Feed forward artificial neural network to predict contact force at medial knee joint: Application to gait modification

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A B S T R A C T

Knee contact force (KCF) is one of the most meaningful parameters to evaluate function of the knee joint. However in vivo measurement of KCF is not always straightforward. Inverse dynamics analysis, as one of the most frequently used computational techniques to calculate KCF, has its own limitations. The purpose of this study was to develop a feed forward artificial neural network (FFANN) to predict the medial condyle KCF corresponding to two different gait modifications known as medial thrust and trunk sway. Four patients implanted with unilateral knee sensor-based prostheses were obtained from the literature. The network was trained based on pre-rehabilitation gait patterns and was recruited to predict the medial KCF associated with rehabilitation patterns. Generalization ability of the proposed network was tested within three different levels including intra subject (level 1), inter condition (level 2) and inter subject (level 3). FFANN predictions were validated against in vivo measurements.

Results showed subject-specific neural network could predict KCF to a certain high level of accuracy (medial thrust: \( NRMSE = 10.6\% \), \( \bar{p} = 0.96 \); trunk sway: \( NRMSE = 9.6\% \), \( \bar{p} = 0.96 \)) based on the ground reaction forces (GRFs) and some independent marker trajectories (level 1) which suggested that not all of the markers are necessary for knee force calculation. Moreover at level 2, a generic FFANN could predict the medial knee force based on electromyography (EMG) signals and GRFs (medial thrust: \( NRMSE = 11.2\% \), \( \bar{p} = 0.96 \); trunk sway: \( NRMSE = 10.5\% \), \( \bar{p} = 0.95 \)) which released the necessity of motion capture and subject specific scaling of a musculoskeletal model. At level 3, neural network could predict the general pattern and features of KCF for a new subject that was not used in the network training (medial thrust: \( NRMSE = 12.6\% \), \( \bar{p} = 0.95 \); trunk sway: \( NRMSE = 13.3\% \), \( \bar{p} = 0.94 \)).

In conclusion, FFANN could predict the medial knee joint loading corresponding to two different knee rehabilitations based on pre-rehabilitation gait patterns. Compared to the inverse dynamics method, artificial intelligence represents a much faster and easier method; together they can be combined to calculate joint loading involving fewer markers and speed up the calculations.

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1. Introduction

Knee contact force (KCF) is one of the most meaningful parameters to evaluate knee joint function. KCF is highly affected by gait patterns [1,2] and knee joint alignment [3,4]. It can also directly affect cartilage stresses [5] and knee osteoarthritis [6]. Therefore KCF has been calculated widely for evaluation of knee joint disease [7], gait modification [8], prosthesis design [9,10] and surgery intervention [11,12]. Especially, for knee rehabilitation [13], knee joint off-loading can decelerate cartilage damage and post-pone joint replacement surgery or decrease wear and prolong clinical life time of knee prostheses after surgery. Due to this fact that medial knee condyle undergoes 60% of the knee joint loading [14], medial KCF reduction has been a topic of particular interest in knee rehabilitation design [15–17]. On the other hand medial KCF cannot be measured directly in vivo unless using a sensor-based knee prosthesis which is not straightforward. Although computational approaches including the inverse dynamics method [7,18], forward dynamics analysis [19] and static optimization [20] can calculate three dimensional KCF aligned in medial–lateral, anterior–posterior and vertical directions, these methods cannot normally calculate the KCF distribution at the medial and lateral knee condyles. Thus, knee adduction moment (KAM) has been widely adopted as a surrogate of medial KCF [21], especially in gait modification designs where KAM reduction has...
been concerned as the main goal of rehabilitation (instead of medial KCF reduction) [15,22,23]. However recent investigations have revealed that KAM peak reduction did not always guarantee the medial KCF reduction [24].

Therefore a few studies have been carried out to develop an inverse dynamics frame work to calculate medial and lateral KCF [25,26]. Nevertheless, predictions from these computational models are highly dependent on the accuracy of the governing equations, mathematical simplifications, input parameters and the degrees of freedom of the model. More importantly, these techniques are quite time consuming, which prevents them from serving as real-time methods. On the other hand in clinical rehabilitation, patients should be trained to internalize the rehabilitation strategy as their daily walking patterns. Accordingly real-time calculation of medial KCF benefits the clinical execution of gait retraining patterns, for example to determine whether the medial KCF would be decreased or to investigate the effects of different daily activities (e.g. stair climbing/descending) on the resultant medial KCF. However the available inverse dynamics methods do not satisfy the necessity of real-time calculation.

