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Predicting the voluntary arm forces in FES-assisted standing up using neural networks

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Abstract. For individuals with paraplegia, standing up requires activation of paralyzed leg muscles by an artificial functional electrical stimulation (FES) controller and voluntary control of arm forces by the individual. Any knowledge of such voluntary control, particularly its prediction, could be used to design more effective FES controllers. Therefore, artificial neural network models were developed to predict voluntary arm forces from measured angular positions of the ankle, knee, and hip joints during FES-assisted standing up in paraplegia. The training data were collected from eight paraplegic subjects in repeated standing-up trials, and divided into two categories for training and validation. The predictions of the models closely followed both the training and validation data, showing good accuracy and generalization. The comparison of the models showed that, although there are striking similarities among the voluntary controls adopted by different subjects, each subject develops his/her own 'personal strategy' to control the arm forces, which is consistent from trial to trial. The level of consistency was dependent on the experience in using FES, injury level, body weight, and other subject-specific parameters.

1 Introduction

Functional electrical stimulation (FES) has been used to restore the motor functions lost after spinal cord injury (Graupe 1994; Kralj and Bajd 1989; Phillips 1991). The restored functions usually utilize two fundamentally different controls: artificial FES control of the paralyzed muscles below the lesion, and voluntary control of the intact muscles above the lesion. For example, both controllers are important in a common procedure for FES-assisted standing up (Fig. 1) in which the subject voluntarily uses his arms in addition to the electrical stimulation of his paralyzed knee extensor muscles. The arms help to balance the body during this maneuver and can sometimes carry as much as two-thirds of the body weight (Dolan et al. 1997; Kamnik et al. 1999). Therefore, the quality of the resulting motion strongly depends on how the arms' musculature is controlled and whether there is an appropriate level of coordination between the voluntary control of the arms and the artificial control of the lower extremity muscles. Such coordination is essential to prevent the independently designed artificial FES controller from conflicting with voluntary arm actions (Donaldson and Yu 1996).

Although the importance of voluntary control in FES-assisted standing up has been known for some time, more recently there has been a renewed interest in the subject (Veltink and Donaldson 1998). In a study of FES control methods by Quintern et al. (1989), the lack of coordination between natural voluntary control and artificial FES control was recognized as an essential problem hindering the development of FES controllers. To provide such coordination, Donaldson and Yu (1996, 1998) proposed a method for minimization of the arm forces during standing up. In their scheme, the arm forces should be measured and the leg muscles stimulated in a manner that unloads the arms. Other researchers built a complete model of standing up in paraplegia by combining a model of the paralyzed lower extremities with a model of voluntary arm control. These models were then used to evaluate FES controllers of the lower extremities and their interactions with the voluntary control of arms. For example, in a three segmental model of standing up, Veltink et al. (1995) simulated the contributions of the arms with vertical and horizontal forces in the shoulder joint. These forces were governed by linear control laws with vertical velocity and horizontal position as set points. However, no validation of the model was given. In our previous studies (Davoodi and Andrews 1996, 1998), we used fuzzy-logic controllers to simulate voluntary control of arms during standing up. The controllers were based on a set of general rules defined according to our observations and

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understandings of the motion. For example, the rules of the fuzzy controller were defined to keep the body's center of mass inside the feet support area and move it upward with a reasonable speed. Although the performance of the model was smooth and qualitatively comparable to the actual observations in paraplegics, it was general and not representative of an individual subject's voluntary control. Similar fuzzy controllers were also used by Riener and Fuhr (1998) to simulate the voluntary shoulder forces and moments in an attempt to build a virtual patient for FES controller design. Unlike our fuzzy control models, which were qualitative and general, their fuzzy control models were tuned to force the shoulder joint to follow the reference trajectories recorded from a paraplegic subject during a single standing-up trial. This model was later modified by Bahrami et al. (1999) to minimize the differences between simulated and recorded movements of the body's center of mass. These models assume that the voluntary arm control is a trajectory-following controller that forces the shoulder joint or the body's center of mass to follow the same trajectories irrespective of what is happening with the rest of the body. However, according to Donaldson and Yu (1998), as the situation changes the voluntary control strategy may remain the same even if the trajectories change. All of the above models are based on assumptions about the goal of voluntary arm control, which need verification.

Clearly, a better understanding of the voluntary control of arms during standing up is a first step toward improving FES controllers for standing up in paraplegia. In this study, we model the individual voluntary control of arms in a group of paraplegic volunteers, and investigate the similarities and differences among them. We are also motivated by the findings in a study by Moynahan (1995), who monitored the electromyographic activity of the arm muscles during standing in paraplegia. She suggested that each subject develops consistent 'personal strategies' for postural control that is different from that of the others. We hypothesize that similar 'personal strategies' exist for control of the arms during FES-assisted standing up. Therefore, a general model is inadequate and there is a need for the development of individualized voluntary control models for each subject. We will use artificial neural networks (ANNs) to model voluntary control of the arms using the data measured from repeated standing-up trials. ANNs are universal function approximators that can be trained to represent highly complex and nonlinear relationships (Haykin 1999).

