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Can shoulder joint reaction forces be estimated by neural networks?

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ABSTRACT

To facilitate the development of future shoulder endoprostheses, a long term load profile of the shoulder joint is desired. A musculoskeletal model using 3D kinematics and external forces as input can estimate the mechanical load on the glenohumeral joint, in terms of joint reaction forces. For long term ambulatory measurements, these 3D kinematics can be measured by means of Inertial Magnetic Measurement Systems. Recording of external forces under daily conditions is not feasible; estimations of joint loading should preferably be independent of this input. EMG signals reflect the musculoskeletal response and can easily be measured under daily conditions. This study presents the use of a neural network for the prediction of glenohumeral joint reaction forces based upon arm kinematics and shoulder muscle EMG. Several setups were examined for NN training, with varying combinations of type of input, type of motion, and handled weights. When joint reaction forces are predicted by a trained NN, for motion data independent of the training data, results show a high intraclass correlation (ICC up to 0.98) and relative SEM as low as 3%, compared to similar output of a musculoskeletal model. A convenient setup in which kinematics and only one channel of EMG were used as input for the NN's showed comparable predictive power as more complex setups. These results are promising and enable long term estimation of shoulder joint reaction forces outside the motion lab, independent of external forces.

1. Introduction

In the process of developing future endoprostheses for the shoulder, information on the mechanical loading of the shoulder is essential. Ideally, this information embraces a long term load profile of the shoulder joint under daily living conditions. The glenohumeral joint reaction force represents the resultant of muscle forces and passive forces like ligament strain working on the shoulder joint, rendering it into a natural candidate for the indication of mechanical loading.

Under laboratory conditions shoulder joint moments and reaction forces have been estimated with a large scale musculoskeletal model for a variety of tasks [Delft Shoulder and Elbow Model, DSEM, (van der Helm, 1994a, 1994b)], using upper extremity 3D kinematics and external force as input. If load profiles are to be recorded under daily conditions, these input variables have to be measured ambulatory.

It has been shown that Inertial Magnetic Measurement Systems (IMMS) are an adequate candidate for the ambulatory measurement of upper extremity kinematics (Cutti et al., 2008; de Vries et al., 2010). Although external force can be measured under laboratory conditions, long term ambulatory recordings should preferably be independent of the complex measurements of external force.

Several alternative methods in the determination of the mechanical loading of the shoulder joint under daily conditions exist. Westerhoff et al. (2009) used instrumented endoprostheses, enabling the direct measurement of JRF-GH under daily conditions. Despite interesting results, this method is rather invasive, limited to a small group of patients who opt for a shoulder joint replacement, and therefore will render only a small sample size for research. Besides that, for a more detailed load profile, additional measurement of movements or actions resulting in higher loads at the endoprosthesis is required. As in EMG driven models, EMG signals reflect the musculoskeletal response and can easily be measured under daily conditions. Several studies have used EMG combined with other variables as input for neural networks in the prediction of kinematics or kinetics. Sepulveda et al. (1993) demonstrated the potential of neural networks in predicting joint angles and joint moments from EMG in human gait; Hahn and O'Keefe (2008) trained neural networks to predict sagittal plane joint moments during normal gait; Liu et al. (1999) used neural networks muscle force prediction from EMG; mapping of EMG to joint angles (Cheron et al., 2003; Shrirao et al., 2009), and the

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prediction of net moments around the elbow joint based on EMG (Song and Tong, 2005). Kingma et al. (2001) compared a linked segment model, an EMG driven model, and a neural network approach in the prediction of spinal loading. Isokinetic knee torque as predicted by a neural network using EMG, joint kinematics and several other variables showed higher accuracy than a forward stepwise regression model (Hahn, 2007). Luh et al. (1999) showed that moments around a single joint axis can be estimated by a neural network (NN), using segment kinematics and surface EMG as inputs.

These results inspired us to investigate a NN approach in the direct prediction of the glenohumeral joint reaction force under unconstrained daily conditions, based on ambulatory obtainable variables like body segment kinematics and EMG. Inertial Magnetic Measurement Systems (IMMS) enable the long term ambulatory measurement of 3D upper extremity kinematics in an almost unlimited measurement volume. Developments in the past decade resulted in truly wearable EMG measurement equipment. With these two systems available all the necessary information can be collected ambulatory.