Consequently artificial intelligence has been introduced to biomechanics data mining as an alternative approach in signal prediction [27–29] and pattern classification [30,31] where neural network is recruited to model complicated input–output relations. For example feed forward artificial neural network (FFANN) has been used widely to predict elbow joint torque [32,33]. Hahn also used a three-layer FFANN to predict isokinetic knee extensor and flexor torque based on age, gender, height, body mass, electromyography (EMG) signals, joint position and joint velocity [34]. Liu et al., presented a FFANN to predict lower extremity joint torques in the sagittal plane using ground reaction forces (GRFs) and related parameters measured during vertical jump [35]. Favre et al., proposed to use a three-layer FFANN to predict the KAM based on force plate data, anthropometric measurements and displacement/velocity of the subject’s center of mass [36]. However as mentioned earlier, KAM cannot always serve for knee rehabilitation purposes. It is clear from these previous applications of FFANN that once the network is trained using input–output examples, it learns and generalizes the input–output relation. Thus it serves as a surrogate model to prevent repetition of time consuming calculations. A trained neural network can make a real-time prediction of output for a new set of inputs or a real-time classification of a new input pattern.

This study aimed to determine whether using pre-rehabilitation gait data to train a FFANN, was it feasible to predict the resultant medial KCF associated with the rehabilitation patterns. Accordingly GRFs, EMG signals and a few sets of independent marker trajectories were adopted as FFANN inputs to predict medial KCF as output. In order to investigate the extent to which a trained neural network could generalize the input–output relation, the trained network was challenged through three different levels of generalization: (i) intra subject, (ii) inter condition and (iii) inter subject. We hypothesized that training the FFANN based on different pre-rehabilitation walking patterns could serve as a real-time cost-effective surrogate model to predict the resultant medial KCF associated with different knee rehabilitation programs.

2. Materials and methods

The proposed approach consisted of three main steps: (i) data pre-processing including down-sampling, smoothing and normalizing the data, (ii) input variable selection (IVS) to choose the most relevant inputs for the intelligent network, and (iii) FFANN prediction of medial KCF based on the selected inputs within three generalization levels. At each level a different arrangement of data space was used to train and test the network.

At level 1, the network was trained based on pre-rehabilitation gait patterns of an individual subject and then tested to predict medial KCF corresponding to the knee rehabilitation gait patterns for the same subject (intra subject). At level 2, a generic network was trained based on pre-rehabilitation gait patterns of all subjects and then tested to predict medial KCF associated with knee rehabilitation gait patterns for each subject (inter condition), while at level 3 the generic network was trained based on rehabilitation gait patterns of all subjects except one and then tested to predict medial KCF for that subject under the same rehabilitation patterns (inter subject).

Finally, the “peak” values of medial KCF and “impulses” were also compared between in vivo measurements and FFANN predictions. Additionally, the “peak” values of medial KCF and “impulses” were also compared between in vivo measurements and FFANN predictions as important features of knee medial compartment loading [24,36–38]. Impulse was defined as the area under medial KCF curve [24] and calculated based on the gait phase definitions by Perry and Burnfield [39].

2.1. Subjects

A subject pool, including four patients (height: 168.2 ± 2.6 cm; mass: 69.1 ± 6.2 kg) with unilateral knee sensor-based prostheses, was adopted from a previously published data base (https://simtk.org/home/kneeloads; accessed on June 2013). Table 1 summarizes these four participants’ characteristics. Four different sessions were considered for each subject as normal, walking pole, medial thrust and trunk sway patterns (except for subject 4 which did not have trunk sway trials). In each session, five over ground gait trials were recorded under the same walking pattern at a self-selected pace. For a complete description of sessions/trials and data collection procedure, one can refer to [40]. In brief, medial thrust included slightly decreased pelvis obliquity, slightly increased pelvis axial rotation and leg flexion [13]. Trunk sway included an increased lateral leaning of the trunk in the frontal plane over the standing leg [2]. In walking pole, subjects used bilateral poles as walking aids to decrease GRFs and change the medial KCF [17].

In each gait trial, experimental data (EMG, GRFs, in vivo knee loading, and marker trajectories) were collected and synchronized using vertical ground reaction force and EMG signals. A total of 14 EMG signals for lower extremity muscles of the prosthetic leg were recorded, including semimembranosus, biceps femuris, vastus intermedius, vastus lateralis, rectus femoris, medial gastrocnemius, lateral gastrocnemius, tensor fasciae latae, tibia anterior, peroneal, soleus, adductor magnus, glutaeus maximus and glutaeus medius (surface electrodes, Delsys Corp., Boston, MA). In vivo knee joint loading was also obtained from instrumented knee prostheses (implanted in the treated leg) with four uniaxial load cells.

