Nonlinear modelling of FES-supported standing up in paraplegia for selection of feedback sensors

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Abstract

This paper presents analysis of the standing–up manoeuvre in paraplegia considering the body supportive forces as a potential feedback source in FES-assisted standing–up. The analysis investigates the significance of particular feedback signals to the human body centre-of-mass (COM) trajectory reconstruction. Two nonlinear empirical modeling methods are implemented (Gaussian process priors (GP) and multi-layer perceptron neural networks (ANN)) and their performance compared regarding the different amount of input information required. The GP provided a better fit to the data, at higher computational cost. The main objective of the study was to compare the different sensory configurations, trading off modelling performance for variables chosen, which allow ease-of-use in everyday application. In this manner, the results provide guidance for the design of user-friendly sensory-supported FES systems providing standing and standing-up in spinal cord injured persons.

1 Introduction

Rising from a sitting to a standing position is a common daily activity in human living. Individuals experiencing rising difficulties have problems living independently, while their prolonged immobilization results in physiological problems. Spinal cord injury patients have particular difficulties in standing-up, due to their lower limb paralysis. To alleviate this, paraplegic patients are trained how to stand–up and compensate for the missing action of their lower extremities during the rehabilitation process. The lifting and stabilizing forces are provided by the arm support requiring an abled patient's upper body. For support, a walker frame, parallel bars, simple stationary standing frame or even chair arm rests are normally used. However, people practicing a fully arm supported standing–up risk later complications of the upper limb joints [1].

In addition to the arm support, standing-up in paraplegia can be facilitated by Functional Electrical Stimulation (FES). FES is a method of eliciting the action potential in the nerves innervating the paralyzed muscles. This way, the muscle contractions are artificially evoked and motor functions recovered [2]. Bajd with coworkers proposed a simple approach to the FES supported standing-up of paraplegic subjects [3]. Within this strategy, today widely used in home and clinical praxis, the stimulation is based on an open loop surface stimulation of the knee extensors. The paraplegic subject in the preparation phase brings his body to an initial pose with the upper body leaning forward, arms almost fully flexed at the elbows and supported by the walker frame, while the hip joints resting at the chair are pulled forward toward the edge of chair as much as possible and feet brought backward. For the start of rising the stimulation is voluntarily triggered by the subject and the body is lifted upward from the initial to the extended upright position. As the stimulation of the knee extensors is open-loop and on/off triggered with the maximal stimulation amplitudes throughout the rising process, the current way of standing up is not optimal in terms of the applied forces and torques in the upper and lower extremities [4]. On the other side, at the end of the standing-up, when knees are almost fully extended, the excessive knee joint torques cause high terminal velocities in the knee joints what can result in ligament injuries [5].

These disadvantages of the traditional approach have led to the development of new approaches to the stimulation control, principally based on the closed-loop control theory. In the first place, the simple control algorithms have been proposed as "bang – bang" controllers tracking the reference trajectory in the phase plane of variables. As state variables, the knee joint angle and angle velocity were used in [5, 6], while in [8] the relationship between the knee and hip joint angle velocities was controlled. In some of these studies, the process of the standing–up was divided into phases and the constant stimulation output provided during the particular phase. The tasks of the phase start event detection and the stimulation amplitude alteration were accomplished by the finite state controller [6, 7]. The linear PID and the nonlinear fuzzy controllers controlling the knee joint angle have also been proposed [9, 10]. Common to these solutions is that the reference values to the controller were determined corresponding to the standing-up of healthy subjects. More advanced proposals, incorporating the paraplegic subject's volition into the stimulation control during rising, have been given in [11, 12]. In both studies the stimulation sequences were determined on the basis of known subject body position and arm reactions. Algorithms have been evaluated only in the simulation or laboratory environment. None has been implemented in home or clinical praxis. The main difficulty is that the information fed back to the stimulator control system is supposed to be provided by the sensors, normally goniometers and accelerometers, attached to the subject's body. Mounting, dismounting and wiring of the sensors is a tedious job and as such considered as not convenient for practical use.

For this reason, we are proposing a method for assessing the subject's body state during rising based on feedback information acquired in a more practical manner. We have chosen the supportive forces acting at the interaction points with the paraplegic's environment as an alternative feedback source. Seat, foot, and arm reactions can be far more easily measured than joint angles, for example. The assessment of the seat and arm supports can readily be accomplished using multidimensional force load cells mounted on the arm supportive frame and seat. Besides, as an even more practical alternative to instrumenting the subject's environment, the wearable assessment of foot reactions is feasible using commercially available shoe insole sensors. Furthermore, the employment of the natural sensory nerve signals from the foot is expected to be functional in the future [13]. As an objective characterizing the body state during rising we have chosen the total body center of mass (COM) motion trajectory. The COM trajectory as a feedback is interesting for continuous and for finite state control approaches. It characterizes the position of the human body and/or the phase of the standing–up process in which in the first phase body segments accelerate anteriorly, in the transition phase decelerate anteriorly and accelerate vertically, and in the third phase achieve standing pose by deceleration in vertical direction [16, 17, 18]. According to Newton's second law, the external forces acting on the body are directly related to the body COM acceleration. Hence, the COM displacement in human transient activities can be estimated by a second time integral of the sum of interaction forces. This method is, however, prone to cumulative integration errors, i.e. drift [14, 15]. To overcome this problem, two nonlinear modeling techniques are implemented in this paper. An ANN model and a GP mixture model were designed for the purpose of mapping the interaction forces to the COM trajectory. In the paper, the model input variable selection, the structure, and the performance evaluation are presented and compared.

2 Methods

A concept of the sensory driven FES supported standing-up is presented in Figure 1. The amplitude and frequency of the knee extensors FES are aimed to be varied according to the COM position during rising transfer. From the perspectives of the supportive force signals exploitation, the model capable of mapping the reaction forces to the COM trajectory is vital. The objective of this study was to build a model for predicting the COM vertical and horizontal displacements on a basis of a limited number of input signals provided by the artificial force sensors.

[Figure 1 about here.]

2.1 Data Set

To provide the representative data set for modeling, the standing up maneuver of eight paraplegic patients with different levels of spinal cord injury and different experiences in FES usage was analyzed. The kinematic and kinetic variables of standing up trials were assessed with a specially built measurement setup. The data acquired were used in the model design and evaluation.

2.1.1 Measurement Instrumentation

The measuring setup used in the standing-up analysis incorporated two systems, first aimed for determining the forces acting to the human body and second for measuring the body motion trajectory. For assessing the reaction forces, two measuring frames were built as copies of a wheelchair seat and a conventional walker. The seating frame was instrumented by the use of six axis AMTI force plate (AMTI, Inc., Massachussetts, USA), while the force and torque vectors on the arm support frame were assessed by the six axis JR3 sensor (JR3, Inc., Woodland, USA) usually utilized as wrist sensor in robotics. Additional AMTI force plate was used for measuring the ground reaction forces under a foot.

The motion kinematics of the body segments was assessed by the OPTOTRAK optical system (Northern Digital Inc., Waterloo, Canada) measuring the 3D positions of active markers (infrared LEDs). Markers, about 1 cm in diameter, were attached to the human body anatomical landmarks with double-sided tape. Human body symmetry during standing-up task was presumed. Hence, measurements were accomplished only for the patient's right side and were calculated for the left side. Figure 2 presents the standing up manoeuvre of paraplegic patient performed in the measuring setup. Optotrak optical markers attached to the knee, elbow and shoulder joints are well seen in the figure.