One major question remains open: are neural networks indeed able to learn the complex relationship between upper extremity kinematics and muscle activity patterns to predict glenohumeral joint reaction force, for the irregular, unconstrained humeral motion under daily conditions?

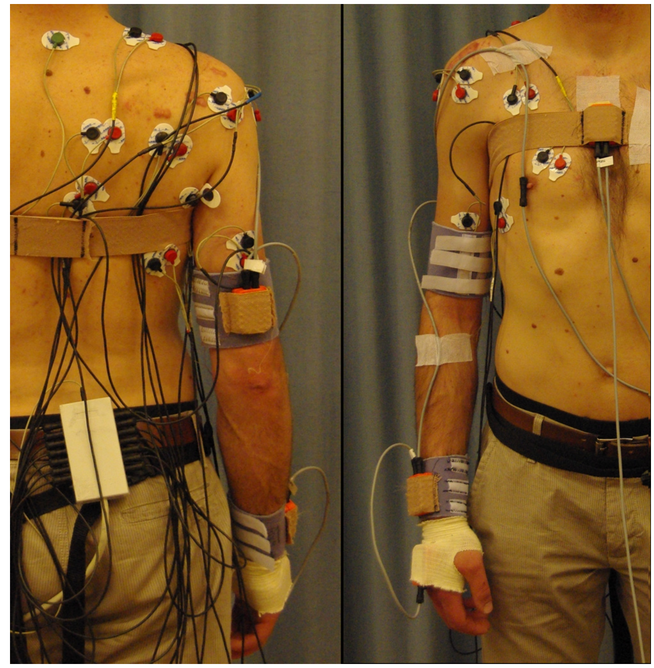

Fig. 1. A fully equipped subject, with four sensor modules on sternum, humerus, forearm and hand, and 13 channels of surface EMG.

2. Methods

One healthy subject (age 29 years, stature 180 cm, weight 78 kg), with no history of shoulder dysfunction, was invited to participate in this pilot study, after consulting a local ethical committee. After explanation of the goal and procedures of the study, informed consent was signed.

Training data for the NN method were generated by performing several series of pre-described upper extremity movements while holding a variety of known masses in the hand, as described in more detail in Section 2.3. Upper extremity 3D kinematics and EMG were measured, external forces on the hand were calculated by multiplying the known mass by measured acceleration. This approach produced both input for the musculoskeletal model (kinematics and external force) and the NN method (kinematics and EMG), all ambulatory measureable. The target for training of the NN, glenohumeral joint reaction force, was calculated using a musculoskeletal model (DSEM). After sufficient training, the NN should be able to predict glenohumeral joint reaction forces using only 3D kinematics and EMG.

To examine a NN method being successful in the prediction of the joint reaction forces under daily conditions, the influence of the following factors has been studied:

1. The type of movements that should be performed; Activities of Daily Living (ADL) or Random Movements;
2. The type of input needed for the NN;
   a. 3D kinematics and surface EMG of 13 muscles of the upper extremity;
   b. Upper extremity 3D kinematics and the EMG of the medial Deltoid, which was considered to be most active during mentioned tasks;
3. Variation of external weights, should the range of weights used for training cover the external forces exerted during ADL movements; or stated differently, how good is a trained NN in intra- and extrapolating?

2.1. Kinematics

Four IMMS were attached to a bus master (MT-X sensors and a XM-B-3 bus master, Xsens Technologies, Netherlands), operating at 50 Hz. The XSens MT-manager software (v1.5.0, SDK v3.1) was used for logging; the implemented Kalman filtering (Roetenberg et al., 2005) was set at the “human scenario”. As depicted in Fig. 1, IMMS were attached on sternum, humerus, forearm and hand.

Sensor to segment calibration was performed following de Vries et al. (2010). Orientation estimations of clavicle and scapula were based on the regression equations by de Groot and Brand (2001). The required initial orientation of clavicle and scapula was measured using a scapula locator, adapted from van Andel et al. (2009). One extra sensor unit was aligned to the local reference frame of an adjustable tripod. Two of the three pivots could be translated in the plane of the scapula locator and were placed on the respective bony landmarks of the scapula to measure initial orientation. Kinematic data from the segments were expressed in the reference frame of the DSEM model, with the positive X-axis from left to right, positive Y-axis vertical upwards, and positive Z-axis pointing backwards.