<table>
<thead>
<tr>
<th>Subject</th>
<th>Gender</th>
<th>Height (cm)</th>
<th>Mass (kg)</th>
<th>Prosthetic side</th>
<th>Shoes</th>
</tr>
</thead>
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<td>New Balance SL-1 Fit walking shoes</td>
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<tr>
<td>Subject 2</td>
<td>Male</td>
<td>172</td>
<td>67</td>
<td>Right</td>
<td>New Balance 609 sneakers</td>
</tr>
<tr>
<td>Subject 3</td>
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<td>167</td>
<td>78.4</td>
<td>Left</td>
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<tr>
<td>Subject 4</td>
<td>Male</td>
<td>168</td>
<td>66.7</td>
<td>Right</td>
<td>Rockport flat bottom sneakers</td>
</tr>
</tbody>
</table>

Table 1 Subjects description (taken from https://simtk.org/home/kneeloads, 2013/06/18).
(posterior-medial, anterior-medial, anterior-lateral and posterior-lateral load cells embedded in the tibial tray of the prosthesis). Medial and lateral KCF were then calculated from these load cells measurements using validated regression equations [21]. Furthermore, marker trajectory data were collected using a 10-camera motion capture system (Motion Analysis Corp., Santa Rosa, CA) and a modified Cleveland Clinic marker set in which markers were located on sternum, neck, thorax, shoulder, elbow, wrist, radius, ulna, lumbar, anterior superior iliac spine, thigh, shank, patella and heel. This marker set also included extra markers on the feet (Fig. 1). Ground reaction forces and moments were also measured using three force plates (AMTI Corp., Watertown, MA).

2.2. Data pre-processing

One complete gait cycle (from heel strike of the treated leg to the following heel strike of the same leg, including stance, double stance and swing phases) was determined according to the vertical GRF. Due to the high frequency rate of EMG and GRFs (1000–1200 Hz) and the low frequency rate of KCF and marker trajectory (100–120 Hz), data were preprocessed as follows:

(i) GRFs were down sampled according to low frequency of KCF/marker trajectory data and then re-sampled to 100 points for one complete gait cycle using the nearest neighbor interpolation method. GRFs amplitudes were also normalized by body weight (BW).

(ii) A total of 32 markers were tracked in three anatomical directions which yielded 96 columns of marker trajectory data. To decrease the number of data columns, three Cartesian components of each marker were combined to produce a 3D unique trajectory for each marker. Marker trajectories and medial KCF were then re-sampled to 100 points for one complete gait cycle.

(iii) In order to deal with high rate variation of EMG signals, root mean square (RMS) was used as one of the most acceptable techniques to represent EMG signals in time domain [41,42]. Due to the stationary assumption of EMG signals within 500 ms intervals [43], EMG signals were divided into 50 ms intervals to calculate the RMS features of EMG signals based on the following equation:

\[ RMS = \sqrt{\frac{1}{N} \sum_{n=1}^{N} (EMG(n))^2} \]

where N=20 shows the number of samples within each interval [44]. A Butterworth filter of order 10 with a cut-off frequency of 1 Hz was also applied to RMS features. Pre-processed EMG signals were re-sampled to 100 points for one complete gait cycle.

2.3. Input variable selection

In order to increase the generalization ability of FFANN, only informative and relevant variables should be selected as inputs [45]. Fisher discriminant analysis (FDA) was used to recognize the most informative EMG signals that can affect KCF. Recorded samples of each EMG channel were classified into two distinct classes corresponding to two knee force intervals defined as class 1 \([0.75KCF_{\text{max}} - KCF_{\text{max}}]\) and class 2 \([KCF_{\text{min}} - 1.25KCF_{\text{min}}]\). FDA was calculated as a discriminant criterion for each EMG channel based on the following equation [29]:

\[ J_k = \frac{(m_1 - m_2)^2}{d_1^2 + d_2^2} \]

where \(m_1 (m_2)\) and \(d_1 (d_2)\) were the mean and standard deviation of class 1 (class 2) related to channel \(k\). Higher \(J_k\) values mean higher variation in the EMG channel due to changes in medial KCF. Moreover, in order to achieve the optimal prediction, partial correlation-kernel mutual information (MI) technique was used to select the most informative and independent markers as FFANN inputs. Partial correlation was calculated between all possible pairs

![Fig. 1. Schematic diagram of marker set-up which was used to capture marker trajectories.](image-url)
of inputs (14 marker trajectories related to the prosthetic side) to select the most independent variables based on the equation below [45]:

$$P_{XY.Z} = \frac{\rho_{XY} - \rho_{XZ}\rho_{YZ}}{\sqrt{(1-\rho_{XZ}^2)(1-\rho_{YZ}^2)}}$$

(3)

In the above equation $\rho$ refers to Pearson correlation. The $P_{XY.Z}$ measures the dependency between $X$ and $Y$, while the $\rho_{XZ}$ measures the dependency between $X$ and $Z$ after the dependency between $Y$ and $Z$ have been discounted. Kernel MI criterion was calculated between marker trajectories of the treated side and medial KCF based on the following equation:

$$I(X,Y) = \sum_{x \in X} \sum_{y \in Y} P(x,y) \log \frac{P(x,y)}{P(x)P(y)}$$

(4)

In which $X$ and $Y$ refer to the input (marker trajectories) and output (medial KCF) variables respectively. In the above equation, joint probability ($P(x,y)$) and marginal probabilities ($P(x)$,$P(y)$) were calculated based on kernel density estimation as below [46]:

$$P(y) = \frac{1}{n} \sum_{i=1}^{n} K(u)$$

(5)

$$u = \frac{(y - y_j)^T S^{-1} (y - y_j)}{h^2}$$

(6)

$$K(u) = \frac{1}{2\pi h^2 \det(S)^{1/2}} \exp(-u^2/2)$$

(7)

$$h = \left\{ \frac{4}{\Gamma + 2} \right\}^{1/4} \cdot \left\{ \frac{n}{1.14} \right\}^{1/4}$$

(8)

In which $l$ is the vector dimension and $S$ is the covariance matrix on $y_j$ and $n$ is the number of samples in vector $y_j$.

