrumented seat with the arms resting on the arm support frame. The height of the seat coincided with the height of a wheel chair, while the arm support frame height was adjusted according to the patient's preferences. The feet were positioned in such a way that the right foot was placed flat on the force plate. After approximately two seconds from starting the data collection, the subject was asked to stand up. The subjects were asked to rise in their preferable way and speed, while using stimulation of knee extensors and arm support. At least five rising trials were recorded for each participant with the 50 Hz sample rate, each trial lasting for 10 s.

2.4. Data analysis

The signals collected from active markers, force plates and wrist sensor were interpolated and filtered by the 4th order Butterworth filter with 5 Hz cut-off frequency. The co-ordinate systems of all sensors were transformed to coincide with the reference co-ordinate system placed on the floor in the center of the arm frame. Since the human body symmetry was presumed, all parameters were gathered only for the patient's right side and calculated for the left side.

The training data for the model consists of angular positions and angular velocities of the ankle, knee and hip joints and the forces and moments at the shoulder joint. The kinematics of the markers and anthropometric data were used to calculate the angular positions of the joints and kinematics of the joint centers and segmental mass centers. Velocities and accelerations were calculated by differentiating the positional data. The kinematics of the arms and the force measurements of the arm support were fed to an inverse dynamic model of the arms to calculate the forces and moments at the shoulder joint.

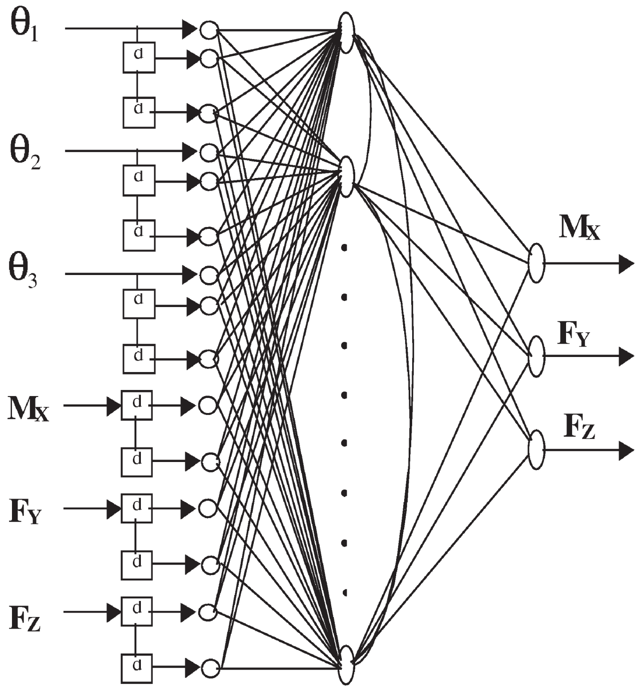

Fig. 2. The topology of the neural network models. Present and past state information plus the past samples of the outputs form the inputs to the model (angular velocity inputs are not shown for clarity). The outputs are the forces and moment at the shoulder joint. Hidden layer is fully connected to the input and output layer. Each hidden node receives connections from previously established hidden nodes (hidden nodes are added one at a time by the training procedure). Not shown for clarity are also the direct connections from the input layer to the output layer.

3. The proposed model

3.1. Topology of the neural network model

The basic structure of the model is a three-layered fully connected feedforward neural network as depicted in Fig. 2. To further enhance this nonlinear function approximator [11], the past inputs and outputs are fed to the input layer to provide the network with the memory required in modeling the dynamic systems. These delayed signals are found to improve performance in the recognition of time series such as speech signal [20].

3.2. Selection of the input variables

We used the visual inspection of the scatter plots and a nonlinear correlation method to identify the most important input variables. The nonlinear correlation technique was based on the nonlinear neural networks. A moderate size neural network was trained to represent the relationship between one of the inputs and one of the outputs. The root mean square error (RMSE) between the actual output and the model predicted output was calculated as an indication of how strongly the output is correlated to the input. The smaller the RMSE the stronger the correlation. The size of the network was kept constant to make sure that the comparison is valid. The Neural Network Toolbox (The Mathworks Inc., USA) was used to train these neural networks.

