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A Neural Network Approach for Determining Gait Modifications to Reduce the Contact Force in Knee Joint Implant

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Abstract

There is a growing interest in non-surgical gait rehabilitation treatments to reduce the loading in the knee joint. In particular, synergetic kinematic changes required for joint offloading should be determined individually for each subject. Previous studies for gait rehabilitation designs are typically relied on a "trial-and-error" approach, using multi-body dynamic (MBD) analysis. However MBD is fairly time demanding which prevents it to be used iteratively for each subject.

This study employed an artificial neural network to develop a cost-effective computational framework for designing gait rehabilitation patterns. A feed forward artificial neural network (FFANN) was trained based on a number of experimental gait trials obtained from literature. The trained network was then hired to calculate the appropriate kinematic waveforms (output) needed to achieve desired knee joint loading patterns (input). An auxiliary neural network was also developed to update the ground reaction force and moment profiles with respect to the predicted kinematic waveforms. The feasibility and efficiency of the predicted kinematic patterns were then evaluated through MBD analysis.

Results showed that FFANN-based predicted kinematics could effectively decrease the total knee joint reaction forces. Peak values of the resultant knee joint forces, with respect to the bodyweight (BW), were reduced by 20%BW and 25%BW in the midstance and the terminal stance phases. Impulse values of the knee joint loading patterns were also decreased by 17%BW*s and 24%BW*s in the corresponding phases. The FFANN-based framework suggested a cost-effective forward solution which directly calculated the kinematic variations needed to implement a given desired knee joint loading pattern. It is therefore expected that this approach provides potential advantages and further insights into knee rehabilitation designs.

Keywords: Gait modification, kinematics, knee joint loading, neural network, multi-body dynamics

Introduction

Non-invasive gait rehabilitation strategies are of significant advantages for patients with knee osteoarthritis (OA). Pre-surgical gait rehabilitation can decrease pain, decelerate joint disease progression and post-pone surgery[1, 2]. Post-surgical gait rehabilitation can also accelerate patient recovery[3, 4], reinforce joint functionality[5, 6], decrease gait asymmetry[7] and augment the durability and longevity of the implanted prostheses[8, 9]. Gait rehabilitation mainly aims to decrease knee joint loading through minor changes in human gait patterns. Recognizing the synergistic kinematic changes, required for joint offloading, however has been a very challenging task. Although various gait modifications have been developed in association with knee joint offloading [10-22], none of them have yet been accepted as a general modification strategy. In fact, large inter-patient variability has been reported in gait kinematics and joint loading patterns[23, 24] which may directly affect the results and the efficiency of gait rehabilitation from one group of patients to another group. In other words, a gait rehabilitation might be effective for joint offloading in a group of participants [13, 16, 25] while it might be ineffective[26] or even detrimental [27] for other groups of patients. Thus, gait rehabilitation strategies should be determined individually for each subject.

Current studies for gait rehabilitation design have been typically carried out based on multi-body dynamics (MBD) analysis[13, 14]. Although MBD can determine the knee joint loadings from known gait kinematics, the nonlinear relationship between kinematic variations and knee joint offloading is still unknown. Available techniques therefore, require iterative “trial-and-error” attempts of MBD analysis to recognize the most influential kinematic variations needed for joint offloading. In each attempt, kinematic waveforms and ground reaction forces (GRFs) should be collected experimentally or produced computationally and then imported into an inverse dynamic analysis to calculate the resultant joint moments. MBD computations should be repeated until a reasonable reduction in knee joint loading is achieved. This “trial-and-error” approach of MBD would be fairly time demanding and prevent this method to be used iteratively for each subject. Thus, a cost-effective surrogate model which replicates the original MBD would be of much advantage.

Furthermore, previous studies have been mainly performed to reduce knee adduction moment (KAM) as a surrogate of medial knee contact force (KCF) [28] but KAM is not always a reliable measure for knee joint offloading: (1) gait modifications that reduce KAM are not guaranteed to reduce KCF[29]; (2) interpreting the KAM is highly dependent on the chosen reference frame (e.g., laboratory, tibia, femur and floating reference frames). This reference dependency can potentially yield to inconsistent results from one laboratory to another [16, 26]. Accordingly, gait modification strategies should directly aim to decrease KCF.

Artificial neural network (ANN) has been commonly used in various fields of biomechanics as a cost-effective surrogate model [30-33]. Once a set of inputs and resultant outputs are presented to the network, ANN *learns* the causal interactions between input and output variables. Given a new set of inputs, the trained neural network (surrogate model) can generalize the relationship to produce the associated outputs. Therefore it releases the necessity of running the original physics-based model or repeating the time-consuming iterations [34]. In human gait studies, ANN has been particularly used as an alternative to MBD analysis to investigate joint moments [35-38], gait kinematics [39] and ground reaction forces [40-42]. It is therefore expected that ANN can also provide further insight into the interactions between gait kinematics and resultant knee joint loads.

Although ANN has been used to calculate knee joint loadings from gait kinematics [43], it has not been used to solve the inverse problem. The underlying hypothesis of this study was that ANN can be used to calculate gait kinematics for a given joint loading pattern. In particular, the main aim of this study was to develop a cost-effective computational framework for designing gait rehabilitation patterns which (1) released the necessity of iterative MBD analysis and (2) directly calculated the specific kinematics needed to achieve a desired reduction in KCF.