[Figure 2 about here.]

2.1.2 Measurement Protocol

The subject was 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. Prior to measurements three testing standing-up trials were accomplished with certain amount of FES assisted standing afterwards. This exercise enabled the subject to get used to the measuring equipment and relieved the spasticity in paralyzed extremities. No further consideration of spasticity effects was encountered since there was no significant evidence of spasticity during standing-up measurements in all subjects.

The functional electrical stimulation used in analysis was the surface stimulation of the M.quadriceps muscle group. The knee extensors were stimulated with an open-loop approach with constant stimulation amplitude throughout the rising process. The stimulation intensity level was determined as the level which brings the legs to fully extended position during sitting. The stimulation was voluntarily triggered on/off by the subject via the push-button mounted at the walker handle. In measurement trials, the subject was asked to take the initial pose and after approximately two seconds from starting the data collection, he or she was asked to stand up in a suitable manner and speed. Five rising trials were recorded for each participant with a 50 Hz sampling rate, each measurement lasting for about 10 seconds. By taking into consideration only five successive standing up trials a good repeatability of the results for particular subject was achieved which excluded the influence of muscle fatigue.

2.1.3 Measured Data Analysis

The signals were collected from active markers, force plates and wrist sensors. The signals were interpolated and low pass filtered using a 4th order, dual pass, Butterworth filter with 5 Hz cut-off frequency. The coordinate systems of all sensors were transformed to coincide with the reference coordinate system placed on the floor in the center of the arm supportive frame. The signal derivatives were calculated by differentiating the data and additional filtering afterwards. On the basis of measurement data, a three-dimensional, thirteen segment model of the human body was developed, embodying feet, shanks, thighs, pelvis, trunk, head, upper arms, lower arms and hands. Each segment of the body had six degrees of freedom and was considered as a rigid body. Each body joint was represented as a perfect ball-and-socket joint with no translation. From the marker positions, the joint center locations were determined and the vector was defined along the segment longitudinal axis connecting the centers of proximal and distal joints. Segmental masses and centers of mass locations were estimated using anthropometric relationships from the De Leva's study [19]. Masses were expressed as percentages of total body mass, and the COM, lying on the segment's longitudinal axis, were estimated as percentage of the distance between proximal and distal joints. The total body COM location in each time instant was determined as a weighted sum of individual COM positions of all body segments. The horizontal and vertical components of the body COM location in sagittal plane were determined according to equations (1). In equations, m_i is the mass, while y_i and z_i are the horizontal and vertical displacements of particular segment.

$$
\begin{aligned}
COM_Y &= \frac{m_1 \cdot y_1 + m_2 \cdot y_2 + ... + m_{13} \cdot y_{13}}{m_1 + m_2 + ... + m_{13}} \\
COM_Z &= \frac{m_1 \cdot z_1 + m_2 \cdot z_2 + ... + m_{13} \cdot z_{13}}{m_1 + m_2 + ... + m_{13}}
\end{aligned}
\tag{1}
$$

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 kilograms and heights from 159 to 185 centimeters. Sample group included patients with different levels of spinal cord injury and different experience of FES usage as summarized in Table 1.

[Table 1 about here.]

In order to achieve comparability of the measured data among paraplegic patients the body COM trajectory assessed in the inertial coordinates was transformed to the COM relative displacement according to subject's initial position. Resulting trajectories of the lower extremity joints, the upper trunk inclination, and lower and upper body supportive forces are shown in Figure 3 representing sample rising trials of eight paraplegic subjects. From the figure it is evident that the duration of the sit-to-stand phase, rising speed, initial pose and the upper and lower extremity action varied considerably among the subjects.

[Figure 3 about here.]

Figure 4 presents the COM displacements in sagittal plane with respect to the subject's initial position. Again, considerable variation in the approach to the sit-to-stand transfer can be observed among the subjects. Some of the patients transfer the upper body forward in the preparation phase and then rise vertically, while in others a dynamic horizontal transfer of the trunk before the vertical lift is present.

[Figure 4 about here.]

From the measured data three data sets were formed. For each of the paraplegic patients, the data set incorporating three standing-up trials was formed as a representative data set. From this set, one half of the data points was randomly extracted, forming a *primary data set* intended to be used in the model training procedure. The other half of those data points formed a *validation data set*. Besides, the *test data set*, for use in model evaluation, was formed of the remaining data, two standing–up trials that were not used in the training process.

2.2 Input Variable Selection

In order to meet the usability requirements for everyday usage, the sensory supported FES system needs to employ as few feedback channels as possible. Every feedback channel contributes to the complexity of the sensory device and to the wiring and mounting difficulties. Therefore, the question what amount of feedback information is minimal but still sufficient for successful recognition of the body state - in our case, the body COM trajectory - is crucial for employing the force feedback into the FES system. We investigated the minimal requirements, in terms of feedback information. The potential feedback sources were divided into ten empirical groups, each group incorporating different numbers of feedback variables.

[Table 2 about here.]

The empirical input variable groups are listed in Table 2. *Group 1* incorporates all the possible signals acquired in the measurement setup, i.e. arm, seat and foot reactions together with their derivatives. In the case of foot reactions, beside the three components of the reaction force, the position of foot center of pressure (COP) was also assessed under the foot. The position is expressed in the coordinates of the foot sole and normalized to the foot length. The components are denoted as cop_x and cop_y. The seat reaction force, assessed by the force plate, is a three dimensional vector, while the arm reactions, when assessed by the JR3 force sensor, consists of three force and three moment components. *Group 2* excludes the derivatives of the signals in order to show their significance to the output. *Group 3* excludes the seat reaction force signals since sensors attached to the seat or wheelchair are less practical for implementation. *Group 4* incorporates only the vertical component of the foot reactions, since this is a case when the shoe insole sensors can be used instead of the force plate. *Group 5* investigates the usage of more simple and less expensive force sensor for measuring the arm support. Only vertical and horizontal arm reaction components were used in this case in combination with the shoe insole sensory signals. *Group 6* investigates the usage of only the shoe insole sensor. Additionally, the possible combinations of the shoe insole sensor with the goniometers, inclinometer or accelerometers were investigated. Thus, the ankle joint angle was incorporated in *Group 7* and the knee joint angle in *Group 8*. *Group 9* verifies the combination with inclinometer mounted at the upper body, while *Group 10* verifies the shoe insole combination with the accelerometers attached to the trunk.

The significance of each group was evaluated using a modeling approach. Two different nonlinear models were used to predict the body COM trajectory on the basis of the input signals of particular group. The root mean square error (RMSE) between the actual COM trajectory and the model predicted output were calculated characterizing the model performance. RMSE values were calculated separately for the horizontal and vertical component of the COM trajectory as:

$$RMSE_Y = \sqrt{\frac{1}{N}\sum_{k=1}^{N}(COM_{Yk}^{m} - COM_{Yk}^{a})^2} \tag{2}$$
$$RMSE_Z = \sqrt{\frac{1}{N}\sum_{k=1}^{N}(COM_{Zk}^{m} - COM_{Zk}^{a})^2}$$

where superscript a stands for actual and m for modeled value of the COM trajectory in a sample k. In (2), parameter N represents a number of data points in particular test data set.