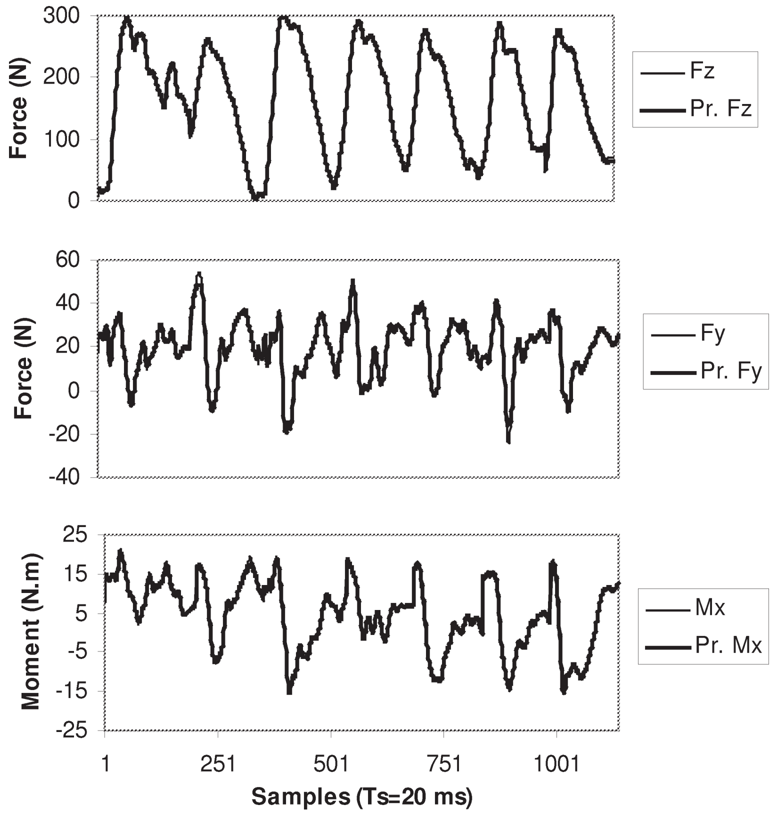

Fig. 3. The predictions (Pr F_Y, Pr F_Z and Pr M_X) of the neural network model developed for subject MT are compared to his measured arm forces F_Y, F_Z and M_X.

3.3. Neural network training method

The neural network models were trained using the Neuralwork Predict (NeuralWare Inc., USA). It uses a cascade method of network construction together with an adaptive gradient learning rule to train the network. In the cascade method of network construction method, training begins with zero hidden layer nodes and new hidden layer nodes are added one at a time with the purpose of predicting the current remaining output error. The process of adding the hidden layer nodes continues until no improvements can be made. The details of the training procedure can be found in [23,24].

4. Results

4.1. Selection of the input variable

There was strong nonlinear correlation to the present samples of the angular position inputs $\theta_1(t)$, $\theta_2(t)$ and $\theta_3(t)$ and strong linear correlation to the most recent samples of the outputs $F_Z(t-1)$, $F_Y(t-1)$ and $M_X(t-1)$. Therefore, these variables were selected as the inputs to the model.

Compared to the selected variables, the correlation to the angular velocities and other delayed samples were weaker and, therefore, were excluded from the model. The correlation to the angular position had

Table 2

Statistics comparing the model predictions to the measured data

Subject		R	RMSE	Avg. abs. error	Max. abs. error	Conf. interval (95%)
MT	F_Z	0.999	3.425	2.297	44.752	6.666
	F_Y	0.992	1.614	1.105	11.867	3.141
	M_X	0.994	0.982	0.577	12.083	1.911
MK	F_Z	0.993	7.959	4.508	93.066	15.500
	F_Y	0.974	2.801	1.758	24.243	5.456
	M_X	0.984	1.447	0.865	13.030	2.819
TM	F_Z	0.977	17.560	7.291	236.709	34.151
	F_Y	0.980	2.782	1.690	37.570	5.411
	M_X	0.995	1.404	0.912	20.720	2.731
SB	F_Z	0.997	5.667	3.947	55.315	11.025
	F_Y	0.981	2.436	1.627	25.939	4.740
	M_X	0.994	1.012	0.633	12.162	1.970
BJ	F_Z	0.997	5.105	3.153	61.782	9.934
	F_Y	0.983	2.342	1.512	21.919	4.557
	M_X	0.997	1.020	0.648	9.617	1.986
ZJ	F_Z	0.992	10.443	5.256	141.434	20.321
	F_Y	0.984	3.326	2.172	35.732	6.472
	M_X	0.995	1.401	0.876	12.633	2.727

Correlation (R); root mean square error (RMSE); average absolute error (avg. abs.); maximum absolute error (max. abs.) and the 95% confidence interval are given.

also peaks at samples 280–400 ms and 700 ms in the past. These variables, however, were not included in the model because they increased the memory required to store the old samples and they had negligible effect in improving the model accuracy.