2. Materials and methods

A published repository of the experimental gait cycles was obtained from the literature (section 2.1). The most influential gait kinematics for knee joint offloading and those body segment trajectories which control the overall lower limb alignments (constraints) were determined (section 2.2). Using the experimental repository, an artificial neural network was trained to predict the most influential gait kinematics (outputs) based on knee joint loading and constraint limb alignments (inputs) (section 2.3). The trained network was then employed to predict the appropriate waveforms of influential kinematics based on given patterns of knee joint loadings. Ground reaction forces and moments (GRF&M) were updated with respect to the proposed kinematic variations (section 2.4). In order to evaluate the efficiency and feasibility of the proposed kinematics, predicted kinematics and updated GRF&M were then imported into a MBD analysis to investigate whether the knee joint loading was decreased effectively (section 2.5). It should be noted that artificial neural network was used for a twofold purpose: (1) to predict the synergetic kinematic variations needed to achieve a desired knee joint loading pattern (section 2.3) and (2) to update the GRF&M profile according to the kinematic variations (section 2.4). Figure 1 shows the schematic diagram of the proposed methodology.

2.1. Subject

A subject pool consisted of four different participants, implanted with unilateral sensor-based knee prostheses (three males, one female; height: 168.3±2.6 cm; mass: 69.2±6.2kg), was adopted from a published repository (https://simtk.org/home/kneeloads ; accessed on 20 December 2013). This repository contained the experimental gait trials of seven different walking patterns: *normal*, *bouncy*, *crouch*, *trunk sway* and *forefoot strike* gait plus two knee rehabilitation strategies: *medial thrust* and *walking pole* patterns. Medial thrust pattern includes a slight decrease in pelvis obliquity and a slight increase in pelvis axial rotation and leg flexion compared to normal gait [13]. In walking pole gait, patient uses two lateral poles as supportive walking aids [17]. For each specific walking pattern, subjects repeated five gait trials under the same walking condition. One complete gait cycle was picked up for each gait trial. A gait cycle was defined as the time interval between foot strike of one leg to the following foot strike of the same leg [44]. Gait cycles were normalized to 100 samples and then averaged over each walking pattern, leading to a total number of 28 gait cycles for four participants. For a complete description of this repository one can refer to [45].

2.2 Input/output selection

2.2.1. Input selection

Presented in this study is a forward approach that is expected to *directly* predict the kinematic waveforms needed to implement a desired knee joint loading pattern. Medial and lateral components of desired KCF were considered as *inputs*. On the other hand, predicted kinematics should preserve the normal patterns of natural walking without any exaggerated limb orientation. Due to this constraint, those body segment trajectories which have been highly similar ($\rho > 0.85$) across normal and natural-looking rehabilitation patterns (e.g., medial thrust and walking pole) were determined through Pearson correlation coefficients. These body segment trajectories were then considered as *constraint inputs*.

2.2.2. Output selection

In order to determine a specific gait modification, the most influential kinematics with significant contributions to the knee joint loading were chosen as *outputs* to be calculated. Reviewing previous studies, kernel mutual information (MI) has been used successfully as a nonlinear variable selection technique which releases the disadvantages of histogram-based MI [46]. This criterion was therefore recruited to measure the amount of information that each individual kinematic provided about knee joint loading [47]:

$$I(X;Y) = \sum_{x_i \in X} \sum_{y_j \in Y} P(x_i, y_j) \log \frac{P(x_i, y_j)}{P(x_i)P(y_j)} \tag{1}$$

In the above equation, X refers to the input variable (medial KCF) whilst Y demonstrates the output variables (gait kinematics). Marginal probability of each variable (*P(x)*, *P(y)*) and joint probability of input and output variables (*P(x,y)*) were calculated based on kernel density estimation as below [47]:

$$P(y) = \frac{1}{n} \sum_{j=1}^{N} K(u) \tag{2}$$

Where

$$u = \frac{(y - y_j)^T S^{-1} (y - y_j)}{h^2} \tag{3}$$

$$K(u) = \frac{1}{2\pi^{\frac{d}{2}} h^2 \det(S)^{\frac{1}{2}}} \exp^{\frac{-u}{2}} \tag{4}$$

$$h = \left\{\frac{4}{d+2}\right\}^{\frac{1}{d+4}} \times n^{\left\{\frac{-1}{d+4}\right\}} \tag{5}$$

in which d is the vector dimension and S is the covariance matrix on y_j . It should be noted that unlike the previous applications of mutual information technique to select the inputs of a neural network[48], this technique was employed to determine the outputs of interest for the proposed neural network.

2.3. Artificial neural network

Feed forward artificial neural network (FFANN) has been widely accepted as a universal approximator [49]. This structure can learn any nonlinear relationship between inputs and outputs regardless of its complexity and dimension. In particular, FFANN was successfully used to predict knee joint loading patterns from gait kinematics in our previous study [43]. In the present study however, FFANN was used to solve the inverse of the former problem and predict the gait kinematics from knee joint loading patterns. The proposed FFANN consisted of a number of processor units (neurons) organized in certain arrangements (layers). Layers were densely connected to each other via numeric weights [34]. Once the neural network was trained for a specific nonlinear relationship, these numeric weights were adjusted to keep the "cause-and-effect" features of the input-output interaction [43]. All of the hidden neurons were activated by "hyperbolic tangent sigmoid" function whilst output nodes were activated with a "pure line" function which simply produced a weighted sum of hidden neurons in the output. Gradient descent back propagation algorithm with an adaptive learning rate (*traingdx)* and an error goal of 10^{-5} were used to train the FFANN.