2.4. Artificial neural network architecture

In the present study feed forward artificial neural network (FFANN) was used to predict the medial KCF. The proposed FFANN structure was implemented in Matlab software (Neural Network Toolbox of Matlab v.2009, The MathWorks Inc.). This structure consisted of processor units (neurons) organized in certain arrangement (layers). Fig. 2 shows the structure of a four-layer FFANN with two hidden layers. In each layer, neurons were connected to the neurons of the next layer via numeric values (weights). Thus a weighted sum of all inputs was fed into each hidden neuron where an activation function acted on this weighted sum to produce the hidden neuron’s output. All of the hidden neurons were activated using “hyperbolic tangent sigmoid” function which linearly scaled its input signal to $[-1, 1]$ interval based on the following equation:

$$y_j^m(n) = \frac{2}{1 + \exp(-2y_j^m(n))} - 1 \quad j = 1, 2, ..., M_m, \quad n = 1, 2, ..., 100$$

(9)

where $y_j^m$ is the output of $j$th hidden neuron located at the $m$th hidden layer, $M_m$ is the number of hidden neurons at the $m$th hidden layer, $n$ is the $n$th instantaneous sample (observation) of the signals and $V_j^m(n)$ is the weighted sum of the signals fed to the $j$th hidden neuron of $m$th hidden layer. For the first hidden layer ($m=1$), $V_j^1(n)$ was a weighted sum of inputs:

$$V_j^1(n) = \sum_{k=1}^{N_i} (X_k(n)W_{jk}) + b_j \quad j = 1, 2, ..., M_1, \quad k = 1, 2, ..., N_i, \quad n = 1, 2, ..., 100$$

(10)

where $W_{jk}$ is the input weight relating $k$th input ($X_k$) to the $j$th hidden neuron with the bias value of $b_j$, $M_1$ is the number of hidden neurons at the first hidden layer and $N_i$ is the number of input variables (nodes) at the input layer. Likewise, for the following hidden layers ($m > 1$):

$$V_j^m(n) = \sum_{k=1}^{M_{m-1}} (V_k^{m-1}(n)W_{jk}) + b_j \quad j = 1, 2, ..., M_m, \quad k = 1, 2, ..., M_{m-1}, \quad n = 1, 2, ..., 100$$

(11)

where $V_k^{m-1}$ is the output of $k$th hidden neuron located at the $(m-1)$th hidden layer, $V_j^m(n)$ is the weighted sum of the signals fed to the $j$th hidden neuron located at $m$th hidden layer, and $M_{m}$ and $M_{m-1}$ are the number of hidden neurons at the $m$th and $(m-1)$th hidden layers respectively. At the final hidden layer, neurons were in turn related to the single output node via numeric values (output weights). Thus a weighted sum of hidden neurons’ outputs was fed into the single output node. The single output node was activated with a “pure line” function:

$$y_{out} = \sum_{k=1}^{M_m} \omega_k V_k^{m} + \bar{y}$$

(12)

in which $\bar{y}$ is the output bias. Gradient descent back propagation algorithm with adaptive learning rate (trainingdx) was used to train the network. In this algorithm, the root mean square error between network predictions and target values (in vivo medial KCF) was defined as a cost function as below:

$$error = \sum_{n=1}^{100} (y_{out}(n) - f(n))^2$$

(13)

where $y_{out}$ was calculated in Eq. (12) and $f(n)$ refers to the $n$th instantaneous sample of in vivo medial KCF. The goal of the training algorithm was to adjust the numeric weights and biases in order to minimize this cost function. At the beginning of the training algorithm, the numeric weights/biases were randomly initialized and the network prediction ($y_{out}$) and the above root mean square error (error) were calculated. Thereafter, the weights and biases were updated based on the equations below:

$$W(l+1) = W(l) + \mu \Delta W \quad l = 1, 2, ..., \text{training epochs}$$

(14)

$$b(l+1) = b(l) + \mu \Delta b \quad l = 1, 2, ..., \text{training epochs}$$

(15)

where $\mu$ is the adaptive learning rate and $\Delta W$ and $\Delta b$ are $\partial \text{error}/\partial W$ and $\partial \text{error}/\partial b$ respectively. The output of the neural network was then calculated again with the updated weights/biases. This procedure was repeated until the error goal (0.0001) was achieved or the maximum training epochs (3000) were reached. In each iteration, if the error was decreased compared to the previous iteration, the learning rate ($\mu$) would be increased, otherwise the learning rate would be decreased and the computed weights and biases were discarded. For a complete description of this training algorithm, one can refer to [47]. Training space was randomly divided into three distinguished parts including train (65%), validation (15%) and test (15%). Train and validation parts were used to train the network and adjust the connection weights/biases. The network prediction errors on the test and validation data sets (test error and validation error) were considered to determine the optimum number of hidden neurons, hidden layers and training epochs. Whilst increasing the number of hidden neurons and layers would reduce the validation error, using too many hidden neurons and layers decrease the network generalization ability due to over fitting and yield to test error increment [48]. This technique has been used widely in the literatures [28,49].