4.2. Model trained for subjects MT

A neural network model was successfully built to predict the voluntary arm forces, F_Z, F_Y and M_X of the subject MT during the standing-up maneuver. The model predictions are compared to the actual values in Fig. 3. The model performs well not only on the training data but also on the validation data never used in the training process. The validation data constitutes the last 20% of the data shown in Fig. 3. Further statistics of the model performance is presented in Table 2.

4.3. Model trained for the rest of the subjects

The performance of the models trained for MK (least experienced), TM (youngest with the highest level lesion), SB (lowest level lesion), BJ (tallest and heaviest), ZJ (lightest and oldest) and MT (most experienced) are summarized in Table 2.

4.4. Comparing the voluntary control strategies

Models developed for individual subjects were evaluated on test data consisting of 8 sample standing-up trials. Each one of the 8 trials belonged to one of the subjects and has never been used in training. The

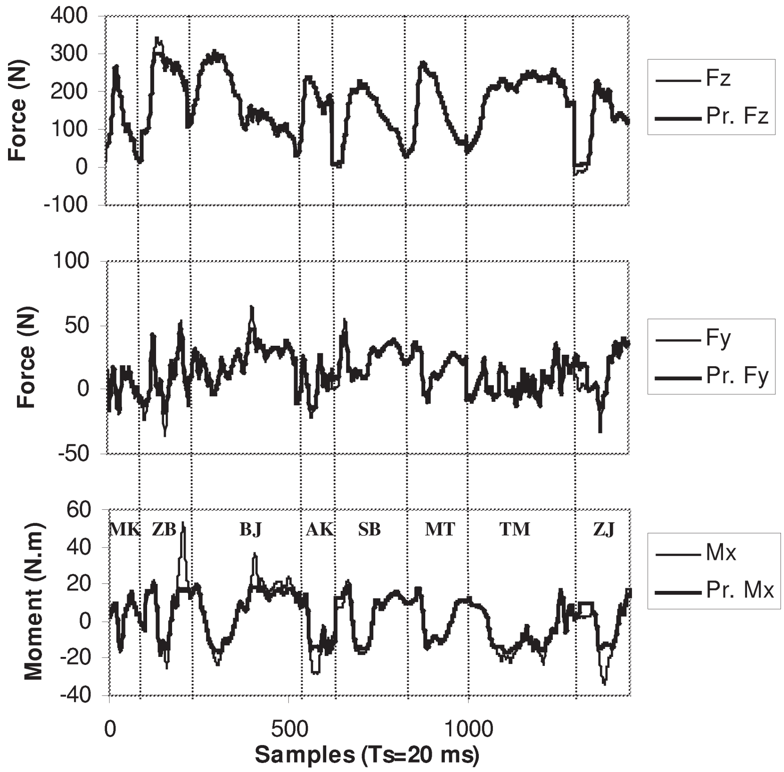

Fig. 4. Performance of the model of MT on the data collected from all of the subjects. Pr F_Y, Pr F_Z and Pr M_X are the predictions of MT's model when fed with the inputs from other subjects' measurements. F_Y, F_Z and M_X are the arm forces measured from all of the subjects. The portions of the data between the dashed lines belong to one subject as indicated in the figure.

objective was to investigate the similarities and differences in the voluntary control strategies adopted by the subjects.

Figure 4 shows how the voluntary control of MT compares to the other subject. This is equivalent to asking the other subjects to use the control strategy of subject MT to control their arms. Table 3 summarizes the performance of this model and the model of the other subjects on the same test data. The subject's control strategy is more similar to the collective behavior when the RMSE is lower or the correlation is higher.

5. Discussions

Since the system is highly nonlinear, a nonlinear correlation analysis was devised and successfully used to identify the relevant input variables.

There was strong correlation to the angular position of the joints than the angular velocity that may suggest the voluntary arm forces during standing-up is primarily position dependent. Also strong correlation to the past samples of the arm forces shows that the proprioceptive feedback plays an important role in the voluntary control of the arm forces. Correlation peaks at angular position samples delayed by 280–400 ms and 700 ms may be attributed to the different control loops involved in the voluntary control of the arms.

