Journal of Biomechanics 49 (2016) 73–79

Contents lists available at ScienceDirect

Journal of Biomechanics

journal homepage: www.elsevier.com/locate/jbiomech
www.JBiomech.com

Can shoulder joint reaction forces be estimated by neural networks?

W.H.K. de Vries [a,b,*], H.E.J. Veeger [a,c], C.T.M. Baten [b], F.C.T. van der Helm [a]

[a] Department of Biomechanical Engineering, Faculty of Mechanical, Maritime & Materials Engineering, Delft University of Technology, The Netherlands
[b] Roessingh Research & Development, Enschede, The Netherlands
[c] Research Institute MOVE, Department of Human Movement Sciences, VU University Amsterdam, The Netherlands

ARTICLE INFO

Article history:
Accepted 15 November 2015

Keywords:
Ambulatory
IMMS
Joint reaction forces
Upper extremity
Neural networks

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

* Corresponding author at: Department of Biomechanical Engineering, Faculty of Mechanical, Maritime & Materials Engineering, Delft University of Technology, The Netherlands.
E-mail address: wdv.work@gmail.com (W.H.K. de Vries).

http://dx.doi.org/10.1016/j.jbiomech.2015.11.019
0021-9290/

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?

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?

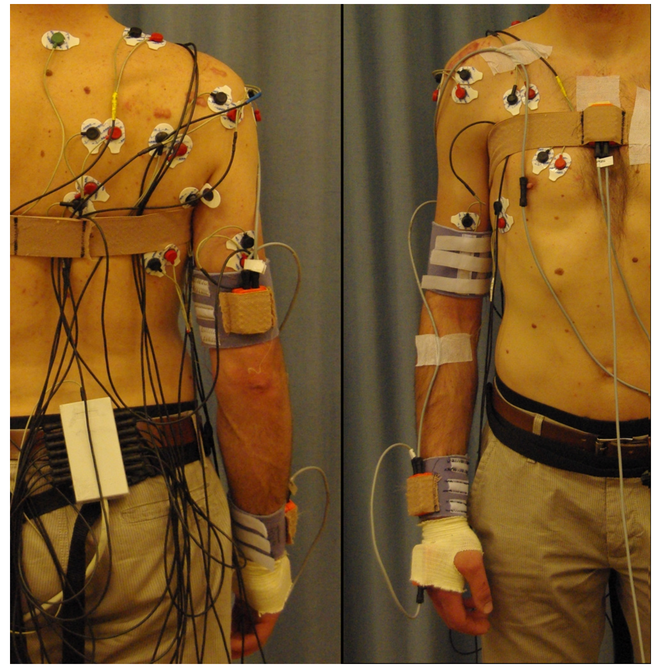

Fig. 1. A fully equipped subject, with four sensor modules on sternum, humerus, forearm and hand, and 13 channels of surface EMG.

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