The proposed network was trained based on pre-rehabilitation gait patterns (normal gait and walking pole pattern) and then tested to predict the medial KCF associated with knee rehabilitation (medial thrust and trunk sway). Prediction capacity of the
network was tested within three generalization levels as (i) intra subject, (ii) inter condition, (iii) inter subject. Each level included different arrangement of data space. Accordingly required numbers of hidden layers and neurons were defined due to the structure of the training data space at each level:

(i) Level 1-intra subject
A four-layer subject specific FFANN with 10 numbers of inputs (seven independent markers and three dimensional GRFs) and one single output (medial KCF), was trained based on pre-rehabilitation gait patterns for each subject. Trained network was then tested to predict the medial KCF of the same subject within two different gait patterns; medial thrust and trunk sway.

(ii) Level 2-inter condition
A generic five-layer FFANN with 15 neurons in each hidden layer was trained based on pre-rehabilitation gait patterns of all subjects. This network had 12 numbers of inputs (three dimensional GRFs and nine informative EMG channels) and one single output node (medial KCF). Trained network was then tested to predict the medial KCF of each subject associated with two different gait patterns (medial thrust and trunk sway).

(iii) Level 3-inter subject
A five-layer FFANN with 17 numbers of inputs (seven independent markers, nine informative EMG channels and vertical GRF) and one single output node (medial KCF) was trained based on medial thrust and trunk sway patterns of all subjects except one. Generalization ability of the network was then tested in prediction of the medial KCF for that subject which was not used in the network training under the same walking conditions. In order to improve the prediction capacity of the FFANN and deal with the inter-subject variety of loading patterns, medial KCF was normalized to body weight at this level to train and test the network.

It should be pointed out that inputs and output of the neural network were time-variant signals; each was represented as a $100 \times 1$ vector including 100 equally-spaced instantaneous samples of the corresponding variable in the time domain.
recorded in a complete gait cycle. The proposed FFANN was also a memory-less structure which established a one-by-one mapping from the input samples (observations) to the resultant output samples.

Network predictions were benchmarked against in vivo measurements in terms of Pearson correlation ($\rho$), RMSE and percentage of normalized RMSE (NRMSE%). To further investigate the accuracy of the predictions, important descriptive features of the medial KCF (peaks and impulses) related to midstance (17 – 50% of stance) and terminal stance (51 – 83% of stance) were also compared between in vivo measurements and FFANN predictions.

3. Results

Prediction ability of FFANN was investigated to calculate medial knee contact force at three different generalization levels. FDA criterion was calculated for a total of 14 EMG channels. Fig. 3 compares the FDA criterion of different muscles among subjects associated with normal gait pattern as an example. According to the results, nine EMG channels including semimembranosus, biceps femuris, vastus intermedius, vastus lateralis, rectus femoris, tensor fasciae latae, peroneal, gluteus maximus, gluteus medius with higher values of FDA criterion were hypothesized as the most informative EMG signals to predict KCF. A one-way analysis of variance (ANOVA) test with the significance level of $p < 0.05$ was implemented in Matlab (v.2009, Statistics toolbox) to test this hypothesis. A significant difference was found between the selected EMG channels and others in terms of FDA criterion with

<table>
<thead>
<tr>
<th>Marker name</th>
<th>Subject 1</th>
<th>Subject 2</th>
<th>Subject 3</th>
<th>Subject 4</th>
</tr>
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<td>0.39</td>
<td>0.31</td>
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<td>0.35</td>
<td>0.28</td>
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<tr>
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<td>0.37</td>
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<tr>
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<tr>
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<td>0.54</td>
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Fig. 4. In vivo measurements (solid line) versus FFANN predictions (+ line) for medial thrust gait pattern. Subject specific FFANN was trained based on pre-rehabilitation gait patterns. The network was tested to predict the medial KCF of the same subject corresponding to medial thrust gait pattern (level 1; intra subject).
\[ p = 5.5527 \times 10^{-5} \] The comprehensive FDA values related to other walking patterns are presented in Appendix A (Table A1).