2.2. EMG

Thirteen muscles around the shoulder joint were selected for the recording of surface EMG, see Table 1. Bi-polar Ag/AgCl electrodes were placed following the guidelines proposed by Hermens and Freriks (1997). EMG data were sampled at 1000 Hz, digitally filtered with a first order high pass filter at 16 Hz and recorded (Biotel 99, Glonner, Planegg, Germany). Offline, EMG signals were rectified and smoothed (unidirectional low pass 2nd order Butterworth filter at 3 Hz) to obtain smooth rectified EMG envelopes (srEMG) in an attempt to have a resemblance in envelope shape close to muscle force output (Olney and Winter, 1985).

2.3. Experimental protocol

Two types of datasets were generated. During the first series of six measurements, labeled as RND (random), the subject performed random upper extremity movements for one minute each, holding a known mass (0, 0.5, 1.0, 1.5, 2.0, or 2.5 kg). The subject was instructed to cover the complete range of motion over all degrees of freedom, and to vary movement speed from slow to moderately fast.

In the second series of four measurements the subject was asked to mimic Active Daily Living (ADL) tasks with a mass (0, 0.2, 0.5 and 1.0 kg) in the right hand for 10 s each. These tasks consisted of brushing teeth, combing hair, perineal care, washing the axils and eating.

2.4. Data analysis

Inspired by the overview of Schollhorn (2004), for the type of data in this experiment a three layer feedforward network was constructed, with a hidden layer of 20 cells. From input to hidden layer a tangent sigmoid transfer function was used, from hidden to output layer a linear transfer function. The number of inputs depended on the stage of analysis:

- Stage 1: 36 input cells were used using segment 3D kinematics (orientation for all segments; forearm acceleration and angular velocity as measured with the IMMS) and 13 channels of upper extremity muscle srEMG;.
- Stage 2: 24 input cells were used based on kinematics and srEMG of the medial Deltoid.

Table 1
Muscles selected for the recording of surface EMG.

1	M. Trapezius ascendens
2	M. Trapezius transversa
3	M. Trapezius descendens
4	M. Deltoideus anterior
5	M. Deltoideus medial
6	M. Deltoideus posterior
7	M. Latissimus dorsi
8	M. Infraspinatus
9	M. Serratus anterior
10	M. Pectoralis major, pars Sternalis
11	M. Pectoralis major, pars clavicularis
12	M. Triceps, caput longum
13	M. Biceps, caput longum

The output layer consisted of three cells to predict the joint reaction force at the glenohumeral joint. Neural networks were trained using Matlab's Neural Network Toolbox (Matlab R2012a, NN toolbox V7.0.3). Network training was epoch based for a maximum of 500. A Levenberg–Marquard backpropagation algorithm with a momentum of 0.8 at a learning rate of 0.05 was applied. To prevent overfitting, training was stopped when internal validation failed to decrease for 10 successive iterations, usually at around 250–300 epochs of the complete dataset (multiple trials) used as input. The training procedure is schematized in Fig. 2A.

Validation of the method comprises the comparison of time series of joint reaction force as predicted by the neural network versus calculated with the musculoskeletal model as depicted in Fig. 2B. The Intra-Class Correlation was chosen as a measure for the resemblance of these two time series (NN and musculoskeletal model) and calculated per condition. Since the ICC is a relative measure of reliability, the Standard Error of Measurement (SEM) was calculated to obtain an absolute index of reliability in the same units as the measurement (Weir, 2005). To enable comparison among different conditions SEM values were expressed as a percentage of the range of the signal (SEM_rel).

The initialization of a neural network comprises random weight assignment to all internal connections, followed by training; when repeated this might lead to different behavior and performance of these networks. Therefore, for each test condition 10 individual networks were initialized, trained and externally validated by simulating the trained NN with an independent dataset, not used for training. From these 10 individually trained neural networks, the neural network producing the lowest SEM_rel was considered the best performing network.