Experimental gait cycles of *normal*, *bouncy*, *crouch*, *trunk sway* and *fore-foot strike* patterns of all subjects were considered as the training data space (20 inter-patient data sets). This data space was randomly divided into three distinguished subsets: train (70%), validation (15%) and test (15%). Train and validation subsets were used to train the network and adjust the connection weights whilst the test subset was not included in the training procedure. The network prediction errors on the test and validation subsets were then 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 an increase in prediction errors on the test subset [50]. This technique has been widely used in the literature to construct the optimal structure of a neural network [32, 33]. Training procedure continued until the maximum numbers of training epochs were reached or until the error goal was implemented. Once the trained network was validated and tested, it was then employed to calculate the appropriate kinematic waveforms (outputs) for a desired knee joint loading pattern (input). In this study, desired knee joint loading patterns were adopted from the *medial thrust* and *walking pole* trials. Subsequently, a five-layer FFANN with one input layer, three hidden layers (20, 25, 25 hidden neurons) and one output layer was constructed. This structure had 10 inputs (medial and lateral KCF plus eight constraint inputs) and four outputs (influential kinematics). Previous studies revealed the superiority of the FFANN compared to the regression surrogates for modeling complex nonlinear interactions [32, 37, 51]. In the present study, linear regression was also established for comparison purposes. All regression analyses were performed using MATLAB (v.2009, The MathWorks Inc.). A one-way analysis of variance (ANOVA) test with the significance level of $p < 0.05$ was conducted (Matlab v.2009, Statistics toolbox) to compare the normalized root mean square errors between experimental kinematics (targets) and those predictions obtained from FFANN and regression surrogates for the test subset .

2.4. Ground reaction force computations

In general, three dimensional ground reaction forces and moments (GRF&M) are measured using force plates. However, GRF&M can also be calculated through a number of computational techniques [41, 52, 53]. Here, an auxiliary four-layer FFANN with one input layer, two hidden layers (20 and 25 hidden neurons) and one output layer was constructed. This network had 15 inputs including 11 key values of predicted kinematic waveforms plus two peak and two impulse values of medial KCF in the midstance and terminal stance phases. These inputs are described in Table 1 and are shown in Figure 2. Midstance (17-50% of stance) and terminal stance (51-83% of stance) phases were defined based on the gait phase definitions by Perry and Burnfield [44] This FFANN had six output neurons to predict the peak values of ground reaction forces (F_x, F_y, and F_z) and ground reaction moments (M_x, M_y, and M_z). Hidden neurons' activation functions (hyperbolic tangent sigmoid), output neurons' activation functions (pure line) and training algorithm (gradient descent back propagation) were similar to the first FFANN in the previous section. The network was trained and validated based on the experimental gait cycles of *normal* , *bouncy*, *crouch* , *trunk sway* and *fore foot strike* gait trials (obtained from the published repository ; section 2.1).The trained structure was then employed to predict peak values of the GRF&M with respect to the proposed kinematic variations. Using linear interpolation technique (MATLAB software), the predicted peak values of GRF&M were used to re-scale and update an averaged ground reaction force profile of a normal gait cycle for each subject. This updated GRF&M profile accompanied the kinematic waveforms for further evaluation in MBD (section 2.5). Figure 3 outlines the sample input and output waveforms of the two neural networks used in this study.

2.5 Multi-body dynamics evaluation

For each subject, predicted gait kinematic waveforms (obtained from FFANN) were substituted in an averaged normal gait cycle of that subject (Appendix, Figure A.1) to generate a complete motion profile. This modified motion profile and updated GRF&M profile were then imported into the three-dimensional multi-body simulation software AnyBody Modeling System (version 5.2, AnyBody Technology, Aalborg, Denmark) to calculate the knee joint loading. The resultant knee joint loadings were expected to be lower than the resultant forces which were achieved from the original averaged normal gait cycle.

A lower extremity musculoskeletal model was used in AnyBody software based on the University of Twente Lower Extremity Model (TLEM) [54]. The TLEM model is available in the published repository of AnyBody software. This model includes approximately 160 muscle units as well as thorax, trunk, pelvis, thigh, patella, shank and foot segments. Hip joint was modeled as a spherical joint with three degrees of freedom (DOF): flexion-extension, abduction-adduction and internal-external rotation. Knee joint was modeled as a hinge joint with only one DOF for flexion-extension and universal joint was considered for ankle-subtalar complex.

3. Results

In the present study, feed forward artificial neural network was employed to predict gait kinematics as outputs based on given knee joint loading patterns as inputs. Left heel, right lateral thigh, left inferior thigh , left lateral thigh, left patella, and left superior/inferior/lateral shank trajectories were highly correlated (p>0.85) between different natural-looking walking patterns (normal, medial thrust and walking pole patterns)(Figure 4). These body segment trajectories were therefore considered as *constraint inputs* to control the natural appearance and orientations of the predicted kinematics. Kernel mutual information also highlighted the significant contributions of four influential kinematics (*kernel MI* > 0.55) to the knee joint loading including hip flexion, knee flexion, anterior-posterior and vertical components of pelvis position. These kinematic waveforms therefore were considered as *outputs* needed to be predicted by FFANN (Figure 5).

The predicted kinematics obtained from the regression surrogate model and FFANN were benchmarked versus experimental kinematic waveforms for the test subset (Appendix, Figure A.2). A significant difference of p=3.8727e-005 was found between the prediction accuracy of FFANN and regression surrogate in terms of the normalized root mean square errors. Accordingly, for the rest of this study, FFANN was considered. In addition, for comparison purposes and in order to show the importance of relevant constraint inputs to be chosen, FFANN predictions were repeated with *all* body segment trajectories as constraint inputs. This in turn resulted in a large increase in the prediction error on the test subset (up to 34%) (Appendix, Figure A.3).

Consequently, the trained FFANN with relevant constraint inputs (chosen through kernel MI) was employed to calculate the kinematic waveforms needed to achieve “desired knee joint loading” patterns. For each subject, kinematic waveforms were predicted corresponding to the knee joint loading patterns adopted from medial thrust (Figure 6) and walking pole (Figure 7) patterns as desired loading patterns. The auxiliary FFANN also predicted the peak values of GRF&M which were used to update the ground reaction force profiles for the medial thrust-based predicted kinematics (Figure 8) and walking pole-based predicted kinematics (Figure 9). For brevity, adjusted GRF&M profiles are presented versus one representative normal gait cycle. For comparison purposes, FFANN-based updated GRF&M profile was compared versus the experimental GRF&M measurements of medial thrust pattern for subject 3 (Figure 8-b).

