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Human lower extremity joint moment prediction: A wavelet neural network approach

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ABSTRACT

Joint moment is one of the most important factors in human gait analysis. It can be calculated using multi body dynamics but might not be straight forward. This study had two main purposes; firstly, to develop a generic multi-dimensional wavelet neural network (WNN) as a real-time surrogate model to calculate lower extremity joint moments and compare with those determined by multi body dynamics approach, secondly, to compare the calculation accuracy of WNN with feed forward artificial neural network (FFANN) as a traditional intelligent predictive structure in biomechanics.

To aim these purposes, data of four patients walked with three different conditions were obtained from the literature. A total of 10 inputs including eight electromyography (EMG) signals and two ground reaction force (GRF) components were determined as the most informative inputs for the WNN based on the mutual information technique. Prediction ability of the network was tested at two different levels of inter-subject generalization. The WNN predictions were validated against outputs from multi body dynamics method in terms of normalized root mean square error (*NRMSE* (%)) and cross correlation coefficient (ρ).

Results showed that WNN can predict joint moments to a high level of accuracy (*NRMSE* < 10%, ρ > 0.94) compared to FFANN (*NRMSE* < 16%, ρ > 0.89). A generic WNN could also calculate joint moments much faster and easier than multi body dynamics approach based on GRFs and EMG signals which released the necessity of motion capture. It is therefore indicated that the WNN can be a surrogate model for real-time gait biomechanics evaluation.

1. Introduction

Human movement prediction has been one of the most interesting and challenging fields in biomechanics. Predictions from such studies can be used in surgical intervention planning (Reinbolt, Fox, Schwartz, & Delp, 2009; Reinbolt, Haftka, Chmielewski, & Fregly, 2008), athletes training (Iyer & Sharda, 2009; Pfeiffer & Hohmann, 2012; Schmidt, 2012) and prosthesis and orthosis design (Au, Berniker, & Herr, 2008; Joshi, Mishra, & Anand, 2011; Rupérez et al., 2012). In addition joint moments are important factors in order to investigate joint reaction forces, which in turn affect joint functions such as tribology characteristics of the joint including friction, wear and lubrication of the articulating surfaces.

Joint loading can be determined by instrumented prosthesis (Fregly et al., 2012) which is not feasible most of the time. It can also be calculated based on multi body dynamics method using the measured gait data in a gait laboratory equipped with 3D motion capture system and force plate. Measured kinematics and kinetics as well as anthropometric data are then used in an inverse dynamics analysis to calculate joint moments (Robert, Causse, & Monnier, 2013). However multi body dynamics approach is generally time-consuming which prevents it from serving as a real-time technique especially in gait retraining programs where the real-time calculation of joint moments is needed to evaluate the efficiency of the rehabilitation program. There are also some major difficulties using multi body dynamics analysis. Such musculoskeletal models are sensitive to muscle-tendon geometry, muscle origin and insertion (Ackland, Lin, & Pandy, 2012; Carbone, van der Krogt, Koopman, & Verdonschot, 2012). On the other hand it is not always straight forward to validate and verify the models. Numerical methods are also important considerations in multi body dynamics analysis which may result in the failure of solutions.

According to the above limitations, artificial intelligence has been recruited in this area due to its ability in pattern recognition and signal prediction. For a complete review on neural network application in biomechanics one can refer to Schöllhorn (2004).

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Especially in the field of joint moment prediction, for example, Uchiyama et al. used a three-layer feed forward artificial neural network (FFANN) to predict the elbow joint torque using electromyography (EMG) signals, shoulder and elbow joint angles for constant muscle activation (Uchiyama, Bessho, & Akazawa, 1998). Luh et al. also used a three-layer FFANN to predict elbow joint torque using EMG signals, joint angle and elbow joint angular velocity (Luh, Chang, Cheng, Lai, & Kuo, 1999). Wang and Buchanan (2002) proposed to calculate muscle activities using EMG signals based on a four-layer FFANN. Predicted muscle activities were then used by a Hill-type model in order to estimate muscle forces and elbow joint torque. Song and Tong (2005) also investigated a recurrent artificial neural network (RANN) for elbow torque estimation using EMG data, elbow joint angle and angular velocity. Hahn (2007) used a three-layer FFANN to predict isokinetic knee extensor and flexor torque based on age, gender, height, body mass, EMG signals, joint position and joint velocity. However this study predicted only net knee flexion extension torque and did not predict other lower extremity joint moments. Liu et al, presented a FFANN to predict lower extremity joint torques in the sagittal plane using GRFs and related parameters measured during vertical jumping (Liu, Shih, Tian, Zhong, & Li, 2009). This study also predicted ankle, knee and hip joint moments only in the sagittal plane for vertical jump. Favre et al, proposed to use a three-layer FFANN to predict the external knee adduction moment based on force plate data and anthropometric measurements (Favre, Hayoz, Erhart-Hledik, & Andriacchi, 2012). This paper also investigated only knee adduction moments and did not consider other lower extremity joint moments. In a recent study Oh et al. also successfully predicted the three dimensional GRFs and moments based on three-layer FFANN using fourteen inputs of body parts trajectories and accelerations. This study also proved the possibility of calculating joint forces and moments based on the GRFs predicted with the intelligent network (Oh, Choi, & Mun, 2013).