2.3 Artificial Neural Network (ANN) Model

As an example of a well-established approach, a moderate size multi-layer perceptron artificial neural network (ANN) was trained and the network performance characteristics examined [20]. The size of the network was kept constant to make sure that the comparison is valid. The neural network was built in the Mathworks Matlab software environment as a two-layer feed-forward network. The first layer incorporated six *tansig* neurons, while the second layer consisted of two *purelin* neurons. The *trainlm* Matlab function was used implementing the back propagation method for training the network. In training, the error cost on the validation set was used to stop training early if further training on the primary training set would hurt generalization to the validation set. The network was trained for up to 300 epochs to an error goal of 10^{-5}. The test set performance was then used to measure how well the network generalizes beyond primary and validation sets.

2.4 Gaussian Process Prior (GP) for Regression and Hierarchical Mixture Models

As an alternative to neural networks, we also used a GP regression model. An introduction to this approach is given in reviews by [21] and [22]. An empirical comparison in [24] showed that GPs were usually as good as or better than neural networks in test comparisons. GPs tend to have a clearer advantage in problems with smaller data sets. The major difference is that the training data are retained by the model and predictions are inferred from those data, rather than the parametric approach of neural networks, where the data points are represented by a finite number of parameters, and discarded. This means that prediction uncertainty in GPs can be made to increase as we make predictions further from the training data (in terms of the input space), but it also has storage and computational issues, compared to neural networks, as training set sizes increase. It also means that models can include new data points relatively easily, without major retraining.

If we are given N data points of training data $\{y_n, x_n, n = 1, \cdots, N\}$, where x is a Q-dimensional vector of *inputs*, and y is the *output*. A Gaussian process is defined in such a way that $y(x)$ has a Gaussian prior distribution with zero mean and covariance function $C(x_i, x_j) = Cov(Y(x_i), Y(x_j))$. An example of such a covariance function is

$$\begin{aligned} & C(x_i, x_j) = C(x_i, x_j; \theta) \\ = \quad & v_0 \exp\left(-\frac{1}{2}\sum_{q=1}^{Q} w_q (x_{iq} - x_{jq})^2\right) + a_0 + a_1 \sum_{q=1}^{Q} x_{iq} x_{jq} + \delta_{ij}\sigma_v^2, \end{aligned} \qquad (3)$$

where $\theta = (w_1, \cdots, w_Q, v_0, a_0, a_1, \sigma_v^2)$, and $\delta_{ij} = 1$ if $i = j$ and 0 otherwise. This covariance function is often used in practice. More discussion about the choice of covariance function and the details of the implemention of the model can be found in [22]. The parameters of the covariance function can be optimised by maximising the likelihood, or you can integrate over them using numerical methods such as Markov-Chain Monte-Carlo methods.

GPs allow a ‘soft model-structure selection’, where the complexity of the model, as measured by the *effective degrees of freedom* [25] can vary automatically with the hyperparameters. It also provides an automatic relevance detection, as the length-scale parameters w_q associated with input q give an indication of how important any given input is – if an element of input vector does not help predict outputs accurately, the w_q will tend to go towards zero, as likelihood is maximised [22].

To illustrate the prediction of uncertainty provided by GP models, we use an example of prediction of COM_x and COM_y for 5 separate standing-up trajectories of patient ZJ. Figure 5 shows the mean and ± 2 standard deviation uncertainty bands from a single GP. The GP included some data from each of the first three trajectories in the training set, and the second two were test data. Note that the uncertainty is low on the predictions on data close to the training data, but increases for the data points further from the training data. The uncertainty also varies within individual batches, depending on the input state, reflecting variations in model complexity, and training data density.

[Figure 5 about here.]

The implementation of GP regression model requires the inversion of a covariance matrix, the dimension of which is the sample size of training data. It becomes computationally expensive for large sample sizes ($N > 1000$), because the computational cost scales as $O(N^3)$. For the data discussed in this paper, if we consider a single standing-up, a single GP regression model is not computationally problematic. However, if we want to combine the data collected from the different standings-up and from the different patients, the sample size may be as large as a few thousand data points, and the use of a hierarchical mixture model, as proposed in [23] is recomended. This model also allows for the heterogeneity for the data-set combining from the different sources, which is a particularly nice property for data acquired in human motion, as is the case in our study.

A proposed hierarchical GP regression model has the following two-level structure: a lower-level single GP regression model defined around (3) is used to fit the data corresponding to each replication (different standing-up) separately, and the structures of the basic models are similar but with some mutual heterogeneity; a higher-level model is defined to model the heterogeneity among different replications. Specifically, suppose that there are M different replications. In the mth group, N_m observations are collected. Let the observation be $y_{mn},\ m = 1,\cdots,M,\ n = 1,\cdots,N_m$. In a hierarchical mixture model of Gaussian processes for regression we have that

$$y_{mn}|z_m = k \ \sim\ GP(\theta_k), \tag{4}$$

where z_m is an unobservable latent indicator variable. If $z_m = k$ is given, the model for group m is a GP regression model $GP(\theta_k)$, as defined around (3). The association among the different groups is introduced by the latent variable z_m, for which

$$P(z_m = k) = \pi_k, \quad k = 1,\cdots,K, \tag{5}$$

for each m. K is the number of components of the mixture model. We assume that K has a fixed given value. For the details of the theory and implementation refer to [23].

3 Modelling Results

In the following section, the prediction results from the nonlinear models are presented. The performances of the proposed ANN and GP regression models are verified on prediction of the body COM position. For each subject and for each input group an individual model was built and verified with the subject's test data set. The model structure depended on the specific subset sensors used to provide the input vector. The input variables were organized as described in section 2.2.

3.1 Model predictions compared to test data

[Figure 6 about here.]

[Figure 7 about here.]

Figures 6 and 7 present the resulting model predictions and the COM displacements measured in the fourth (testing) trial of real standing-up. In the figures, the results for the horizontal and vertical component of the COM trajectory are shown separately in the left and right column, respectively. Each graph in the figure is divided into eight sections, successively demonstrating the results for eight subjects who participated in the study. The sections are divided with the vertical dotted lines and denoted with the subject's initials on top of the figure. Figure 6 outlines the results of ANN modeling approach, while the results of GP modeling approach are given in Figure 7. For example, the first section in the second row in the right of Figure 6 compares the ANN model output with the real COM vertical displacement in the fourth standing-up of subject AK when utilizing the model input variables from Group 2. In Figures 6 and 7 the deterioration of the model performance as a consequence of decreasing the number of model input channels can be observed.

[Figure 8 about here.]

To objectively evaluate the performances of the models, the RMSE values between the modeled and actual COM trajectories were calculated according to (2). Other model evaluation measures such as the 95 % confidence interval or correlation produced similar results. Therefore, only the RMSE was used for evaluation of the models. In Figure 8, the RMSE values characterizing the testing trials from Figures 6 and 7 are presented. The values are presented by means of bar graphs. The arrangement of bar graphs corresponds to the arrangement of graphs in Figures 6 and 7. Figure 8 is divided into two columns and ten rows. The left and right column demonstrates the RMSE values of ANN and GP modeling approaches, respectively. Performance of each model is characterized with two RMSE values describing the matching of the horizontal and vertical COM components to the model responses. Ten rows evaluate ten different input configurations.