Additionally in order to prevent using redundant inputs, partial correlation-kernel MI was calculated between all possible pairs of the marker trajectories and the output (medial KCF). Seven markers including three markers of shank (superior, inferior, and lateral), three markers of thigh (superior, inferior, and lateral) and anterior superior iliac spine marker were chosen as the most independent and informative marker trajectories to predict medial KCF (Table 2). According to Table 2 markers related to heel, midfoot superior, midfoot lateral and toe were not as informative as other markers (lower kernel MI values). Although kernel MI values for patella, sacral and back marker trajectories were similar to the selected markers, but due to the partial correlation criteria, these marker trajectories were highly dependent on shank, anterior superior iliac spine and thigh marker trajectories respectively (\( \rho \geq 0.98 \)).

3.1. Intra subject

FFANN predictions are compared versus in vivo measurements for medial thrust (Fig. 4) and trunk sway (Fig. 5) patterns. Table 3 summarizes the structure of subject-specific networks and the accuracy of predictions. According to the results, FFANN could predict medial KCF to a high level of accuracy for medial thrust (NRMSE = 10.6\%, \( \rho = 0.96 \)) and trunk sway (NRMSE = 9.6\%, \( \rho = 0.96 \)) patterns. Cross correlation values ranged from \( \rho = 0.93 \) to \( \rho = 0.98 \) and all the errors (NRMSE) were less than 14\%. Important features of medial KCF, impulses and peak values related to midstance and terminal stance, were also predicted accurately for both gait modifications (Figs. 6 and 7). Regarding the knee loading features, the average errors between predicted features and those calculated from in vivo measurements were 6.5\% BWs and 3.9\% BWs for the midstance and terminal stance impulses, and 4.2\% BW and 3.3\% BW for the midstance and terminal stance peak values, respectively.

3.2. Inter condition

Predictions of the generic FFANN were compared versus in vivo measurements for medial thrust (Fig. 8) and trunk sway (Fig. 9). According to the results (Table 4) errors were slightly increased at

Table 3

<table>
<thead>
<tr>
<th>Subject</th>
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<th>Trunk sway</th>
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Fig. 5. In vivo measurements (solid line) versus FFANN predictions (+ line) for trunk sway gait patterns. Subject specific FFANN was trained based on pre-rehabilitation gait patterns. The network was tested to predict medial KCF of the same subject corresponding to trunk sway gait pattern (level 1; intra subject).
Fig. 6. Mean and standard deviation for the main features of the medial KCF corresponding to medial thrust pattern. Impulses and peak values were calculated from FFANN predictions and compared to those calculated from in vivo measurements for three generalization levels; level 1 (intra subject), level 2 (inter condition) and level 3 (inter subject).

Fig. 7. Mean and standard deviation for the main features of the medial KCF corresponding to trunk sway pattern. Impulses and peak values were calculated from FFANN predictions and compared to those calculated from in vivo measurements for three generalization levels; level 1 (intra subject), level 2 (inter condition) and level 3 (inter subject). Subject 4 did not have trunk sway trials.
this level, compared to the corresponding errors at level 1 (medial thrust: \( \text{NRMSE} = 11.2\% \), \( \rho = 0.96 \); trunk sway: \( \text{NRMSE} = 10.5\% \), \( \rho = 0.95 \)). Cross correlation values ranged from \( \rho = 0.94 \) to \( \rho = 0.98 \) and all the \( \text{NRMSE} \) values were equal or less than 20%. Although the prediction errors were increased slightly, predicted impulses and peak values were still consistent with in vivo measurements. Comparing the features of KCF calculated from FFANN predictions with those calculated from in vivo measurements, the average errors were 7.2%BWs and 8.2%BWs for midstance and terminal stance impulses, and 4.9%BW and 6.4%BW for the corresponding peak values (Figs. 6 and 7).

3.3. Inter subject

Figs. 10 and 11 compare FFANN predictions versus in vivo measurements for medial thrust and trunk sway patterns respectively. It should be noted that each time the FFANN was trained with a different training set consisting of medial thrust and trunk sway patterns of all subjects except one; consequently different FFANN structures were needed for prediction. As mentioned earlier, medial KCF was normalized to body weight at this level.

According to the results (Table 5), prediction errors were increased compared to the corresponding errors at levels 1 and 2 (medial thrust: \( \text{NRMSE} = 12.6\% \), \( \rho = 0.95 \); trunk sway: \( \text{NRMSE} = 13.3\% \), \( \rho = 0.94 \)). However FFANN could predict the overall pattern and features of the medial KCF (Figs. 6 and 7). The average errors between the features calculated from predictions and those obtained from in vivo measurements were 9.3% BWs and 10.6% BWs for midstance and terminal stance impulses, and 10.1% BW and 10.2% BW for mid stance and terminal stance peak values.

4. Discussion

Our study demonstrated that training FFANN based on pre-rehabilitation gait patterns can be employed to predict the medial KCF for different knee rehabilitations. Medial thrust and trunk sway gait modifications were selected as test data because these patterns are supposed as effective gait modifications that can reduce knee joint loading. It should be pointed out that medial KCF has two main peaks, located in midstance and terminal stance phases, which are highly correlated with knee diseases and pain level [36]. Moreover, the medial thrust pattern has been mainly designed to decrease the medial KCF at these two phases. Thus, mid stance and terminal stance phases have been of much more interest in the literature concerned with knee rehabilitation [1,24]. Peaks and impulses have also been widely investigated to describe knee loading patterns [24,37,38]. Accordingly these features of medial KCF in midstance and terminal stance phases were adopted to assess the FFANN predictions.