Feasibility and efficiency of the predicted gait kinematics were evaluated through MBD analysis (AnyBody software, section 2.5). For each subject, total knee joint loading was calculated based on the adjusted motion profiles (normal gait cycles in which predicted kinematic waveforms were substituted) and updated GRF&M profiles. Both medial thrust-based predicted kinematics and walking pole-based predicted kinematics could decrease the knee joint loading compared to the normal gait pattern (Figure 10). For comparison purposes, experimental kinematics of medial thrust and walking pole rehabilitation patterns, available in the published repository, were also imported into the MBD analysis. Computed total knee joint loadings are presented in Figure 10. Compared to normal walking pattern, medial thrust-based kinematics (predicted by FFANN) could decrease knee joint loading by 15%BW*s and 23%BW*s in the impulse values and by 19%BW and 22%BW in the peak values in the midstance and terminal stance phases. Walking pole-based kinematics (predicted by FFANN) also reduced knee joint loading by 19%BW*s and 25%BW*s in the impulse values and by 21%BW and 28%BW in the peak values at the corresponding phases (averaged over four subjects) (Figure 11).

4. Discussion

A feed forward artificial neural network was trained over a number of different gait trials and then was recruited to calculate the appropriate kinematics (outputs) for a given knee joint loading pattern (inputs). The FFANN structure was trained based on *in vivo* knee joint loadings obtained from instrumented knee prostheses. The proposed framework however, can also be trained using knee joint reaction forces computed through MBD analysis. Indeed all types of artificial neural networks require an initial computational expense to be trained over a primary training data space. The network learns the causal input-output interactions through this primary training data space. It should be pointed out that this initial cost would be much lower than the iterative “trial-and-error” analyses required in conventional rehabilitation designs using MBD analysis.

First, in each attempt of MBD analysis, the subject is hired to implement a gait pattern. The kinematic waveforms and GRF&M data are collected experimentally or calculated computationally to compute the resultant knee joint loading patterns. The design procedure is therefore established using an *inverse* solution to obtain “*force*” from “*kinematics*”. Due to the unknown nonlinear interaction between gait kinematic variations and knee joint loading reduction, convergence of the solution may need numbers of attempts to achieve a reasonable reduction in the knee joint loading. Moreover, the solution and convergence probably differ from one subject to another. On the other hand, once a FFANN was trained based on a few numbers of gait trials (20 gait cycles for four subjects), it had the ability to *directly* calculate the appropriate kinematic waveforms from desired knee joint loading patterns (*forward* solution). Moreover, the trained FFANN could predict the corresponding kinematic variations for each of four different participants. Second, in order to produce a primary training data space for FFANN, several MBD analyses can be employed in parallel which may significantly reduce the required time of computations. In a conventional MBD-based rehabilitation design however, MBD analysis cannot be recruited in a parallel framework since the MBD computation results in each attempt specify how the kinematic waveforms and GRF&M profiles should be modified for the next attempt.

It should be pointed out that although a trained FFANN can lean and generalize a causal relationship to new situations, FFANN can only interpolate the training examples. In other words, predictions of FFANN are accurate and valid for those inputs which lay within the training data space. In the present study, the proposed FFANN was trained based on normal gait pattern as well as several exaggerated gait patterns (e.g., bouncy, crouch, fore foot strike and trunk sway). These gait patterns covered the span of executable gait patterns for each subject. Medial thrust and walking pole patterns (test data space) were natural-looking rehabilitation patterns with non-significant kinematic variations compared to normal gait. Thus, the kinematic waveforms of both patterns lay within the initial training data space.

The current approach is consistent with the previous studies for rehabilitation design in which a few influential gait kinematics are of particular interest to be varied while others are assumed to be normal [10, 13, 14, 55, 56]. The rationale behind this technique can be justified according to two main reasons: (1) gait kinematics with low contributions to the knee joint loading, may have significant contributions to the adjacent joints (e.g. hip joint). Varying such kinematics may cause unwanted adverse changes in other joints loading patterns. As a conservative consideration therefore, targeted gait rehabilitations are mostly defined based on the minimum numbers of the kinematic variations. In other words, only those kinematics with significant influence on the knee joint loading should be altered; (2) after a rehabilitation strategy is designed theoretically, a patient should be trained clinically over the defined pattern. Fewer numbers of kinematic variations, required to be executed, will ease the training procedure. Extra facilities and attempts will be required for patient training if the rehabilitation strategy involves more numbers of kinematic variations. In the present study, rehabilitation strategies were therefore suggested based upon four influential kinematic waveforms recognized through the kernel mutual information analysis.

Ground reaction forces mainly depend on the gravity, body mass and acceleration. Accordingly, variations in gait kinematics lead to unavoidable changes in GRF&M acting on the human body. Both kinematic variations and GRF&M changes in turn contribute to changes in the knee joint loading. In order to evaluate the predicted kinematic waveforms in a MBD analysis, GRF&M profiles should be updated. An auxiliary neural network was therefore constructed to update the peak values of GRF&M based on descriptive key values of the kinematic waveforms and desired knee joint loading patterns. These key values have been suggested in literature for a number of studies such as gait analysis [57-59], gait classification [60] and evaluation of joint loading [61], and joint inter-coordination [62]. Peak and impulse values of the knee joint loading in the midstance and terminal stance phases have also been used as important descriptive features of the knee joint loading in literature [13, 29, 36]. Predicted GRF&M profiles were in a good agreement with clinical reports [13]. For example, whilst statistical differences were reported to be noticeable between GRF&M profiles of walking pole and normal gait patterns (see Figure 9), GRF&M profiles of medial thrust were expected not to differ significantly from normal gait pattern (see Figure 8) .