From Figures 6 to 8 we can see that both approaches give quite good results, although GP modelling seems to provide a more accurate model. An example of one of these subplots with 2σ uncertainty bounds was given in Figure 5. The bar graphs confirm our assumptions about the information importance of the input groups. The degradation of the model performances with respect to the number of input channels can be noticed.

It is interesting that pattern of variability among subjects is not similar in ANN and GP results. For example, the worst results for COMY in ANN modeling were achieved with the subject ZJ who was standing-up, according to Figure 4, with the extensive forward excursion before rising. On the other hand, the worst results in GP modeling were achieved with the subject MK who was standing-up primarily vertically. The GP tends to be worse in the vertical rather than the horizontal component, which may be because of a zero-mean assumption in the standardisation used. This seems well-suited to the horizontal component, but more information about the patient, such as height, for example, is needed to improve on the vertical component.

3.2 Relative importance of input signal groups

To get a better insight into the significance of particular group of input signals to the model output all the testing RMSE values of all the subjects were averaged and compared in two bar graphs presented in Figure 9. The bar graphs illustrate the averaged ANN modeling results on the left and the averaged GP modeling results on the right side of the figure. Again, the results are presented separately for the horizontal and vertical component of the COM trajectory.

[Figure 9 about here.]

The overall modeling results presented in Figure 9 illustrate the information significance of input groups defined in Table 2. The peak of RMSE values is attained when only the instrumented foot insole information is used for the feedback in *Group 6*. Observing the results for particular input group it is firstly interesting that the models exhibit better performance when the signal derivatives are excluded from the input (see the results for the *Group 2*). This phenomenon can be attributed to the numerical differentiation of noisy force signals, which can be improved on by appropriate filtering. Secondly, the results for the *Groups 4* and *5*, representing the results of the most practically realizable systems, demonstrate comparable performance to the other groups. The third finding is that the best modeling results in the vertical direction are attained in both approaches when information about the knee joint angle is incorporated. However, the results of the input *Group 8* also exhibit poor performance in the horizontal direction. Finally, the averaged results indicate that the incorporation of information about the ankle joint angle, trunk inclination angle, and trunk acceleration at the input is only a comparable alternative to force reactions.

4 Conclusions

The analysis of feedback information in a standing–up of paraplegic patients has been presented in this paper. The analysis focused on the exploitation of the supportive force signals for the purposes of the body state estimation. In this manner, the body COM trajectory has been estimated utilizing two different nonlinear modeling approaches. The results of the study proved that the force-feedback-based FES system is viable and realistic. Regardless of the fact that the study was accomplished with data acquired in an laboratory environment with sophisticated measurement equipment, conclusions can be drawn for practical portable systems. On this basis, the minimal requirements for the number and complexity of force sensors have been searched with the method of comparison among different sets of feedback. Results show that both the foot and arm reactions are vital for the COM trajectory reconstruction, while the sensory complexity (number of channels) depends on reconstruction accuracy requirements. However, it was beyond the scope of this study to search for the optimal feedback set for a particular sensor-supported FES system.

4.1 Summary of sensor group investigation

The sensor set proposals are practical for an implementation with a smaller number of input channels and consequently slight decrease of performances are visible in the results for *Group 3*, *Group 4*, and *Group 5*. In *Group 3* a sophisticated force sensor under a foot is required, while the need for the seat force sensor is eliminated. Furthermore, these results are almost fully comparable with the results of *Group 4* which introduces the utilization of a commercially available shoe insole sensor with only COP position and vertical support outputs instead of a sophisticated multichannel device. The results of *Group 5* demonstrate that the introduction of the arm support force sensor with fewer channels does not significantly influence the model performance. However, we can see in the *Group 6* results that the further reduction of the feedback information, in this case characterizing the upper body action, introduces considerable error into the model's output. As side comparison, we investigated the significance of kinematic parameters to the COM trajectory reconstruction and showed that information about knee joint angle is most descriptive. We also demonstrated that the joint angle, trunk inclination angle and trunk acceleration could be substituted, at no cost to performance, with force feedback signals, which are far less cumbersome for practical everyday usage.

4.2 Comparison of GP and ANN approaches

The study on the first hand provided knowledge on feedback significance and will thus ease the design of sensory supported FES systems. On the other hand, the study can also serve as a practical comparison between the ANN and GP nonlinear modeling methods. The modeling performance suggests that although GPs are computationally more expensive, they provided a better fit to the data, and also have the advantage that they provide an estimate of the conditional density for predictions, rather than just the conditional mean, as provided by the neural network. The hierarchical GP was computationally much more efficient than a single GP, and also coped well with the heterogeneity among patients. Since we observed great variability in standing-up among paraplegic subjects (subjects differed in sex, age, weight, height and the level of spinal cord injury, while data even varied in the same subject due to variance in initial position and muscle fatigue), results suggest that the models used in this paper should be further calibrated to an individual subject.

In terms of computational requirements, the neural network has a very small memory footprint, requiring storage only of the network weights which is the product of the number of inputs $\times$ number of hidden units $\times$ number of outputs, while the GP might be storing several thousand training examples, and inference to new points involves multiplication of the inverse covariance matrix (which can be calculated off-line, prior to use), by the covariance with the test point, which for a single test point would involve $N^2 + N$ floating-point multiplication and addition operations for N training points. For the hierarchical model we have $\sum_i^M (N_i^2 + N_i)$, operations where N_i are the sizes of the subsets.

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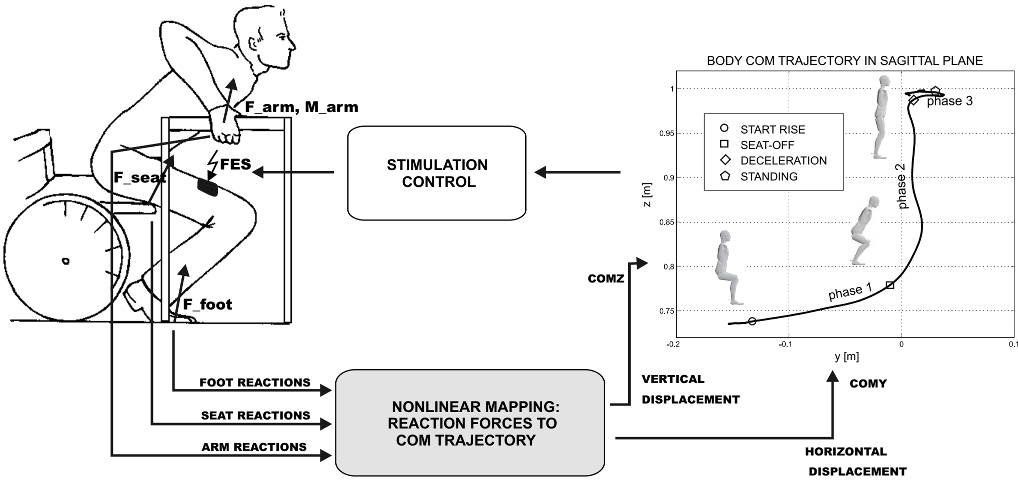

Figure 1: Sensory driven control concept in the FES supported standing–up of paraplegic patient