2 The modeling task

Figure 1 shows a popular method of FES-assisted standing up (left) and its planar representation (right). The method, introduced first by Bajd et al. (1981), uses both the arms and the electrical stimulation of the paralyzed knee extensor muscles for standing up.

In the planar model, the sit-to-stand maneuver is viewed as a task in which the primary objective is to co-

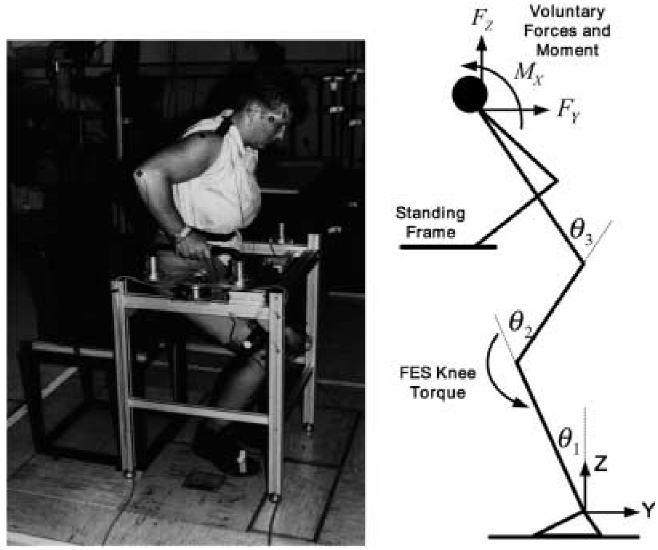

Fig. 1. FES-assisted standing up by a paraplegic subject (*left*) and its simplified model in the sagittal plane (*right*). Two controllers work in parallel. The artificial control of the electrical stimulation to the paralyzed leg muscles extend the knee joint, and the voluntary control of the arm forces lift the body and provide balance. The reaction forces and moments at the shoulder joint, F_Z, F_Y, and M_X, represent the overall force actions of the arm musculature at the shoulder joint. *Dotted lines* are used as the references for measuring the ankle, knee, and hip joint angles

ordinate the movements of the three segments; shank, thigh, and trunk, for successful standing up. Therefore, the arms are replaced with their resultant forces and moments in the shoulder joints, because as far as the three-segment system is concerned, the overall effort of the arms are seen only in the forces and moments at the shoulder joint. This view simplifies the model because there is no need to include arm models, which are rather complex. This simplified model is also easier to interpret because the magnitude and direction of the forces and moments in the shoulder joint can be directly related to the balance and rising speed of the sit-to-stand maneuver. Therefore, the three-segmental system is affected by two actuators: electrically stimulated knee-joint extensor muscles that control the angular position of the knee-joint and the voluntarily controlled shoulder forces, and moments that control the position of the shoulder joint and angular orientation of the trunk. The modeling task is to find a model that, for the given state of the three-segmental system, could produce shoulder forces and moments similar to those observed experimentally. To develop such a model, we need to identify the necessary inputs to the model. The actual decision-making process employs sensory information from vestibular, visual, proprioceptive, and exteroceptive systems (Kandel et al. 1991), which are not available for direct measurement. Therefore, we decided to use a different set of measurable variables that could partially – but sufficiently for the task at hand – replace the sensory information accessed by the central nervous system (CNS). In reality, the visual, vestibular, and proprioceptive systems may use many different sensory channels but we did not want to model exactly the same information channels but a minimum set of practically measurable variables that contain enough information for the model. The complete state 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 arm musculature and the hand contact forces) were used to resemble the proprioceptive and exteroceptive information from the intact upper extremities. These variables proved to be a good substitute to the actual redundant sensory information used by the CNS (that we could not practically measure), as they provided enough information to the models mimicking the behavior of the actual voluntary control.

3 Experimental procedures

3.1 Subjects

Eight paraplegic subjects participated in the study, comprising five men and three women. Their ages ranged from 19 to 57 years, weights from 53 to 94 kg, and heights from 159 to 185 cm. The sample group included subjects with different levels of spinal cord injury and different experiences with FES usage, as summarized in Table 1.

3.2 Instrumentation

Motion of the body was measured with an OPTOTRAK optical system (Northern Digital Inc., Canada), which measures the 3-D positions of active markers (infrared LEDs). Markers were attached to anatomical landmarks at the ankle, knee, hip, pelvis, shoulder, elbow, wrist, and head. The forces on the arm support frame were measured by a six-axis JR^3 robot wrist sensor (JR3 Inc., USA). Assuming that the human body is symmetrical during the standing-up motion, measurements were made only for the patient's right side, and were calculated for the left side.