Several combinations of input type, movement type, and weight ranges were examined during this validation, as depicted

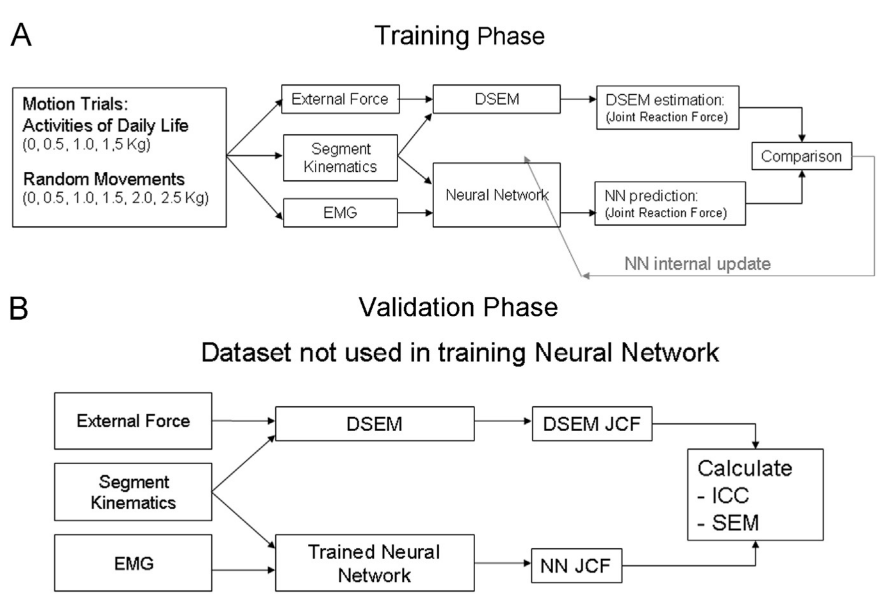

Fig. 2. (A) Schematic of the procedure used to train a neural network with back propagation in predicting joint reaction forces at the glenohumeral head. During the training phase, known external forces are required as one of the inputs for the musculoskeletal model (Exerted Force = [known mass in the hand] times [measured acceleration of the hand]). The comparison of neural network output and its target (calculated by the musculoskeletal model), and the update of internal parameters of the neural network is implemented in the Matlab neural network toolbox which was used for the construction and training of this procedure. (B) Validation was performed by simulating an independent dataset with the network, and compare its prediction with results as calculated with the musculoskeletal model.

Table 2
Results of simulation with a trained NN in predicting JRF-GH, Relative SEM for the several conditions tested. Each cell contains Relative SEM values of the best performing NN of 10 individually trained. Left column depicts which set of EMG (13 channels, or just one), and what type of motion trials were used for NN training; ADL type, ADL and RND, or only RND. Each row depicts what type of motion trial was simulated (ADL type, or RND), with a low (interpolation) or Heavy Weight (extrapolation). Simulation took place with measurement trials not used in the training of the NN.

Training	Simulation ADL Light Weights			Simulation ADL Heavy Weights			Simulation RND Light Weights			Simulation RND Heavy Weights		
3D Component	X	Y	Z	X	Y	Z	X	Y	Z	X	Y	Z
Kinematics, 13 channels EMG												
ADL												
ICC	0.91	0.97	0.97	0.86	0.96	0.93						
SEM_rel	11	5	6	8	4	6						
ADL&RND												
ICC	0.93	0.95	0.95	0.85	0.94	0.94	0.93	0.94	0.96	0.89	0.91	0.88
SEM_rel	10	7	7	9	5	7	8	6	6	7	5	9
RND												
ICC	0.83	0.86	0.91				0.91	0.93	0.94	0.90	0.92	0.86
SEM_rel	19	14	12				11	7	7	7	4	9
Kinematics, 1 channel EMG												
ADL												
ICC	0.88	0.98	0.95	0.88	0.95	0.93						
SEM_rel	13	4	7	7	5	6						
ADL&RND												
ICC	0.94	0.98	0.96	0.88	0.95	0.95	0.92	0.94	0.93	0.86	0.94	0.84
SEM_rel	9	3	6	7	5	6	10	6	7	8	4	10
RND												
ICC	0.84	0.88	0.90				0.90	0.96	0.95	0.89	0.93	0.88
SEM_rel	21	13	13				11	5	7	7	4	9

in Table 2. For the conditions with the label "Light Weights" the trials with 0.2 kg weight was excluded from training of the neural networks and subsequently used for simulation with the trained NN. These "Light Weights" conditions served as a test case for the performance of the NN while interpolating. For the conditions with the label "Heavy Weights" the trials with the heaviest weight (for ADL movements 1.0 kg, for Random Movements 2.5 kg) were excluded from training and subsequently simulated by the trained NN. As such, these "Heavy Weights" conditions served as a test case for NN performance while "extrapolating".