Table 3

Statistics comparing the model predictions to the measured data from all of the subjects

Subject		R	RMSE	Avg. abs. error	Max. abs. error	Conf. interval (95%)
MT	F_Z	0.992	10.549	5.299	177.588	20.526
	F_Y	0.960	4.610	2.837	31.223	8.971
	M_X	0.947	5.053	2.846	36.561	9.831
MK	F_Z	0.978	17.645	10.531	133.418	34.333
	F_Y	0.930	6.269	3.775	35.680	12.198
	M_X	0.961	4.240	2.436	31.821	8.251
TM	F_Z	0.924	31.834	21.027	143.503	61.942
	F_Y	0.969	4.004	3.014	31.973	7.792
	M_X	0.953	5.480	3.164	42.685	10.663
SB	F_Z	0.964	23.023	14.757	130.741	44.798
	F_Y	0.925	6.638	4.496	33.407	12.917
	M_X	0.947	4.772	2.812	33.738	9.286
BJ	F_Z	0.955	24.385	12.907	191.774	47.447
	F_Y	0.944	6.852	4.059	41.321	13.334
	M_X	0.951	4.656	2.623	23.810	9.060
ZJ	F_Z	0.977	19.885	13.296	172.180	38.690
	F_Y	0.971	4.345	3.170	38.666	8.456
	M_X	0.966	3.749	1.773	34.336	7.295

Correlation (R); root mean square error (RMSE); average absolute error (avg. abs.); maximum absolute error (max. abs.) and the 95% confidence interval are given.

The neural network model developed for MT performed well on both the training and the validation data. Therefore, it is possible to accurately model the voluntary arm forces during standing-up. The good performance on the validation data shows that the model has generalized well and that the subject's control strategy is consistent from trial to trial. Therefore, subject MT has developed a unique control strategy for the use of her arms and uses it consistently.

Similar models were successfully developed for the other subjects. However, the consistencies in the use of the adopted control strategies were not the same. The adopted control strategy and consistency in performing it depends on parameters such as experience of FES use, level of injury, weight, height and age of the subject. Comparing the data in Table 2 shows that subject MT who was the most experienced FES user (have been in the program longer), had the highest consistency. This is evident from the very low confidence interval, lower absolute errors and lower RMSE. The highest inconsistency belonged to TM who has the highest level lesion (T3–4). This is in contrast with her long history of FES use as shown in Table 1. The insufficient control over the trunk muscles due to the high level lesion most probably prevents him from effectively stabilizing her trunk. The unstable trunk could disturb the maneuver and therefore require more corrective actions from the arms that in turn results in less consistent control strategy.

In Fig. 4, the control strategy adopted by MT is tested on all other subjects. Although it is more similar to some subjects than the others, it shares a general trend with all the subjects. This is an expected result because during the standing-up motion, the arms must play a similar role, i.e., provide balance and help in rising. Therefore, there may be general rules that govern the control of the arm forces in all of the subjects. However, there are also rules that are specific to the individual subjects, which is apparent from the incompatibilities shown in Fig. 4. The control strategy adopted by MT had striking similarities with MK and SB but differed in some aspects with the others. Table 3 quantifies the similarity of each subject's control strategy to the collective behavior of the group. Here again MT as the most experienced subject behaves closer to the average behavior of the population. The confidence interval and the RMSE are the lowest in the table. MT on the other hand has the highest dissimilarity which is again attributable to her high lesion that forces her to adopt a control strategy that is not only more variant but also different from others.

6. Conclusion

Apart from some subject specific rules, the voluntary control strategy adopted by the paraplegics follow general principles that may be attributed to the similar objectives the arms have during standing-up. The control strategy adopted by each individual can be accurately modeled. The models become more accurate when the subjects behave more consistency due to for example more experience.

Finally, the knowledge of the subject's voluntary control strategy could be used to design FES controllers that are well coordinated with the intact upper body to achieve similar objectives. The FES controllers can use these models to predict the upper body behavior in advance and therefore choose proper control actions. These models can also be used along with the musculoskeletal models of the lower extremities to develop a cybernetic model. This model can then be used in a learning procedure such as the reinforcement learning or the genetic algorithms to develop optimal FES controllers. The latter is our method of choice and is currently underway.

Acknowledgements

The author (RD) is a recipient of a scholarship awarded by the Iranian Ministry of Culture and Higher Education. We also gratefully acknowledge the support of the Canadian Natural Science and Engineering Research Council (NSERC) and the Alberta Heritage Foundation for Medical Research (AHFMR).

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