3.3 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 wheelchair, while the arm support frame height was adjusted according to the patient's preferences. Prior to the measurements three standing-up trials were performed to relieve spasticity in the paralyzed extremities and familiarize the subject with the measuring equipment. In recorded trials, the subjects were asked to take an initial seated pose and to stand up in their preferred way and speed, starting approximately two seconds after the initiation of data collection. The subjects voluntarily triggered the constant-level stimulation of the quadriceps muscle group via a push-button mounted on the walker handle. The stimulation intensity was set to the level that saturated the knee extensors in the sitting position. At least five standing-up trials, each lasting 10 s, were recorded for each participant with a 50-Hz sampling rate.

3.4 Data analysis

The data collected from wrist sensor and active markers were interpolated and low-pass filtered with a fourth-order, dual-pass Butterworth filter with a 5-Hz cutoff frequency. To determine the locations of the joint centers in each extremity, the three markers in the joints were connected to form a plane as shown in Fig. 2. Each joint-center location was determined by translation of the marker in the direction normal to the plane by an amount equal to one-half the segment diameter (measured at the marker attachment point). Segmental mass, mass center, and moments of inertia were estimated from anthropometric relationships (De Leva 1996). Positional marker data were differentiated and filtered to find the marker velocities and accelerations. These data were then used to calculate the motion of the segmental mass centers and the angular positions and angular velocities of the joints. Forces and moments acting at the joints were calculated recursively using Newton-Euler inverse dynamic analysis (Spong and Vidyasagar 1989). Since, the motion of the arms during standing up is not confined to the sagittal plane, a 3-D inverse dynamic model of the human right arm was developed, embodying upper arm, lower arm, and hand. Each segment had six degrees of freedom and was considered to be a rigid body. Reaction forces and moments at the shoulder joint were recursively calculated, starting from the handle reactions and proceeding toward the shoulder joint. Sagittal-plane components of the shoulder joint forces and moments (doubled to account for the left hand) along with the angular

Table 1. Paraplegic volunteers who participated in the study

Subject	MK	ZB	BJ	KA	SB	MT	TM	ZJ
Sex (M/F)	M	M	M	M	M	F	F	F
Age (years)	23	22	23	44	31	28	19	57
Weight (kg)	58	94	85	74	64	75	59	53
Height (cm)	168	184	185	180	183	171	178	159
Injury level	T9	T10–11	T9	T10–11	T10–12	T4–5	T3–4	T11
FES use (months)	2.5	24	5	6	11	60	42	36
Number of trials	8	5	5	8	9	7	11	9

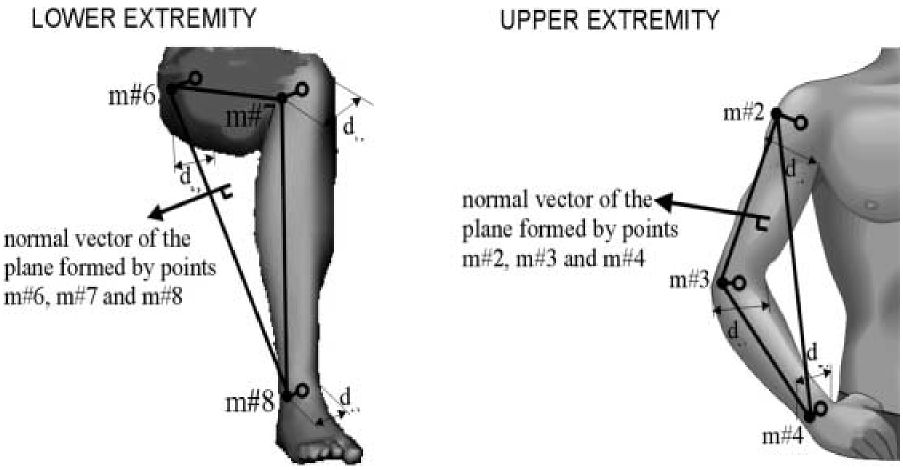

Fig. 2. Procedure for locating joint centers in the extremities using measured marker positions. See the text for more detail

Table 2. Specifications of the final ANN models of voluntary arm control in eight paraplegic subjects and in a virtual average subject AVG. All the networks have direct connections, cascaded connections, and input-layer transformations. Therefore, the number of input-layer nodes includes the original six inputs and the additional input transformations

Subject	MK	ZB	BJ	KA	SB	MT	TM	ZJ	AVG
No. of input layer nodes	14	17	20	20	24	16	23	22	19
No. of hidden layer nodes	0	0	0	8	3	0	0	0	0
No. of output layer nodes	3	3	3	3	3	3	3	3	3

positions and angular velocities of the ankle, knee, and hip joints were used as the training data for the ANN models.

4 The ANN model

4.1 The ANN model topology and training method

Neuralworks Predict software (NeuralWare Inc., USA) was used to build and train the ANN models. It uses a basic three-layer fully connected feedforward ANN (Haykin 1999), with optional features that may be added if necessary. The network is constructed by a cascade method and trained by an adaptive gradient learning rule (Fahlmann and Lebiere 1988). In the cascade method of network construction, training begins with no hidden layer nodes. 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 the prediction error falls below the given threshold. Additional features may be added to the ANN models to enhance their performance. The direct connection feature allows the input layer to be connected to the output layer. Another feature allows the transformation of the inputs by common (e.g., linear and exponential) functions to form new input variables. The cascaded connections feature allows connections from previously established to more recently established hidden nodes. To further enhance the model, 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 have been shown to improve performance when applied to the modeling of dynamic processes (Lang et al. 1990). Detailed specifications of the final ANN models for each subject are given in Table 2.