All of the above studies have used traditional neural network to predict joint moments. However a major disadvantage of neural network is that local data structures are discarded in FFANN learning process (Cordova, Yu, & Li, 2012). In addition, the initial weights are adjusted randomly at the beginning of the training algorithm which can slow down the training process (Haykin, Haykin, Haykin, & Haykin, 2009). Another disadvantage is that the network may fall in to a local minimum during the training procedure so the network output never converges to the target (van der Smagt & Hirzinger, 1998).

In order to cope with these disadvantages, wavelet neural network (WNN) has been introduced as an alternative method. WNN combines the theory of wavelet with ANN structure in order to benefit general approximation ability of neural networks as well as localization property of wavelets. A WNN is a three-layer FFANN with a hidden layer in which neurons are activated by wavelets as activation functions so the local data structures are considered in both time and frequency domains. This type of intelligent networks has been used successfully in pattern classification (Subasi, Alkan, Koklukaya, & Kiymik, 2005; Subasi, Yilmaz, & Ozcalik, 2006), function estimation (Zainuddin & Pauline, 2011), system identification (Billings & Wei, 2005; Wei, Billings, Zhao, & Guo, 2010), signal prediction (Chen, Yang, & Dong, 2006; Pourtaghi, 2012; Zhang & Wang, 2012) and especially in bankrupting and price forecasting (Chauhan, Ravi, & Karthik Chandra, 2009; Mingming & Jinliang, 2012) which has significantly nonlinear dynamic patterns. According to the above studies, it may be possible to design WNN for joints moments prediction. To the best of our knowledge WNN has not been used before in human gait biomechanics prediction.

This study had two main purposes; *first* to develop a generic multi-dimensional WNN as a real-time surrogate model for joint moment prediction; *second*, to compare the prediction accuracy of WNN with three-layer FFANN. To aim the purposes, four subjects walked with three different conditions (normal gait as well as two different knee rehabilitation programs) were obtained from the literature. A generic multi-dimensional WNN was designed and trained at two different levels of inter-subject generalization. To avoid time consuming procedure of marker trajectory collection and processing, and consider the previous studies (Favre et al., 2012; Hahn, 2007; Liu et al., 2009), EMG and GRFs were considered as network inputs. WNN predictions were validated against inverse dynamics analysis and compared with those predicted by a three-layer FFANN.

2. Materials and methods

2.1. Subjects

Four different patients unilaterally implanted with knee prostheses including three males and one female (height: 168.25 ± 2.63 cm; mass: 69.18 ± 6.24 kg) were taken from a previously published data base (https://simtk.org/home/kneeloads; accessed on, 5 September 2013). Three different sessions were considered for each subject including normal, medial thrust and walking pole patterns. In each session, five gait trials were recorded under the same walking condition. For a complete description of sessions and trials one can refer to Fregly et al. (2012). In brief, medial thrust pattern, a successful rehabilitation pattern for knee joint off-loading, included a slight decrease in pelvis obliquity and a slight increase in pelvis axial rotation and leg flexion compared to normal gait (Fregly, Reinbolt, Rooney, Mitchell, & Chmielewski, 2007). In addition walking pole included two lateral poles as walking aids which has been effective to reduce knee joint loading (Willson, Torry, Decker, Kernozek, & Steadman, 2001). It should be pointed out that although several gait cycles were measured in each gait trial, only two complete gait cycles of each trial were used, leading to a total of 120 data sets (four subjects ∗ three sessions ∗ five trials ∗ two gait cycles).

2.2. Data pre-processing

Due to high frequency rate of GRFs and EMG signals (1000–1200 Hz) and low frequency rate of calculated joint moments (100–120 Hz), data were preprocessed before using as WNN inputs. GRFs were down sampled according to the calculated joint moments and then re-sampled to 100 points for a complete gait cycle using the nearest neighbor interpolation method. GRF amplitudes were also normalized by body weight (BW).

A total of 14 EMG signals were recorded including semimembranosus (semimem), biceps femuris (bifem), vastus intermedius (vasmed), vastus lateralis (vaslat), rectus femoris (rf), medial gastrocnemius (medgas), lateral gastrocnemius (latgas), tensor fasciae latae (tfl), tibia anterior (tibant), peroneal, soleus, adductor magnus (addmagnus), gluteus maximus (gmax) and gluteus medius (gmed). In order to deal with high rate variation of EMG signals, root mean square (RMS) was used as one of the most accepted techniques to represent EMG signals in time domain (Staudenmann, Roeleveld, Stegeman, & Van Dieen, 2010). EMG signals were divided in to 50 m s intervals to calculate RMS features of EMG signals based on the following equation:

$$\mathrm{RMS} = \sqrt{\frac{1}{N}\sum\nolimits_{n=1}^{N}(\mathrm{EMG}(n))^2} \tag{1}$$

where $N = 20$ and shows the number of samples within each interval (Arslan, Adli, Akan, & Baslo, 2010). Butterworth filter of order 10 with a cut off frequency of 1 Hz was also applied to RMS features. Preprocessed EMG signals were re-sampled to 100 points for one complete gait cycle.