The FFANN-based framework suggested a *forward* solution for designing knee joint rehabilitation. Therefore, it can provide potential advantages and further insights into knee rehabilitation design. For example, kinematic waveforms predicted by FFANN, can serve as a starting point (initial guess) for conventional MBD-based designing approaches. Moreover, the FFANN framework can be fed with desired knee joint loading patterns which have not been achieved so far. For example, it is still not exactly clear whether any rehabilitation strategies can be designed to reduce knee joint loading at 25% of the stance phase. FFANN may be fed with a desired reduction at specific stages of a gait cycle. Estimated kinematics can then be evaluated clinically to investigate the possibility of a rehabilitation strategy capable of achieving this goal. As another example, knee joint loading patterns obtained from medial thrust and walking pole gaits can be combined and considered as the desired loading pattern (e.g., medial knee joint loading of medial thrust pattern plus lateral knee joint loading of walking pole rehabilitation) to investigate the feasibility of a compromised set of kinematics which inherits the potential advantages of both rehabilitation strategies.

One of the most important limitations of this study was lack of clinical investigation on estimated kinematics. However from a technical point of view, the predicted kinematic waveforms are expected to be feasible: (1) a total of eight body segment trajectories (constraint inputs) were considered to keep the natural orientation of the estimated kinematics; (2) the FFANN was trained based on executable walking patterns. Once the network learns this dynamics, it uses this dynamics as the acting function to respond to new sets of inputs. Due to the above reasons, it is unlikely that our model would generate highly aberrant kinematics. It should be noted that even if the predicted kinematics will be feasible to implement, further investigation is still necessary for compensatory or unexpected effects on the other joints or on the contra-lateral limb. The second limitation was that knee joint was modeled as a hinge joint with only one DOF (flexion-extension). Although six DOFs are possible for the knee joint , the dominant movement of the knee joint takes place in the sagittal plane, so a number of previous studies have modeled the knee as a hinge joint , especially for knee rehabilitation design purposes [13, 63, 64]. Nevertheless, the computational approach that was developed in the present study can be equally used with more complex musculoskeletal models. It should be noted that predicted kinematic waveforms were computationally replaced in an averaged normal gait cycle to generate a complete motion profile for MBD evaluation. Generally, after designing a gait rehabilitation strategy, based on a few kinematic variations, patients will be asked to execute the prescribed kinematics in their gait patterns. Other gait kinematics, which are not prescribed in the rehabilitation strategy, will be therefore synchronized while patient is walking. In the present study however we mainly aimed to introduce the computational approach (FFANN) for gait modification designs. Due to lack of experimental set-up and clinical validation, predicted kinematic waveforms were only computationally replaced in a normal gait cycle to be evaluated in a MBD approach. Nevertheless, the results are not expected to vary noticeably since the predicted kinematics does not differ significantly from normal gait patterns (see Figures 5 and 6). Finally it should be pointed out that no special assumption was made to include or exclude a participant. In other words, the proposed computational framework was constructed based on a few numbers of ordinary subjects with unilateral knee implants. The proposed methodology is therefore expected to be equally applicable for any given subject. However, for patients with abnormal varus or valgus knee joint alignment , pathologic gait patterns or those subjects with other joint diseases , other gait trials may be needed to train the neural network. Caution is required to train subjects on the predicted kinematics and further clinical validation should be carried out to investigate other effects of the proposed kinematics on the other joints.

5. Conclusions

A FFANN-based computational framework was developed to calculate the appropriate kinematic waveforms needed to achieve desired knee joint loadings corresponding to medial thrust and walking pole patterns. Evaluating the predicted kinematic waveforms in a multi-body dynamics analysis, impulse values of the knee joint loadings, with respect to bodyweight (BW), were decreased by 17%BW*s and 24%BW*s in the midstance and the terminal stance phases. Peak values of the knee joint loadings were also reduced by 20%BW and 25%BW at the corresponding phases. This computational framework provided a cost-effective approach capable of designing gait rehabilitation strategies for individual subjects which released the necessity of iterative multi-body dynamic analysis.

Conflict of interest statement

The authors have no conflict of interests to be declared.