4.2 Training data

As the result of the data analysis, the angular position, angular velocity, and reaction forces and moments were calculated for all of the joints. These data were used to build the training data for the ANN models. Angular positions and angular velocities of the ankle, knee, and hip joints were the inputs, and the forces and moments at the shoulder joint were the outputs. Only a fraction of the recorded data was from the actual sit-to-stand maneuver, with an initial preparation (before seat takeoff) and a rather long final stabilization phase. Therefore, to form the training data, the initial preparation phase was removed because the subject was still supported by the seat. Since, the main objective was to model the voluntary arm forces in sit-to-stand phase, the final stabilization phase was also partly removed to prevent it from skewing the model behavior. The data from the repeated trials of each subject were then concatenated to form the training data for that subject. This resulted in eight training data sets for eight subjects that will be used to develop the ANN models representative of each subject's voluntary control. An additional virtual subject (AVG) was also introduced by concatenating the data from eight standing-up trials of eight different subjects. The ANN model for subject AVG will be used to represent the average voluntary control of the group. In each training data set, the last 20% was set aside for validation of the ANN models. The remaining data were used in the model building process as the training (70% by round robin selection) and test data (the remaining 30%).

4.3 Selection of the input variables

Current and delayed samples (up to 1 s) of the inputs and outputs in subject MT's training data set were considered for variable selection. Examination of the scatter plots revealed strong nonlinear relationships between the inputs and outputs. Therefore, linear correlation techniques were ruled out and a combination of three techniques was used along with the authors' judgment to select the most important input variables. Initially, the scatter plots were examined to find the most evident correlations between the inputs and outputs. Then a method was devised to examine the degree of nonlinear correlation between an input and an output in isolation. In this method, Matlab's neural network toolbox (Mathworks Inc., USA) was used to train a fully connected feedforward neural network to model the relationship between an input and an output variable. For a fair comparison, the size of the neural network model (one input, one output, and 25 hidden layer nodes) was kept constant. The higher prediction accuracy of the developed models was used as an indication that there is a strong nonlinear correlation between the two variables. This method examined an input-output pair in isolation, which may not be sufficient. Therefore, a genetic algorithm optimization method (Goldberg 1989) was used to find a subset of input variables that form an optimal predictor. This method is one of the features in the software package Neuralworks Predict that performs an extensive search to find subsets of the input variables that along with the ANN model forms an optimal predictor.

5 Results

5.1 Standing-up trials

Trajectories of the joints and arm forces in typical standing-up trials of the eight paraplegic subjects are shown in Fig. 3. The duration of the sit-to-stand phase, rising speed, and the arm forces vary considerably among the subjects. F_Y and M_X are primarily responsible for maintaining the body's center of mass inside the base of support, and are lower in magnitude than F_Z. F_Z is primarily responsible for pulling the body upward and is therefore higher in heavier subjects. Interestingly, some subjects (ZB, TM, and ZJ) maintain a high level of F_Z even after assuming the upright posture.

5.2 Selection of the input variables

There was strong nonlinear correlation between the outputs and the present samples of the angular position inputs $\theta_1(t), \theta_2(t)$, and $\theta_3(t)$. There was also a 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 correlations with angular velocities and other delayed samples were weaker and therefore were excluded from the model. The correlation to the angular position also had peaks at samples 280–400 ms and 700 ms in the past. These variables, however, were not included in the model because they greatly increased the memory required to store old samples while providing negligible improvements in the accuracy of the model predictions.

5.3 ANN models

Nine ANN models were successfully built to predict the voluntary arm forces (F_Z, F_Y, and M_X) of eight paraplegic subjects and subject AVG during standing up. As a measure of variability in the voluntary control of arm forces, the 95% confidence intervals for the models are shown in Fig. 4. Other model evaluation measures such as the root-mean-square error or correlation produced similar results. Therefore, only the 95% confidence intervals were used for evaluation of the models. A higher value of the confidence interval (e.g., in subjects TM and ZB) shows that the voluntary control represented by the model has more variations and, therefore, more unpredictable behavior. Conversely, lower values (e.g., in subjects MT, SB, and BJ) represent a subject's consistency in executing predictable voluntary control. The predictions of the voluntary control of subject ZJ (a moderate performer in Fig. 4) are shown in Fig. 5. The models perform well not only on the training data but also on the validation data (the last 20%) that were never used in the training process.