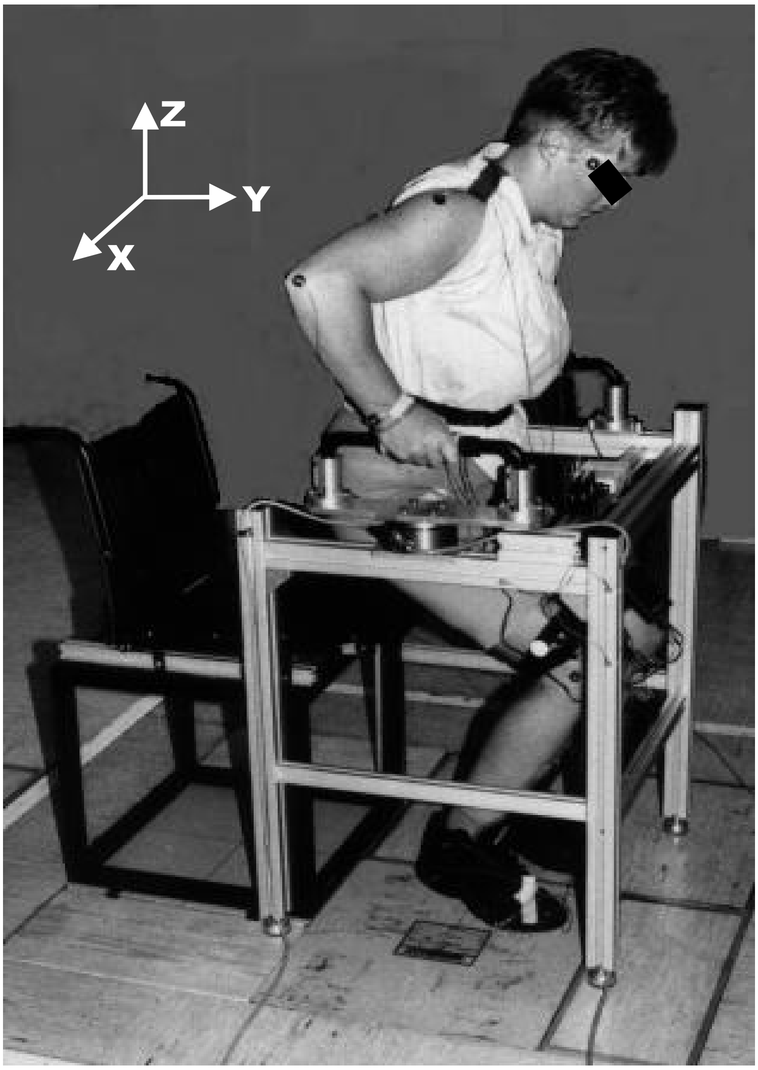

Figure 2: Standing–up of paraplegic patient and a measurement setup

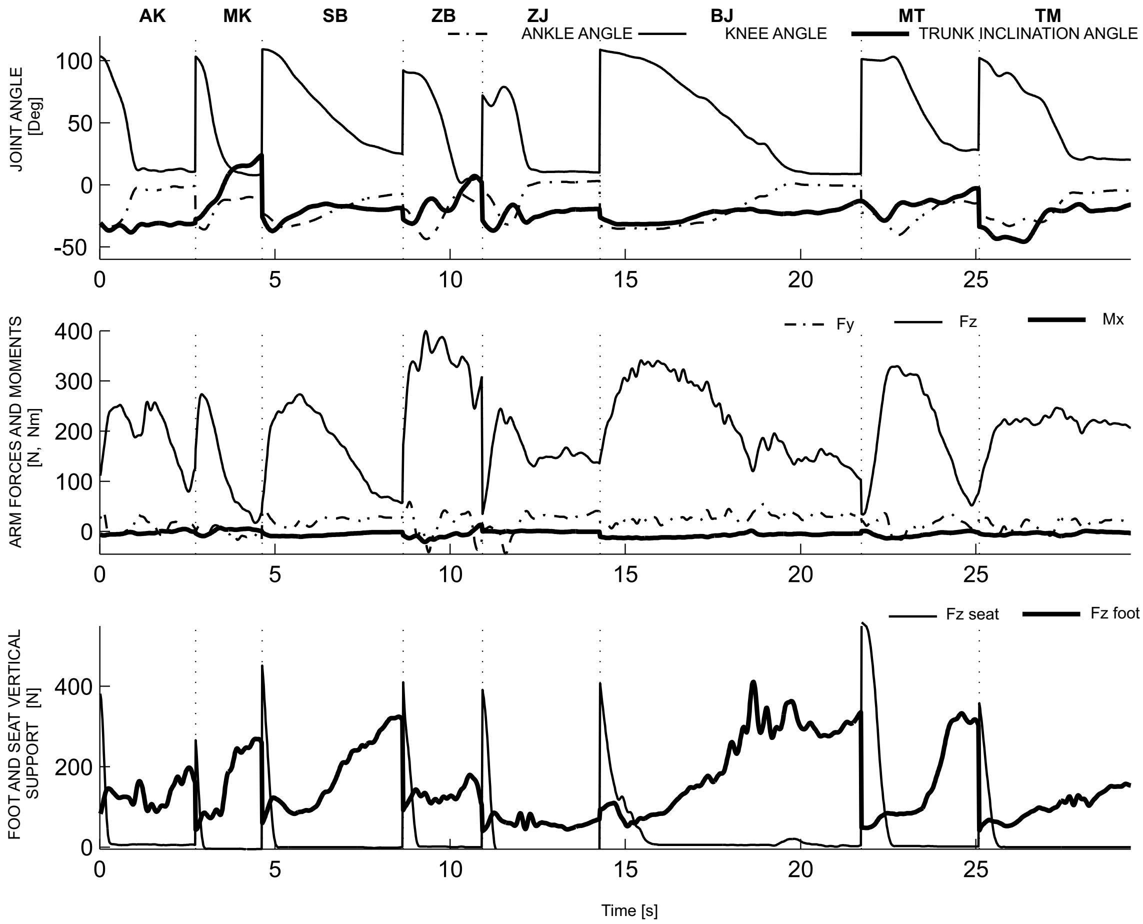

Figure 3: Motion trajectories and supporting actions of the upper and lower extremities in sample trials of eight paraplegic subjects. The portion of the data between the dotted lines belongs to sample standing-up of one subject

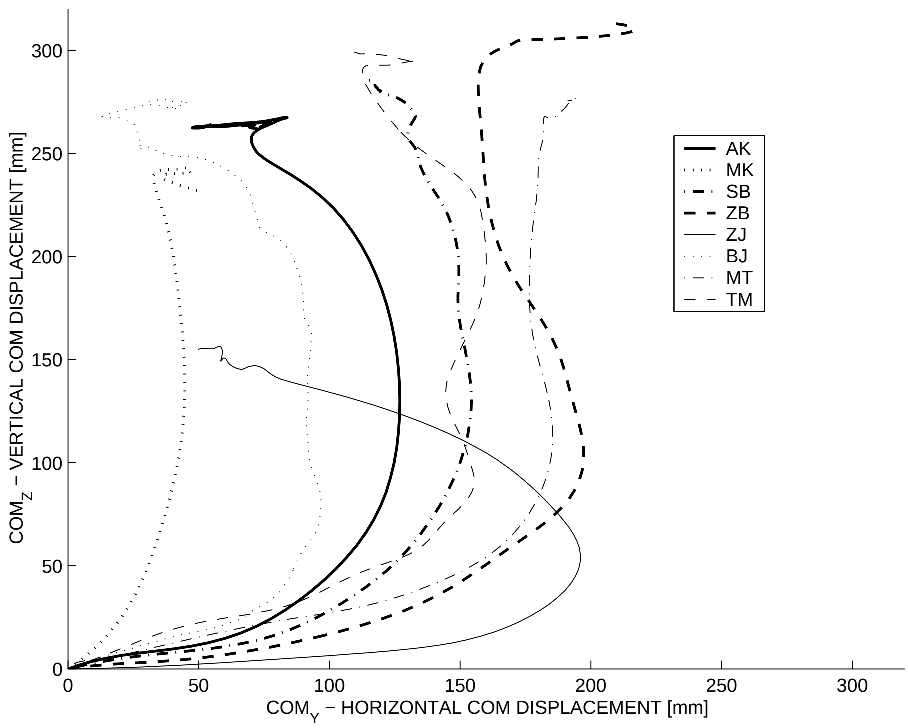

Figure 4: Sample COM displacements in sagittal plane for eight paraplegic subjects