3. Results

The neural networks showed good convergence during training, meaning that the neural networks were able to learn the relationship between input and target (preferred output for the training dataset). Over all conditions, for the best performing network the ICC values ranged from 0.98 to 0.83, whereas the SEM_rel varied from 3% to 21%, between NN-predictions and corresponding output from the musculoskeletal model. For the best performing NN of each conditions these ICC and the SEM_rel are depicted in Table 2.

Results from stage 1, (3D kinematics and 13 channels of EMG) for ADL type movements indicate that performance was best when NN were trained with ADL type movement trials and external load within the training range, resulting in a SEM_rel of 11%, 5% and 6%, for the *x*, *y* and *z* dimensions respectively. Initially it was assumed that RND type movements would cover the complete range of motion of the upper extremity, and thus would deliver a generally trained NN, for "any" type of motion. However, the combination of ADL and RND type movements as training dataset for the network did not improve performance in predicting joint reaction forces for ADL type movements, raising the SEM_rel to 10%, 7% and 7%. When using only RND type movements as training data, the performance of NN in predicting joint reaction forces for ADL type movements decreased further to SEM_rel values of respectively 19%, 14% and 12%. On the contrary, when predicting joint reaction forces for RND type movements using RND, or a combination of RND and ADL type movements as training data sets for the NN, SEM_rel values ranged between 6% and 11%, strengthening the notion that NN should be trained with task specific data.

NN predictions for ADL type movements performed with higher weights than those used for the training of the NN resulted in SEM_rel values ranging from 4% to 9% for ADL type motion, and 4% to 11% for RND type motion. These results indicate that even in extrapolation, the neural network approach remains consistent in its predictive power.

Results from the second stage, in which segment kinematics and just one single channel of EMG served as input for the NN, show similar results as stage one, where 13 channels of EMG were used. These results show the potential of the NN approach with an appealing simplicity in equipment needed: The ambulatory measurement of shoulder joint reaction forces, with one sensor per segment, and only one channel of EMG.

Fig. 3A shows data of a NN, trained with ADL type movements, and simulating an independent ADL type movement while holding a Light Weight (0.2 kg) in the hand. Movements performed were brushing teeth, combing hair, perineal care, washing axils and eating (bringing hand to mouth). NN prediction overshoot can be observed at the peaks in the references signal, and a certain offset for some parts of the trial. In Fig. 3B, showing results for NN trained with kinematics and one channel of EMG, predicting joint reaction forces for Heavy Weight trials of RND movement, deviations can be observed at the peaks in the signal, where NN do predict lower values than the joint reaction force as calculated by the musculoskeletal model. However, the distribution of the joint reaction force over time, as predicted with the neural network method, shows good correspondence with the reference signal, and allows for an initial estimation of shoulder joint loading over time.