5.4 Comparison of the voluntary controls

One way to compare the voluntary control of arms in two subjects is to ask one subject to try the voluntary control strategies of another subject to produce his/her arm forces during standing up. Although impossible in practice, this can be done very easily with the ANN models of the subjects' voluntary controls; feeding data from one subject into the ANN model of another subject is equivalent to having the subject try another's voluntary control. The resulting predictions can then be compared to the measured arm forces when the subject uses his/her own voluntary control. The results of the comparison for the lifting force (F_Z) and balancing force and moment (F_Y and M_X) are shown in Figs. 6 and 7, respectively. For example, the first column in the left of Fig. 6 compares subject MK's voluntary control of F_Z to that of the other subjects. Lower values of the confidence interval in this column means that the voluntary control of subject MK has better predictions of the behavior in the other subject, and therefore they are more similar. The height of the column, which

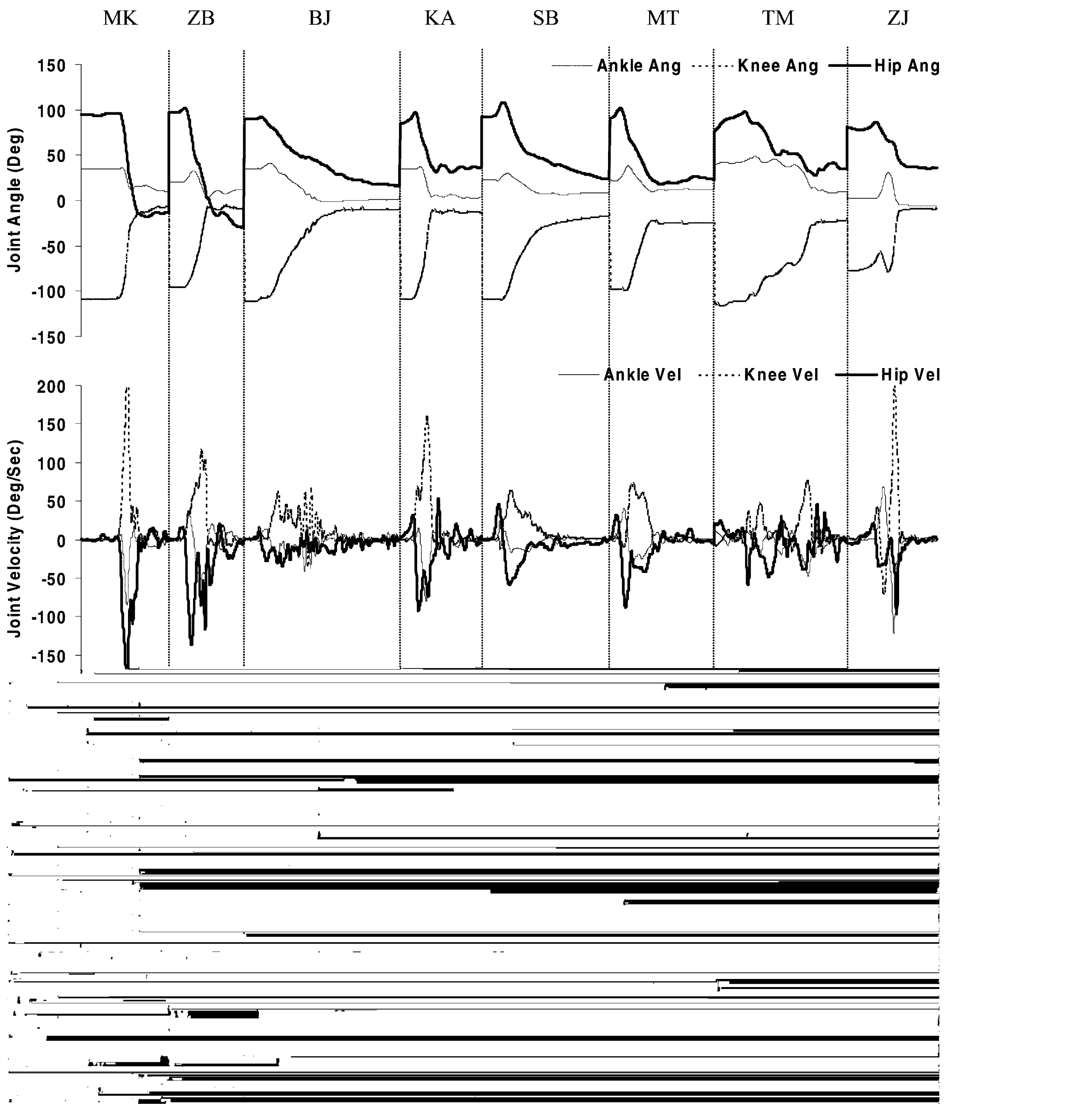

Fig. 3. Trajectories of the joints and voluntary arm forces during standing up in sample trials of the eight paraplegic subjects. The portions of the data between the *dotted lines* belong to sample standing-up of one subject

accumulates the confidence intervals of the paired comparisons, is an overall score that compares subject MK's voluntary control to that of the group. Using this score, the voluntary controls of subjects AVG and KA have the most and the least similarity to the average behavior of the group, respectively. The scores for the rest of the subjects are somewhere in between. For example, Fig. 8 shows the results of trying subject SB's voluntary control, which scores close to the middle in Figs. 6 and 7, by all other subjects. As shown in the figure, subject SB's voluntary control of the lifting force is most similar to that of subject TM, and least similar to that of subject ZB. Similar comparison for the balancing force and moment gives different results.