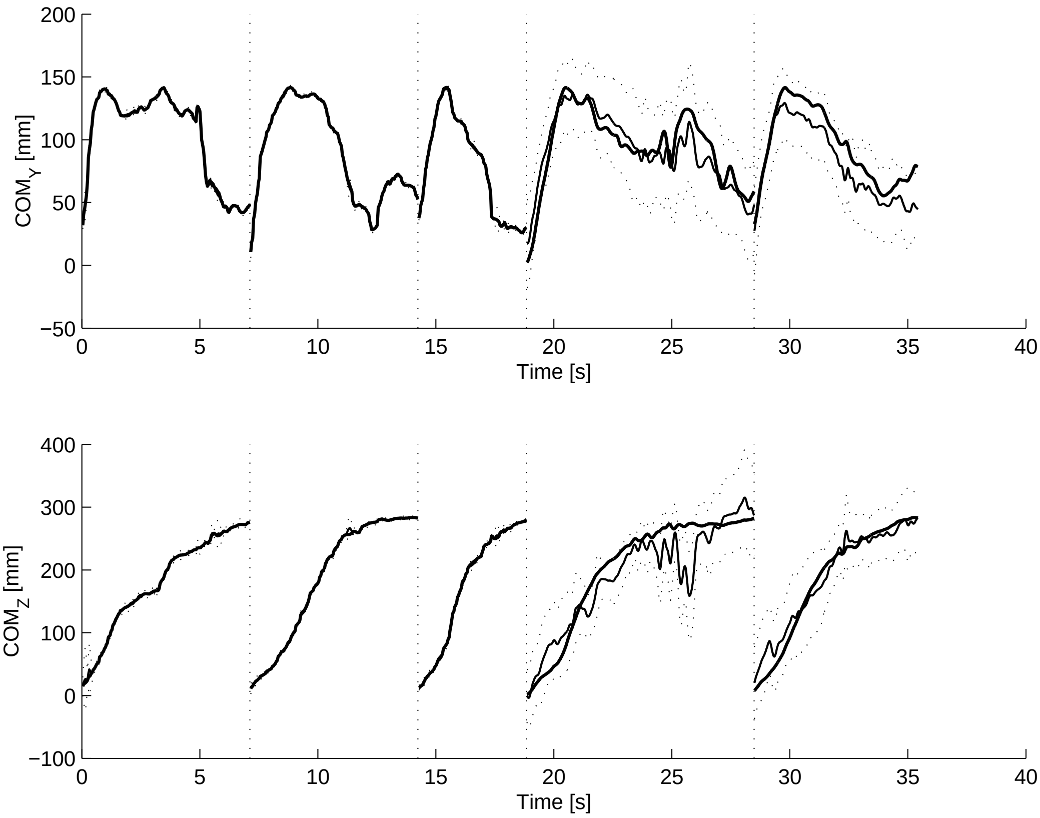

Figure 5: Example of GP prediction, showing mean and 2 std. deviations for 5 separate standing-up trajectories of patient BJ. The x-axis indicates time. The first three sets were included in the training set, and the second two were test data. Actual COM trajectory is represented by bold solid line, the GP model response is represented by solid line and its 95% confidence interval is represented by dotted line

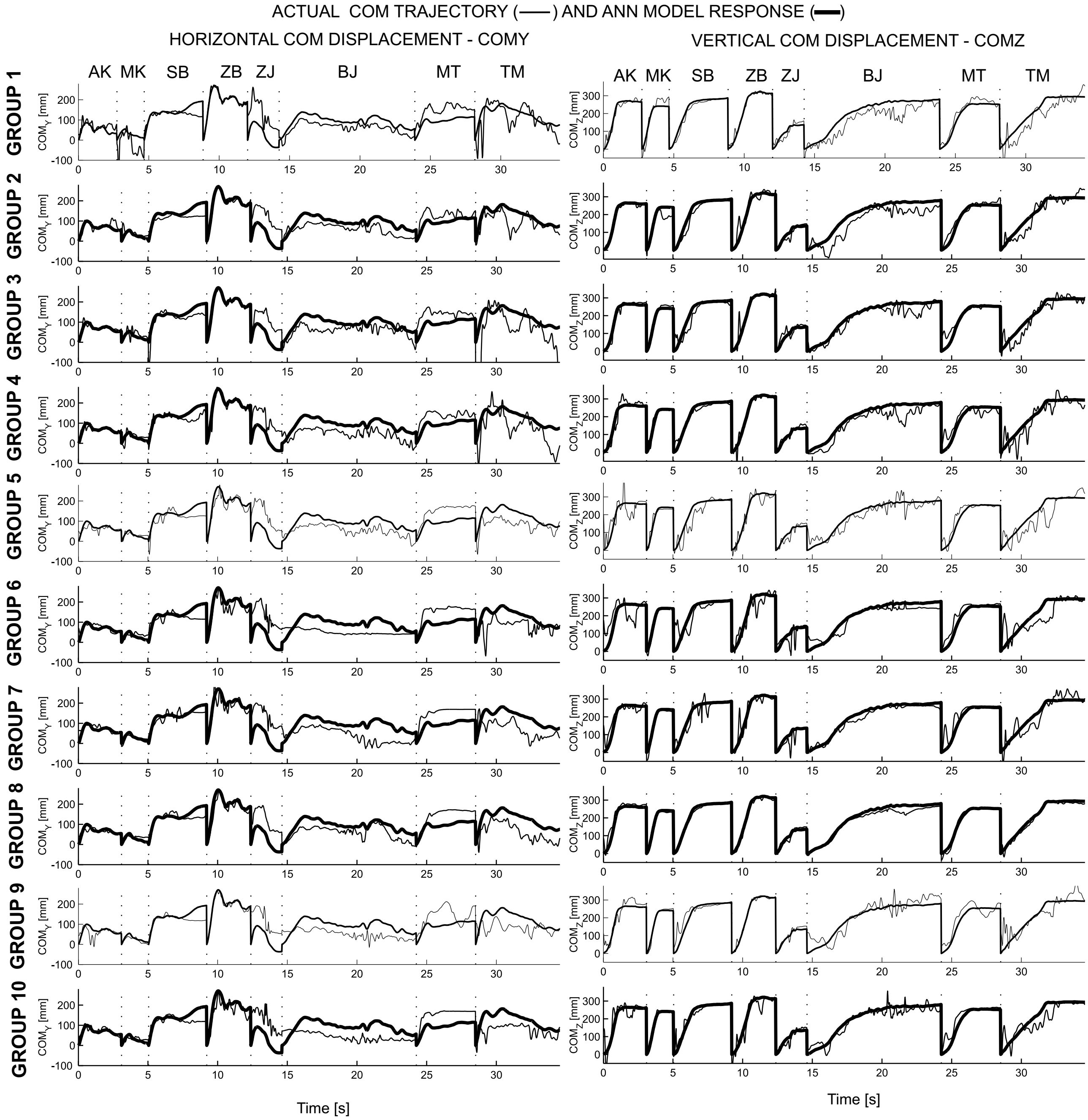

Figure 6: Comparison of resulting ANN model predictions and the COM displacements measured in the fourth (testing) trial of real standing-up for eight paraplegic subjects and ten different groups of input variables