Previous studies have shown that Fisher discriminant analysis (FDA) can be used successfully to recognize the most relevant EMG signals that affect loading patterns [53,54]; however contribution of lower extremity EMG signals to the knee joint loading has not been investigated using this technique. According to the results, GRFs and informative EMG signals (semimembranosus, biceps femuris, vastus intermedius, vastus lateralis, rectus femoris, tensor
fasciae latae, peroneal, gluteus maximus, and gluteus medius) could be used to calculate medial KCF, which releases the necessity of motion capture (level 2, inter condition). To highlight the importance of selecting informative EMG channels as inputs, FFANN predictions were repeated with all of 14 EMG channels included as inputs for the proposed generic five-layer FFANN at level 2. Results showed that use of all 14 EMG signals which included less informative and irrelevant ones, resulted in a large increase in the prediction error (up to 38%) and reduced the FFANN generalization ability (Appendix A, Fig. A1).

Additionally, to select the most informative markers, kernel MI was used because of two main reasons. First, it is a nonlinear IVS technique that releases the disadvantages of histogram-based MI [55]. Second, it measures the relevancy between each input and output variable without any pre-assumption about the data structure. However this technique does not measure the independence between input variables which might yield to select informative but redundant inputs. Accordingly partial correlation was calculated to measure the amount of independency between inputs. Partial correlation–kernel MI revealed that only those markers related to shank, thigh and anterior superior iliac spine were independent and informative enough to use for KCF predictions. Decreasing the number of markers could also reduce the pre-processing time.

At level 1 anthropometric characteristics of each subject were indirectly imported to a four-layer FFANN via GRFs and marker trajectories as inputs and the network was trained subject-specifically. Increasing the difficulty of the prediction task, this input combination was not sufficient at level 2 and level 3. At level 2a five-layer FFANN was trained based on pre-rehabilitation walking patterns of four subjects, and GRFs and EMG signals were used as inputs for this generic network. Level 3 was the most complicated one in which a five-layer FFANN was tested to predict the medial KCF for a new different subject which was not seen by the network before. Therefore a complete input data space included vertical GRF, EMG signals and marker trajectories were used. In fact, at level 3, FFANN was challenged with inter-subject variety of loading patterns. Accordingly, vertical GRF and medial KCF were normalized by body weight to decrease the training data diversity and increase the network prediction ability. It should be noted that unlike levels 1 and 2, at level 3 only vertical GRF was included as FFANN input. Regarding that the vertical component of GRF ( > 110%BW) is generally higher than medial–lateral ( < 10% BW) and anterior–posterior ( < 20%BW) components, vertical GRF sufficed to represent the discrepancy of different subjects with different amounts of body weights.

<table>
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<tr>
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<th>Trunk sway</th>
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Fig. 9. In vivo measurements (solid line) versus FFANN predictions (+ line) for trunk sway gait pattern. Generic FFANN was trained based on pre-rehabilitation gait patterns of all subjects. The network was tested to predict medial KCF of each subject corresponding to trunk sway gait pattern (level 2: inter condition).
According to the in vivo measurements (Tables 3–5), accuracy decreased slightly at the third level (medial thrust: $NRMSE = 12.6\%$, $p=0.95$; trunk sway: $NRMSE = 13.3\%$, $p=0.94$). However according to Figs. 6 and 7, the descriptive features of medial KCF (peak values and impulses) calculated from in vivo measurements were still highly correlated to those obtained from the predictions, and the average errors were less than 11%. Moreover the network could still predict the general pattern of the medial KCF (Figs. 10 and the average errors were less than 11%. Moreover the network were still highly correlated to those obtained from the predictions, according to Figs. 6 and 7, the descriptive features of medial KCF (Fig. 10 and 11). Consequently, results showed that increasing non-specific training sets slightly reduced the accuracy of FFANN predictions.

It should be pointed out that subject 4 did not complete trunk sway trials, which resulted in the lack of training data sets for trunk sway especially at level 3 in which the trunk sway patterns of only two subjects were included in the training data space and the network was tested to predict the knee loading pattern of a different subject which was not included in the training set. Lack of the training data for trunk sway yielded to a greater error in medial KCF prediction corresponding to trunk sway (NRMSE = 13.3\%, $p=0.94$) compared to medial thrust prediction (NRMSE = 12.6\%, $p=0.95$) at level 3.