6 Discussion

The sample standing-up trials in Fig. 3 show considerable differences in the trajectories of the joints, speed of rise, and the level and pattern of arm support forces. By examining these data, Kamnik et al. (1999) concluded

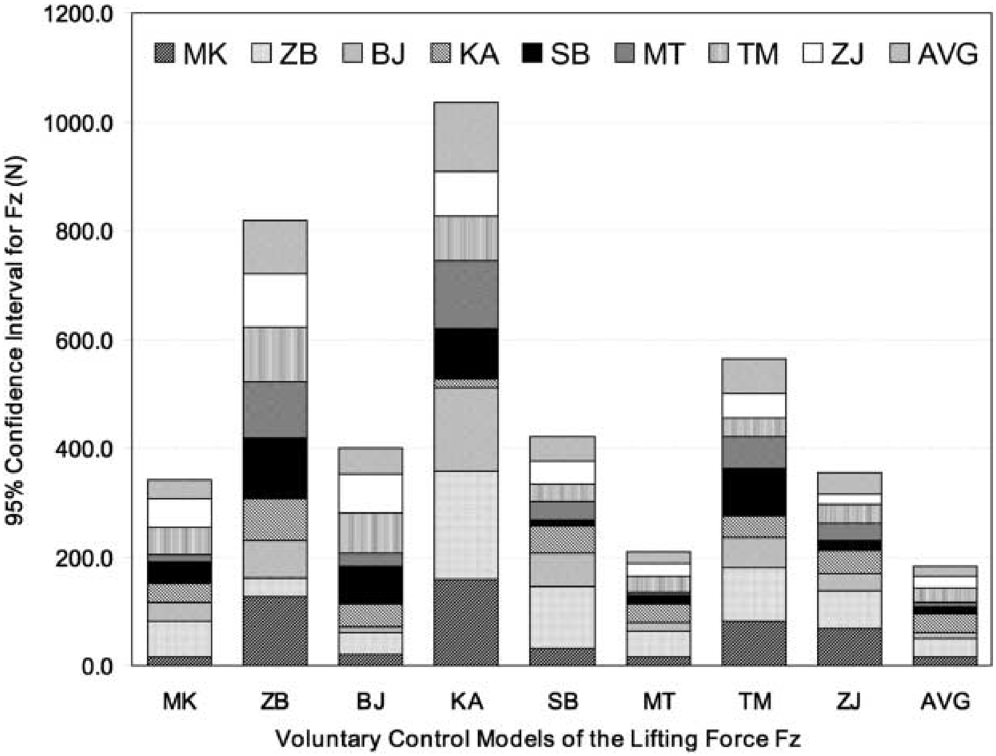

Fig. 6. 95% confidence intervals of the ANN models of lifting force (F_Z), when the models are tried on the data from the other subjects. In each column, the voluntary control of one subject is compared to each one of the other subjects. The height of each column is an overall score showing how different each subject's voluntary control is from the overall average behavior of the group. A higher value of the confidence interval shows that the difference between the voluntary controls of the two subjects is high