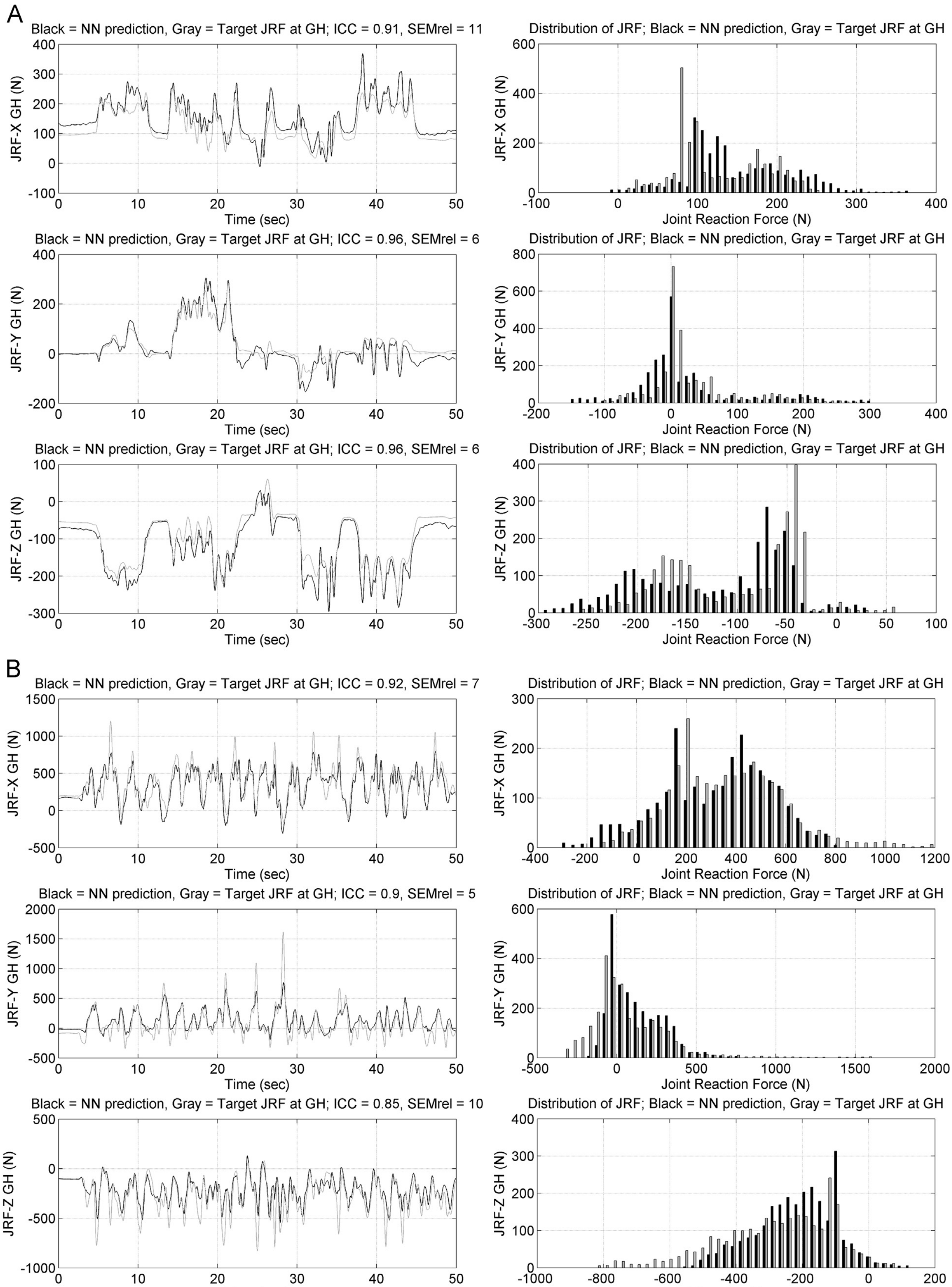

Fig. 3. Depict time series, and distributions of glenohumeral joint reaction forces, from both NN predictions (black lines) and the musculoskeletal model (gray lines), the latter being the reference signal. (A) Results from a NN with kinematics, sensor data and 13 channels of EMG as input, trained on ADL type movement, predicting Low Weight ADL type movement. (B) Results from a NN with kinematics, sensor data and only one channel of EMG as input, trained on RND type movement, predicting a Heavy Weight RND type movement.

4. Discussion

The intention of the current experiment was to evaluate the neural network approach as a reliable and practical method, to enable a long-term estimation of joint reaction forces under daily conditions using ambulatory obtained data. A practical method should have an appealing simplicity concerning the amount of equipment used and preparation time needed. Aiming at such simplicity, neural networks were trained for several conditions. Two types of movements were used, mimicking Activities of Daily Living, and Random Movements. Furthermore, two groups of input parameters were examined; kinematics and 13 channels of EMG; kinematics and one channel of relevant EMG. NN predictions of glenohumeral joint reaction forces were referenced against a musculoskeletal model. Although there is room for improvement, results were promising and relevant influences to the predictive power of the method have been identified.