It should be pointed out here that FFANN predictions were validated and compared against in vivo measurements since conventional inverse dynamics models can only calculate three dimensional KCF but not medial and lateral distribution of knee joint loading. Although a few recent studies have improved the inverse dynamics approach to calculate medial KCF [25,26], this approach is time demanding and computationally expensive. For example using Opensim software [56], anthropometric measurements of the subject are required to scale the musculoskeletal model. Scaled model is then used in the inverse kinematics (IK) analysis to calculate joint angles from a comprehensive collection of marker trajectories. In order to calculate joint loading, the scaled model should be first imported to reduced residual analysis (RRA) in which musculoskeletal center of mass is modified so as the calculated joint angles would be in consistence with experimental GRFs. The modified scaled model, calculated joint angles and experimental GRFs are then imported to compute muscle control (CMC) module in which muscle activities are calculated. Finally lower extremity joint moments are calculated using inverse dynamics analysis (ID) based on the CMC module calculations. This computational procedure might take more than 1 h to be completed. On the other hand, unlike inverse dynamics analysis, artificial intelligence approach does not need musculoskeletal model or subject-specific scaling of the model. Moreover the proposed FFANN used only a few markers for a direct calculation of knee joint loading whilst in inverse dynamics analysis all markers are needed to firstly calculate joint angles and muscle activities. Matching the experimental markers with those pre-defined markers included in the musculoskeletal model can increase the pre-processing time and computational errors.

Although inverse dynamics method can be quite time consuming, it is one of the most accepted computational approaches in biomechanics due to its ability for physical modeling. Artificial intelligence can be used in conjunction with inverse dynamics analysis to decrease the calculation time. A recent study used artificial neural network to solve the static optimization equations as part of inverse dynamics calculation procedure and speed up
the calculation process, potentially used as a real time biomechanical analysis technique [57]. Moreover redundant markers can be discarded to decrease the calculation time in inverse dynamics technique.

Based on the similar data base used in this study, an EMG-driven musculoskeletal model was developed in an inverse dynamics approach to predict KCF for the third subject of the current data base [58]. Compared to the present study, the blind original model which was developed and calibrated using an inverse dynamics model, could predict the medial KCF for medial thrust gait pattern with $RMSE=315.0 \ (N)$ equal to 41\%BW. This model was then modified based on in vivo KCF measurements to achieve $RMSE=261.2 \ (N)$ equal to 34\%BW. Although the prediction accuracy does not differ highly from the present study ($RMSE=222.0 \ (N)$, for subject 3 at level 1); FFANN was much easier and faster with high generalization ability to predict medial KCF even without adjusting to the anthropometric characteristics (level 3). It is also noteworthy that once the blind EMG-driven musculoskeletal model was developed, the model needed to be modified based on in vivo medial KCF in order to decrease the calculation error from $RMSE=315.0 \ (N)$ to $RMSE=261.2 \ (N)$. Considering the required modification of the blind model, it is no more a disadvantage of FFANN to use measurements for training.

Finally it should be noted that there were also some limitations with this study. One limitation was that the relatively small data pool of four subjects was used. It would be valuable to test the prediction capacity of FFANN for a larger subject pool. In addition subjects used different types of shoes which may lead to a large pattern variation for a limited subject pool. Future well controlled and designed studies should be performed to address these limitations.

5. Conclusion

This study demonstrates the feasibility of feed forward artificial neural network to predict medial knee contact force based on ground reaction forces, informative electromyograms and a few
independent marker trajectories, through different generalization levels. For intra subject variations with different gait patterns (level 1), ground reaction forces and seven marker trajectories were required as inputs and all the prediction errors were less than 14%. Prediction based on a few independent markers also reduced the required computational time. Ground reaction forces and electromyography signals were required for inter condition variations within different subjects (level 2) which released the necessity of using motion capture in medial knee contact force prediction. All of the prediction errors were below 20% at this level. For a new subject that was not seen by the network before (level 3), the prediction accuracy was decreased slightly however the proposed intelligent approach was still able to predict the features of medial knee joint loading (peaks and impulses) to a certain high level of accuracy. Future research efforts are required to integrate physics-based analyses with intelligent algorithms to serve as real-time techniques for evaluating joint loadings due to gait modifications and rehabilitation strategies.

Acknowledgments

This work was supported by “the Fundamental Research Funds for the Central Universities and National Natural Science Foundation of China [E050702].”

Appendix A

See Fig. A1 and Table A1.

Fig. A1. Prediction of medial KCF pattern corresponding to “medial thrust” rehabilitation at level 2 (inter condition): in vivo measurements (solid line) versus FFANN predictions using selective EMG signals as inputs (* line) and FFANN predictions with all of EMG signals included as inputs (dashed line).
Table A1
Fisher discriminant values for different subjects walked with different gait patterns. The highlighted muscles had higher values of Fisher discriminant compared to other muscles.

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<th>Subject 4</th>
<th>Semimembranosus</th>
<th>Biceps femoris</th>
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<th>Rectus femoris</th>
<th>Medial gastrocnemius</th>
<th>Lateral gastrocnemius</th>
<th>Tensor fasciae latae</th>
<th>Tibia anterior</th>
<th>Peroneal</th>
<th>Soleus</th>
<th>Adductor magnus</th>
<th>Gluteus maximus</th>
<th>Gluteus medius</th>
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References


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