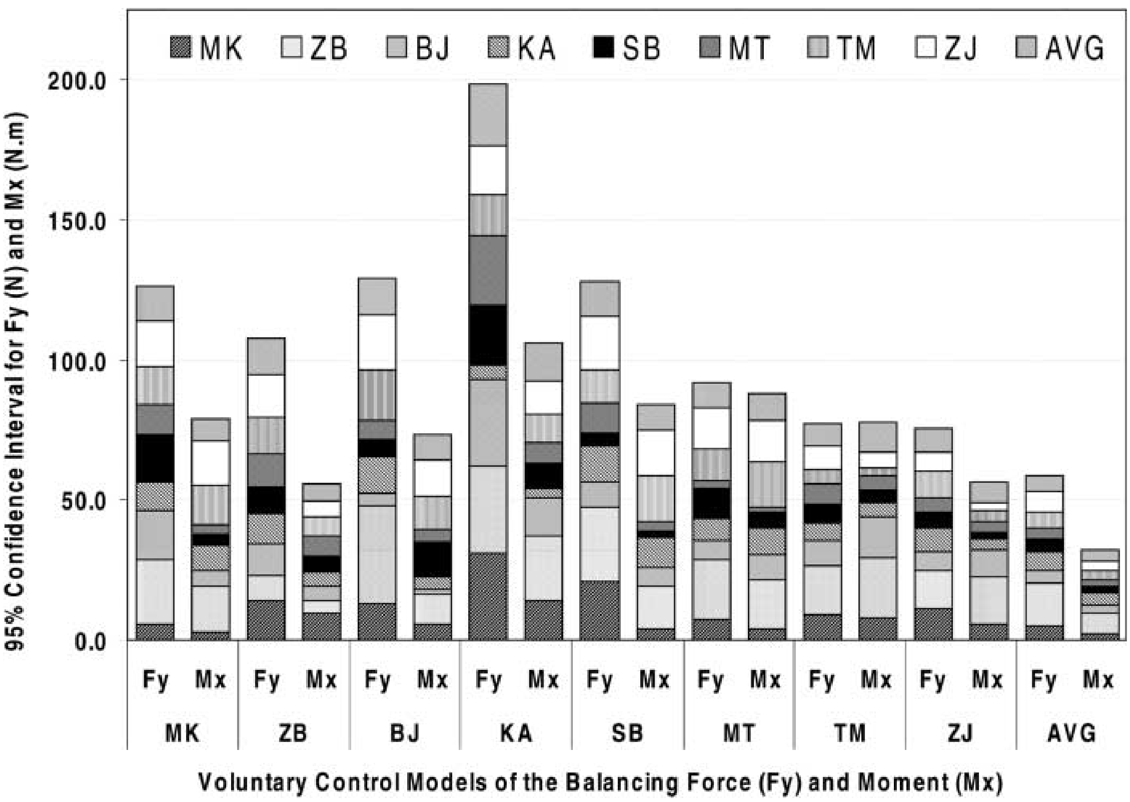

Fig. 7. 95% confidence intervals of the ANN models of balancing force (F_Y) and moment (M_X), when the models are tried on the data from the other subjects. In each column, the voluntary control of one subject is compared to each one of the other subjects. The height of each column is an overall score showing how different each subject's voluntary control is from the overall average behavior of the group. A higher value of the confidence interval shows that the difference between the voluntary controls of the two subjects is high

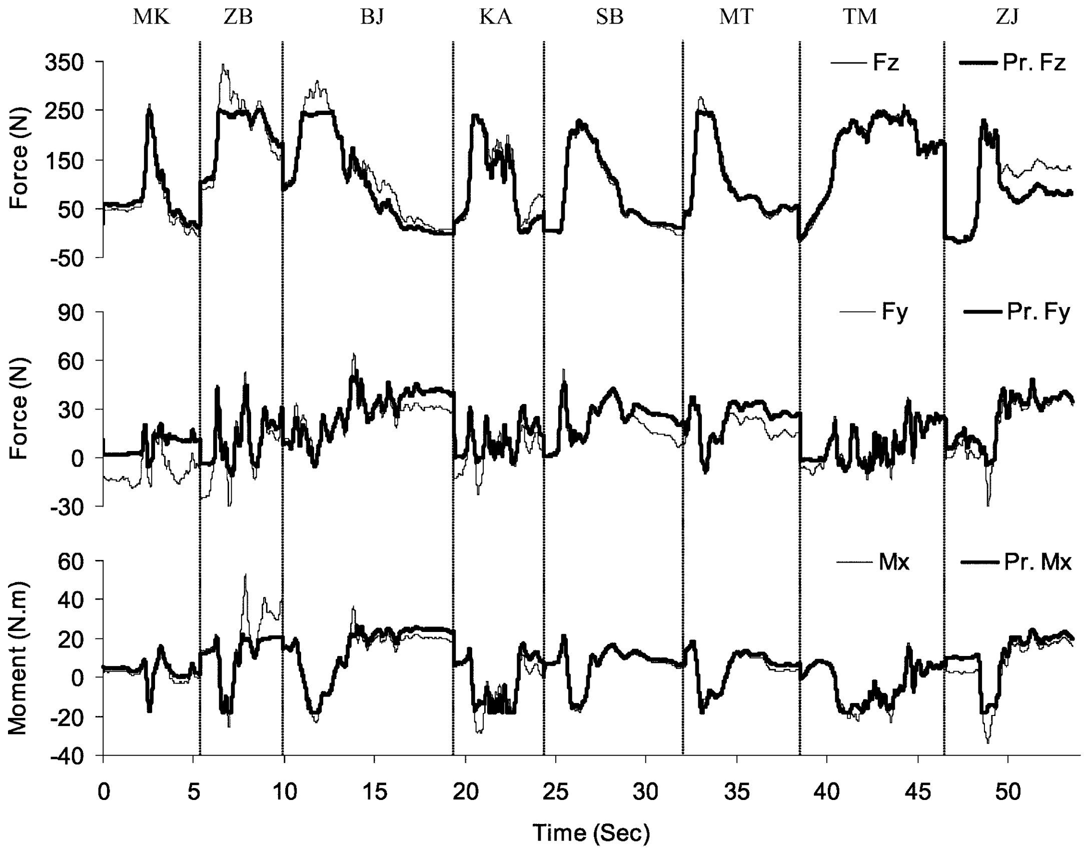

Fig. 8. Predictions of the ANN model for subject SB on the data from sample trials of the eight paraplegic subjects. $Pr.F_Y$, $Pr.F_Z$ and $Pr.M_X$ are the predictions of subject SB's voluntary control model for the measured arm forces F_Y, F_Z and M_X of the other subjects. The portions of the data between the *dotted lines* belong to one subject

versatile, must follow a set of rules to satisfy these requirements. Also, despite inter-subject variations, each subject settles for a preferred way of standing up. This further reduces variability in the required voluntary control of the arms. These simplifying factors must be kept in mind when interpreting the results in this study.