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Figure 1

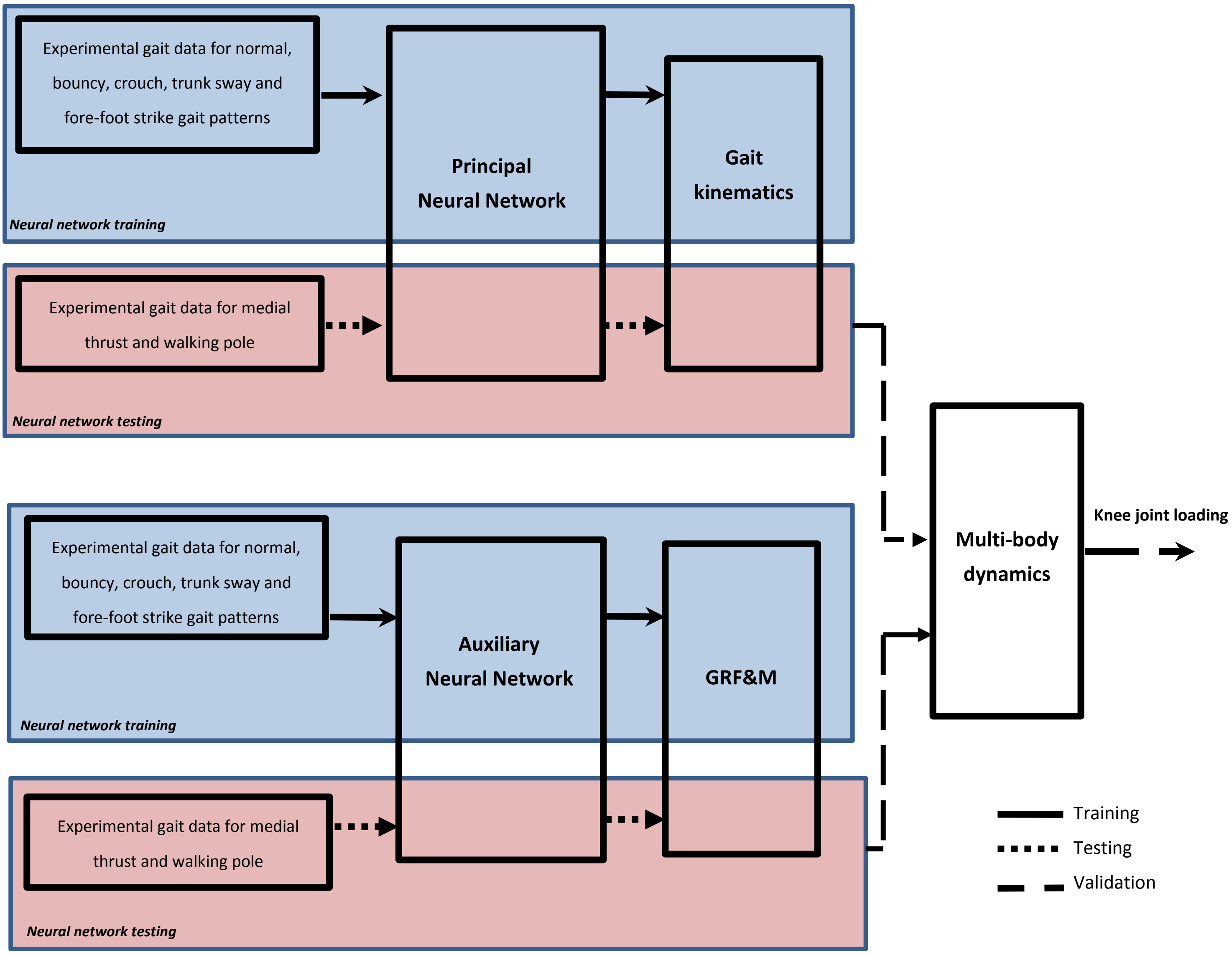

Figure 1 A schematic block diagram of the proposed framework

Figure 2

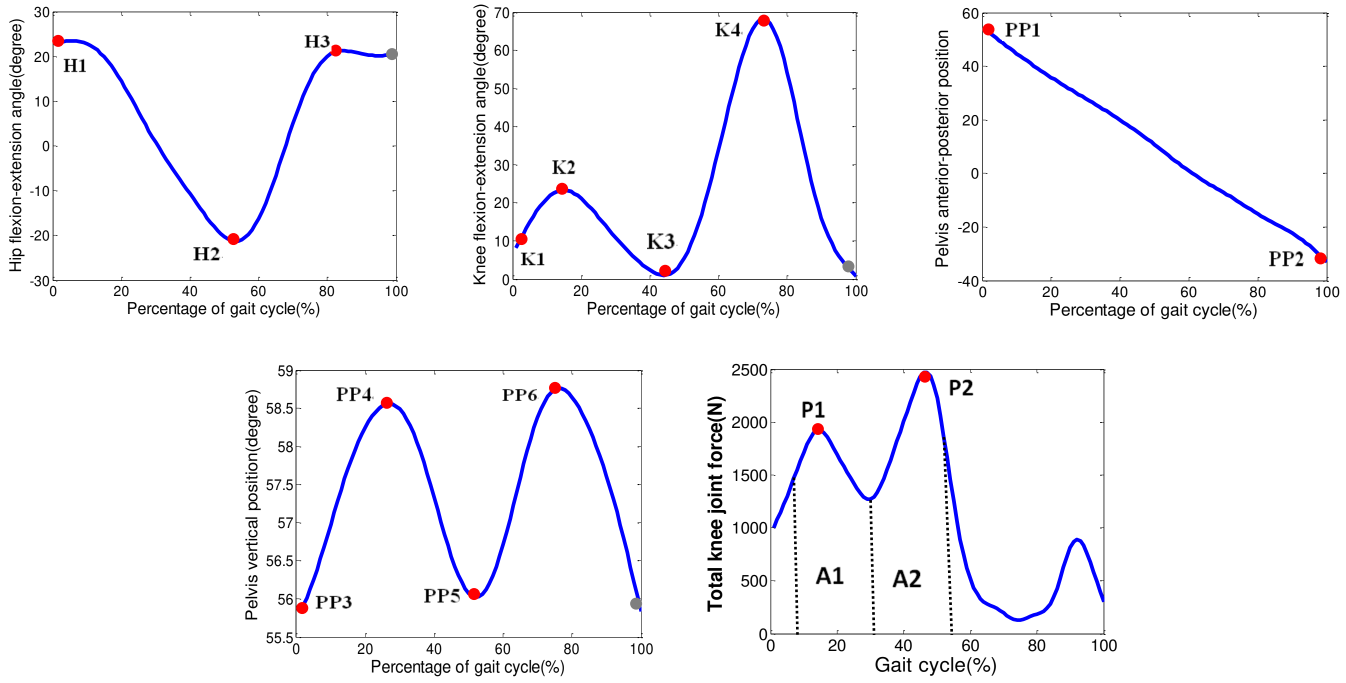

Figure 2 Input variables of the auxiliary FFANN (red circles) including key values of the predicted gait kinematics plus peak & impulse values of the desired medial KCF. Due to the periodicity of the gait, kinematic values at the end of the gait cycle (gray points) were equal to the initial values at 0% of the gait cycle; except for pelvis anterior-posterior translation.