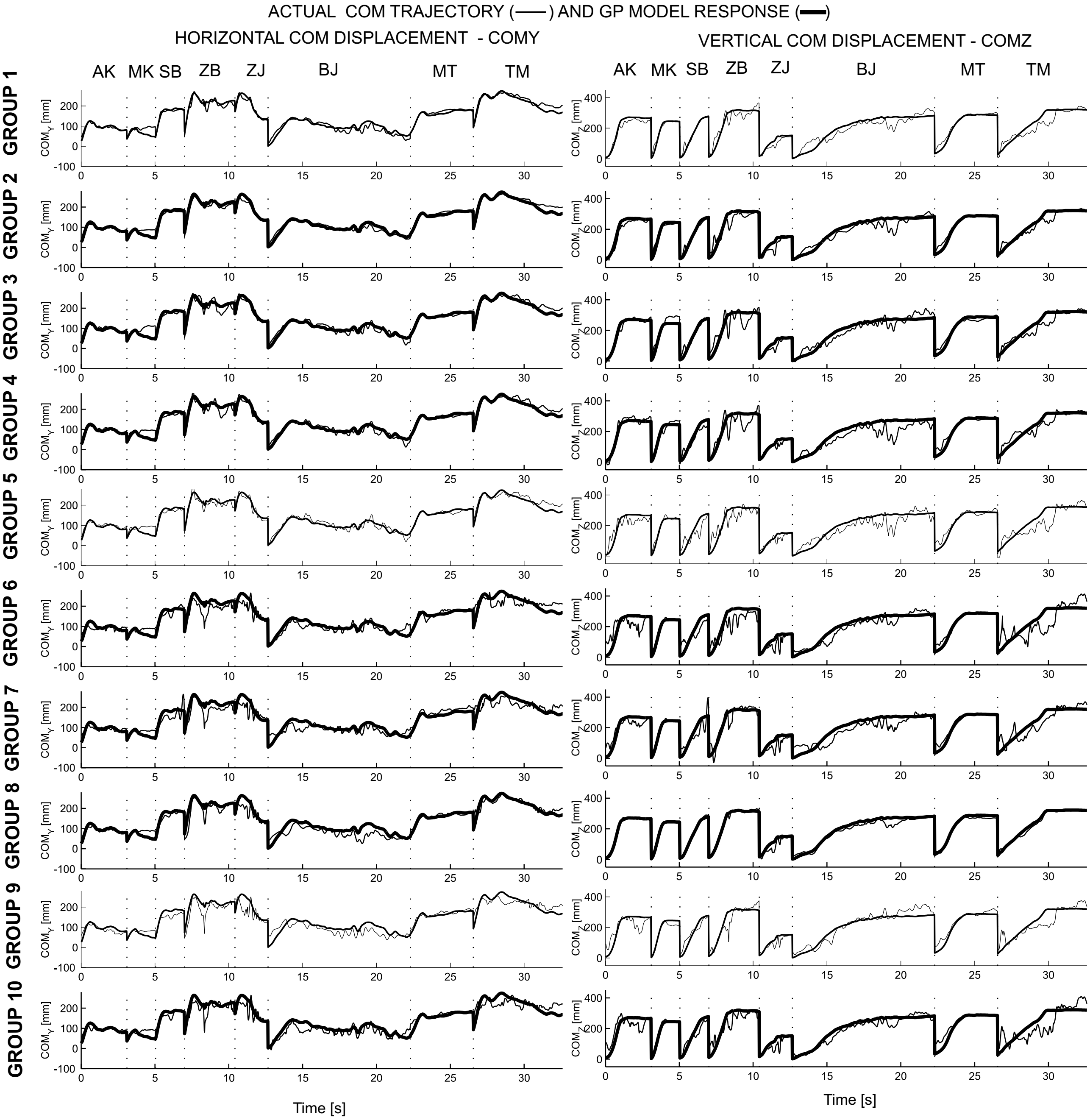

Figure 7: Comparison of resulting GP model predictions and the COM displacements measured in the fourth (testing) trial of real standing-up for eight paraplegic subjects and ten different groups of input variables