In selecting the input variables, we limited ourselves to a set of measurable variables that completely defined the state of the controlled system. Despite the fact that this variable set has smaller dimension and less variety than the actual sensory information used by the voluntary control system (Kandel et al. 1991), it was still a large set. Therefore, we had to select the most important input variables to form a ANN model of reasonable size. Since the system is highly nonlinear, linear correlation analysis could be misleading. Therefore, a combination of a nonlinear correlation analysis, an optimization method, and most importantly, the authors' judgment was used to identify the most relevant input variables. There was stronger correlation to the angular position of the joints than the angular velocity, which suggests that the voluntary arm forces during standing up are primarily position dependent. Also, strong correlation to past samples of the arm forces shows that sensory feedback of the arm forces (or equivalently the forces in the arm muscles and hand contact) plays an important role in the voluntary control of arm forces. In addition to high correlation of the model outputs to the most recent inputs, there were also correlation peaks to inputs delayed by 280–400 ms and 700 ms that may suggest there are short- and long-delay control loops involved in this postural adjustment task (Jaeger 1986).

The ANN models performed well on both the training and the validation data sets. The good performance on the validation data showed that the models have generalized well and that the voluntary arm control consistently follows a set of control rules from trial to trial. Therefore, each subject develops his/her own unique control law and uses it consistently. This verifies the development of 'personal strategies' by paraplegics to control their arms during standing up, which is compatible with the observations of Moynahan (1995) in paraplegics during standing. The level of consistency in executing the 'personal strategy' were not the same, however, and depended on parameters such as experience in using FES, level of injury, and the subject's weight. Subject MT, who had the longest FES training and therefore was the most experienced subject, had the least variations in his voluntary control. This is evident from the very low confidence intervals in Fig. 4. The highest variations belonged to subject TM, who had the highest-level lesion, and subject ZB, who was the heaviest subject. The insufficient control over the trunk muscles due to the high-level lesion most likely prevents subject TM from effectively stabilizing her trunk. The unstable trunk could disturb the maneuver and therefore require more corrective actions from the arms that in turn result in more variations. The heaviest subject, on the other hand, loads his arms very heavily (Fig. 3) and may have more reasons to be afraid of falling, which may result in more corrective and preventive actions.

Subject AVG is a virtual subject that represents the average behavior of the group. The ANN model for subject AVG is therefore, a general model that represents the common features among the eight subjects. The successful development of this model proves the existence of such common features. This is an expected result because during standing up, the arms must play a similar role for all paraplegics, which is to provide balance and help in rising. The existence of general rules governing the control of arms is compatible with our previous study (Davoodi and Andrews 1998), where we developed a fuzzy-control model of the arm forces. As mentioned above, this model was based on our understanding that the arms try to keep the body's center of mass inside the feet support area and maintain a minimum upward velocity. The results of the current study only suggest that there are general rules applicable to all subjects, but it is not clear whether our interpretations of these rules in Davoodi and Andrews (1998) were correct. This needs further investigation.

The voluntary controls of the subjects are compared in Figs. 6–8. The differences show that there are control rules that are specific to each individual that make his/her voluntary control unique. These person-to-person differences in the adopted voluntary control are compatible with the observations of Moynahan (1995) for the case of standing in paraplegia. Subject KA's voluntary control is most different from the other subjects. In Kamnik et al. (1999), subject KA is characterized as a subject who makes better use of the FES by putting more load on his legs. The large difference between his strategy and the rest of the subjects indicates that his strategy is not widely used by the other subjects (i.e., they do not trust their electrically stimulated legs to support their body). This seems to be true, at least for the dynamic phase of sit-to-stand motion. After assuming the standing posture and locking the knee joints, though, most of the subjects can unload their arms and transfer most of their body weight to their legs.

The results of this study show the possibility of developing ANN models capable of cloning the personal strategies of paraplegics to control their arms during standing up. Such individualized models can potentially be useful in tailoring the FES controllers to individual subjects. The model of the voluntary arm forces may be combined with the musculoskeletal models of the lower extremities to develop a realistic cybernetic model of a paraplegic subject. This model can then be used with a learning procedure such as reinforcement learning (Davoodi and Andrews 1998) or genetic algorithms (Davoodi and Andrews 1999) to develop optimal FES controllers. An individualized ANN model may also be used in the procedures described in Donaldson and Yu (1996, 1998) and Riener and Fuhr (1998) to predict the arm forces in advance and adjust the stimulation level of the leg muscles to unload the arms.

Finally, the voluntary control models have potential applications in a variety of fields such as the analysis of human control, design of unmanned vehicles, real-time training, human-robot coordination, and the transfer of skill from one human to another (Nechyba and Xu 1997).

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