Figure 3

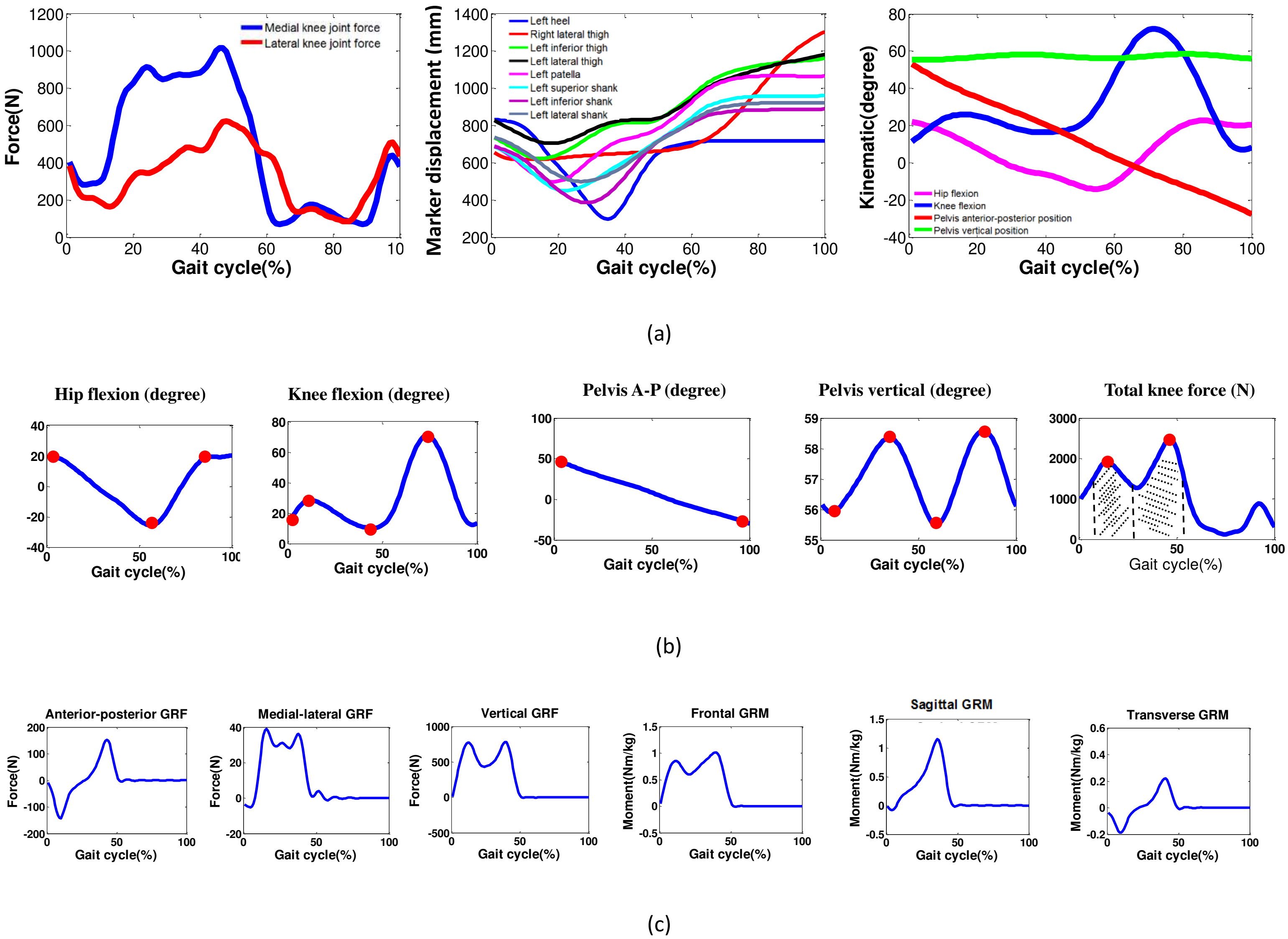

Figure 3 (a) Sample input and output waveforms for the principal FFANN. Medial and lateral knee joint forces plus marker displacement trajectories served as inputs to predict kinematics as outputs, (b) descriptive features of kinematics and kinetics which served as input variables for the auxiliary FFANN , (c) GRF&M profile as outputs of the auxiliary FFANN.

Figure 4

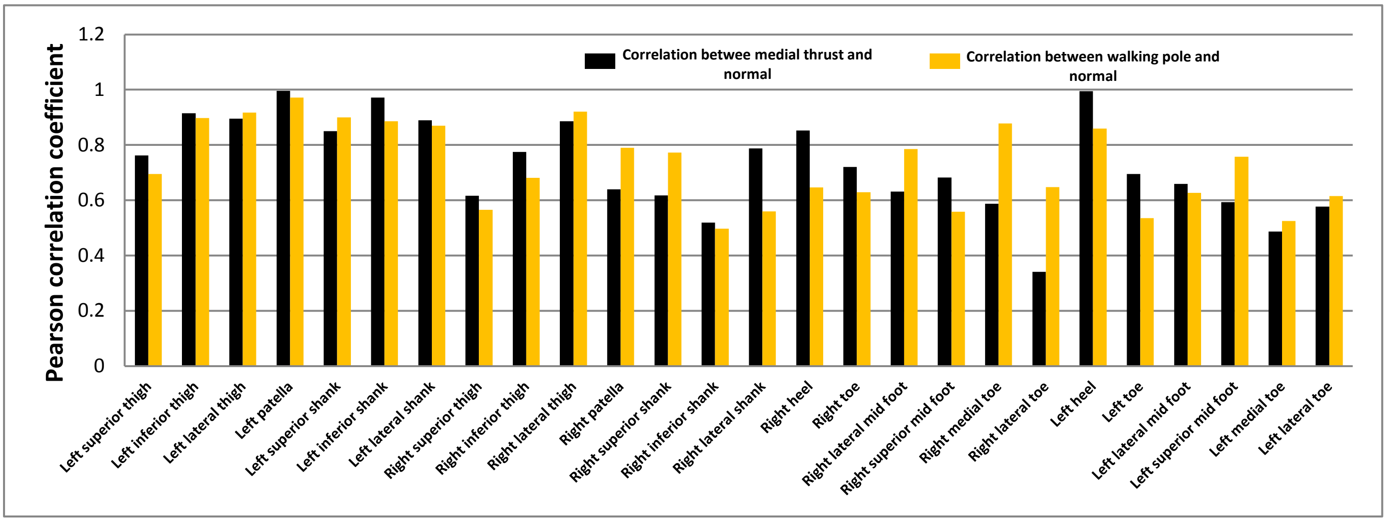

Figure 4 Pearson correlation coefficients were calculated across different body segment trajectories over different natural-looking walking patterns (normal, medial thrust and walking pole patterns)