Fig. 3A indicates the performance for conditions where neural networks were trained using ADL type kinematics and full EMG as input, predicting ADL type movements with a light load. Almost same results were obtained for the Heavy Weight condition. When trials with RND type movement were added to the training data set, predictive power decreased a little. When using only RND type movement in training, and predicting ADL type movement, predictive power decreased further, as can be noticed from Table 2. This was unexpected, since it was initially assumed that the addition of more variation to the training data set of the NN should result in a "better" prediction of the NN. This suggests that training data for the NN should be focused to the type of movement of interest. It also questions the reliability of the neural network prediction for activities not included in the training of the neural networks. The ongoing challenge of proper handling of unforeseen actions in the application of the described ambulatory method has at least two theoretical solutions. The first solution is applying a two step approach. A first phase is aggregating a catalog of performed motions or ADL during a full day, which can be used in the second phase (another day) to produce training data for the neural network (subject is asked to perform activities from the catalog).

A second solution is postponing the collection of training data to the end of a full day of measurements. From the collected data a top 5 (or top 10) of performed movements is selected for the measurement of training data for the neural networks. For both solutions a proper classification method should be available to aggregate such a activity catalog.

The use of 13 channels of upper extremity EMG is not a convenient setup for ambulatory measurements. For the sake of a practical setup Stage 2, with only one channel of EMG, was introduced and examined. The fact that results from Stage 2 simulations corresponded well with results from Stage 1, this suggests that this setup is favorable for ambulatory measurements.

In the current experiment data from only one subject was analyzed. For this specific subject a neural network is trained to learn the individual complex relation between 1) measured EMG and kinematics and 2) joint reaction force. Although for a specific activity a gross resemblance in muscle activity over subjects exists, the aforementioned dedicated relation has to be defined per subject. Based on results from the literature (Song and Tong, 2005; Liu et al., 1999), where for multiple subjects neural networks were trained to learn the relation between e.g. EMG, kinematics and joint moments, it was assumed that neural networks are able to establish these relations for different subjects, and therefore differing signals. Future research will address neural networks ability to deal with inter-subject variability for the ADL tasks described. The appealing concept of training a general neural network on pooled data from several subjects can than also be addressed.

Glenohumeral joint reaction force as estimated by the musculoskeletal model was used as target signal in the training of NN, and as reference for comparison. Model estimations of muscle activity have been qualitatively validated against EMG patterns (van der Helm, 1994a, 1994b); estimations of glenohumeral joint reaction force have been quantitatively validated recently against in vivo measured joint reaction forces (Nikooyan et al., 2010). For dynamic tasks up to 90° of humeral elevation values were comparable, although peak forces were underestimated by the model; for higher angles a deviation in force direction was observed, and for force exerting tasks an underestimation of the models JRF was found. Possibly this behavior of the musculoskeletal model results in an inconsistent training set, thereby disturbing the learning process of the NN method, resulting in the observed differences. Potentially the application of a NN method to in vivo measured JRF might show better correspondence, thereby expanding opportunities in obtaining a general load profile of the shoulder.

Application of the neural network method to patient measurements deserve special attention. First of all, the used musculoskeletal model should be adapted to mimic the subjects abilities, for instance rotator cuff tears should be simulated in the model as described by Steenbrink et al. (2009). Secondly, if any pathological adaptation is present in upper extremity muscle activity, a redundant number of channels of EMG as input for the neural network should be considered. And thirdly, the type of motion used for training neural networks should be within the subjects ability.

To enable the discrimination between the damaging effects of peak forces versus sustained duration of raised levels of JRF, for a broad range of movements as encountered under daily conditions, both levels should be estimated for a longer period of time.

5. Conclusions

Shoulder joint loading in terms of JRF-GH can be estimated by a NN trained on ambulatory obtainable variables like srEMG and IMMS data of the upper extremity. The dataset should comprise sufficient "task specific" training trials. A convenient setup with IMMS on upper extremity segments and only one channel of relevant EMG showed comparable results to a setup with IMMS and 13 channels of EMG.

Conflict of interest statements

The authors disclose any financial and personal relationships with other people or organizations that could inappropriately influence (bias) our work. The authors can also state that the study sponsors had no involvement in the study design, collection or the decision to submit this manuscript for publication. This manuscript, including related data, figures and tables has not been previously published and is not under consideration elsewhere.

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