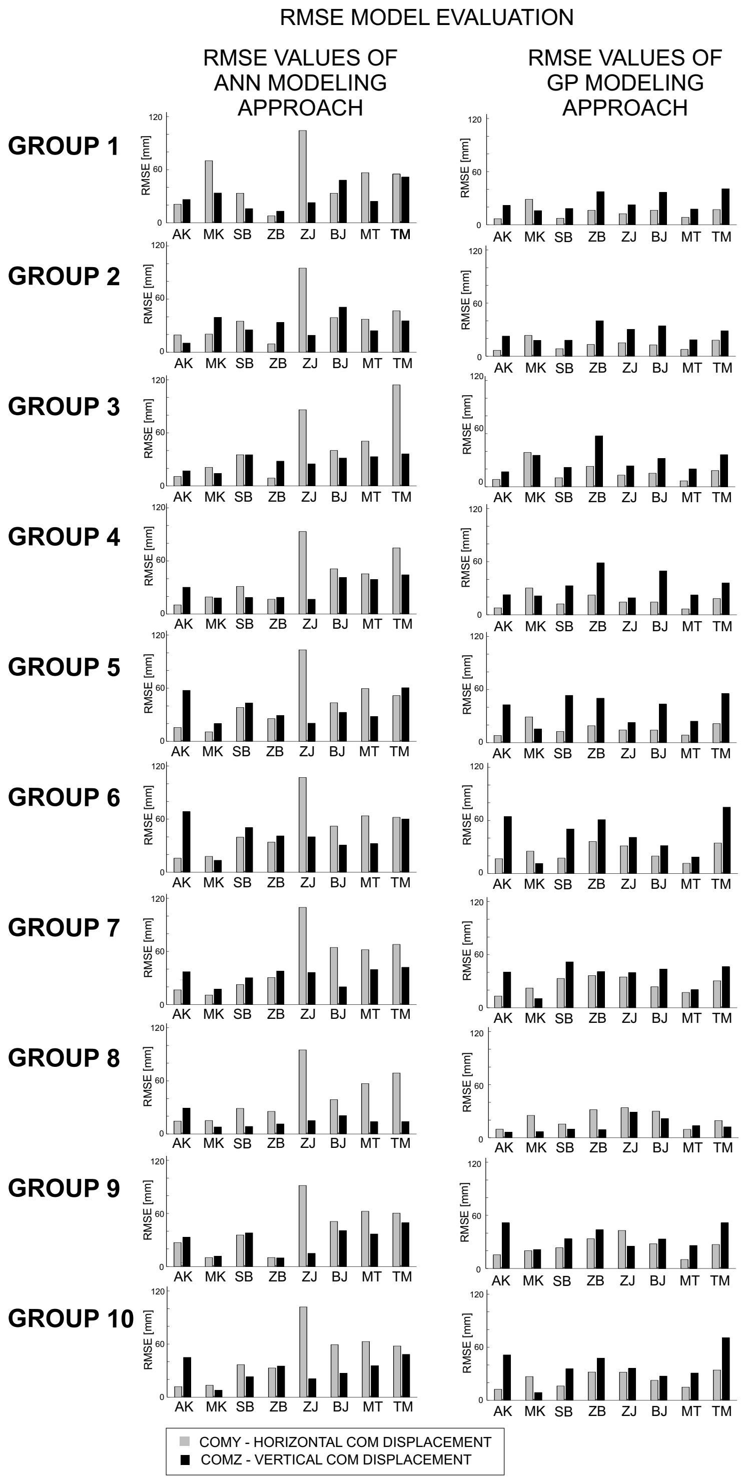

Figure 8: RMSE model evaluation values of ANN and GP modeling approach of the fourth (testing) trial of real standing-up for eight paraplegic subjects and ten different groups of input variables

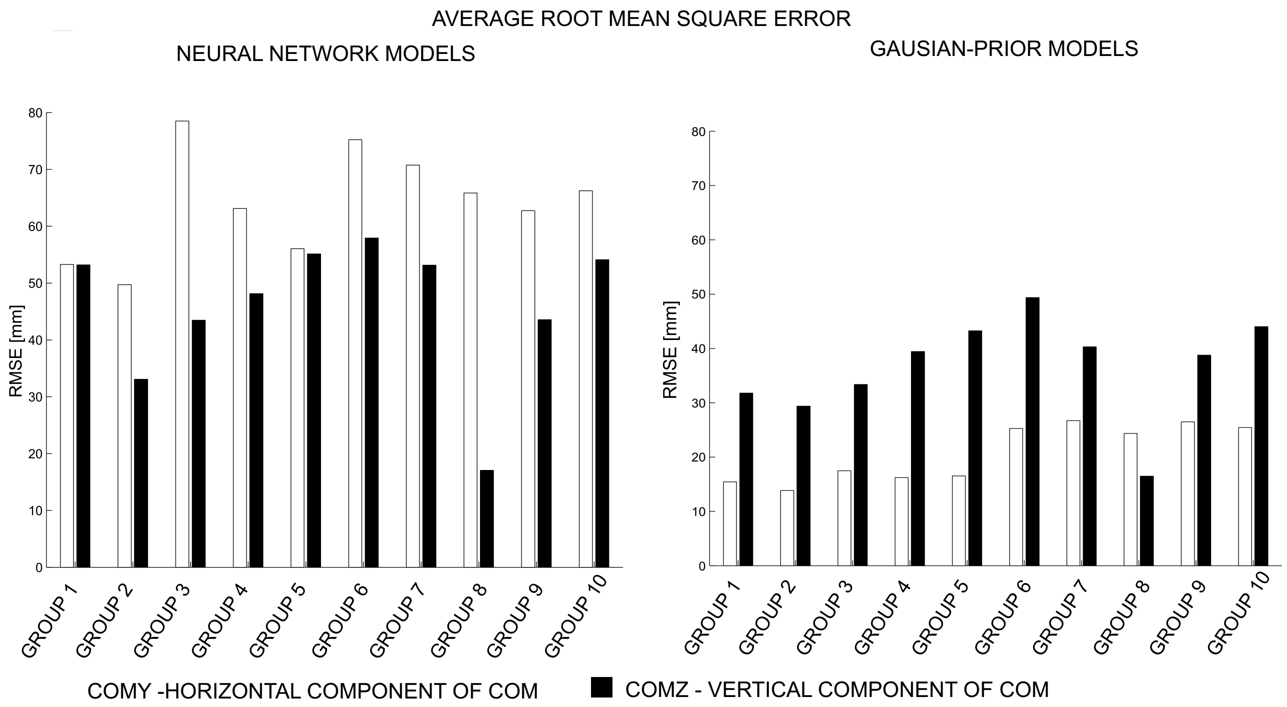

Figure 9: Overall modeling results for each group of inputs, summed over all patients.

List of Tables

Patient initials	*Sex*	*Age* [years]	*Height* [cm]	*Weight* [kg]	*Lesion level*	*Post injury time* [years]	*FES usage* [years]
AK	M	44	180	74	T10-11	1.5	0.5
MK	M	23	168	58	T9	1.5	0.2
SB	M	31	183	64	T10-12	1	0.9
ZB	M	22	184	94	T3-4	3	2
ZJ	F	57	159	53	T11	4.5	3
BJ	M	23	185	85	T9	1.2	0.5
MT	F	28	171	75	T4-5	7	5
TM	F	19	178	59	T3-4	5	3.5

Table 1: Data of paraplegic patients participating in the study

Group 1	FOOT ($cop_x, cop_y, F_x, F_y, F_z, \dot{F}_x, \dot{F}_y, \dot{F}_z$), SEAT ($F_x, F_y, F_z, \dot{F}_x, \dot{F}_y, \dot{F}_z$), ARM ($F_x, F_y, F_z, M_x, M_y, M_z, \dot{F}_x, \dot{F}_y, \dot{F}_z, \dot{M}_x, \dot{M}_y, \dot{M}_z$)
Group 2	FOOT ($cop_x, cop_y, F_x, F_y, F_z$), SEAT ($F_x, F_y, F_z$), ARM ($F_x, F_y, F_z, M_x, M_y, M_z$)
Group 3	FOOT ($cop_x, cop_y, F_x, F_y, F_z, \dot{F}_x, \dot{F}_y, \dot{F}_z$), ARM ($F_x, F_y, F_z, M_x, M_y, M_z, \dot{F}_x, \dot{F}_y, \dot{F}_z, \dot{M}_x, \dot{M}_y, \dot{M}_z$)
Group 4	FOOT ($cop_x, cop_y, F_z, \dot{F}_z$), ARM ($F_x, F_y, F_z, M_x, M_y, M_z, \dot{F}_x, \dot{F}_y, \dot{F}_z, \dot{M}_x, \dot{M}_y, \dot{M}_z$)
Group 5	FOOT ($cop_x, cop_y, F_z, \dot{F}_z$), ARM ($F_y, F_z, \dot{F}_y, \dot{F}_z$)
Group 6	FOOT ($cop_x, cop_y, F_z, \dot{F}_z$)
Group 7	FOOT ($cop_x, cop_y, F_z, \dot{F}_z$), ANKLE JOINT ANGLE ($\phi_{ankle}, \dot{\phi}_{ankle}$)
Group 8	FOOT ($cop_x, cop_y, F_z, \dot{F}_z$), KNEE JOINT ANGLE ($\phi_{knee}, \dot{\phi}_{knee}$)
Group 9	FOOT ($cop_x, cop_y, F_z, \dot{F}_z$), TRUNK INCLINATION ANGLE ($\phi_{trunk}, \dot{\phi}_{trunk}$)
Group 10	FOOT ($cop_x, cop_y, F_z, \dot{F}_z$), TRUNK ACCELERATION ($a_y, a_z$)

Table 2: Feedback signals in ten input groups