Figure 5

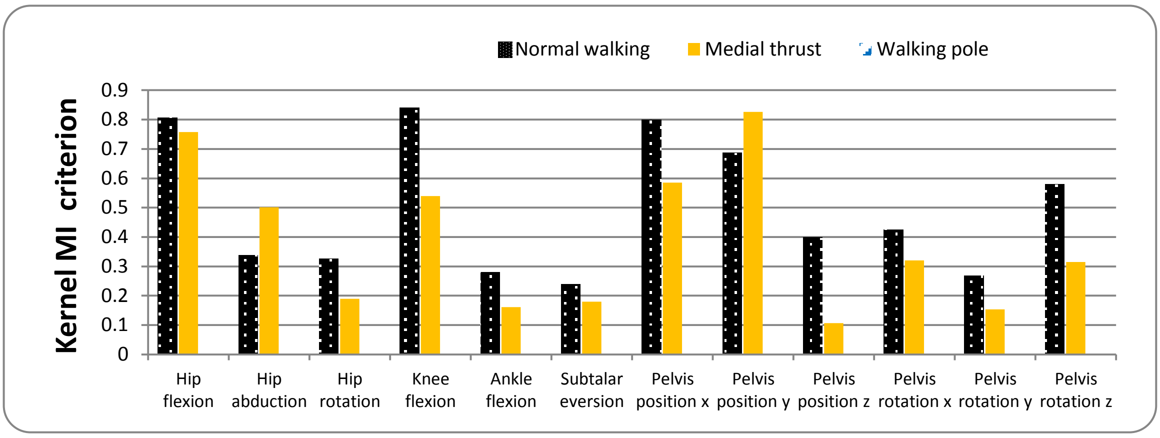

Figure 5 Kernel mutual information values between gait kinematics and medial KCF; *x, y and z* refer to anterior-posterior, vertical and medial-lateral directions.

Figure 6

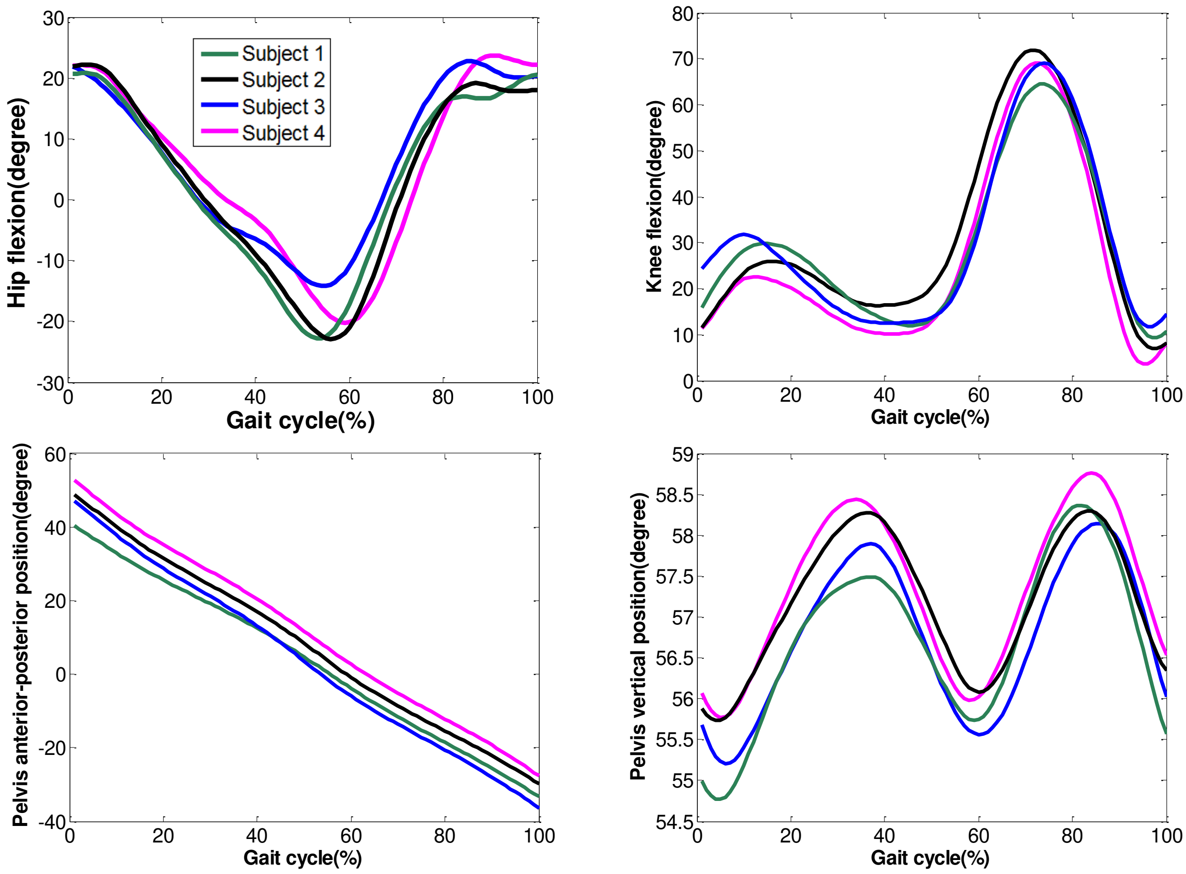

Figure 6 Predicted kinematic waveforms (outputs) corresponding to the knee joint loading patterns adopted from the medial thrust rehabilitation strategy (inputs).

Figure 7

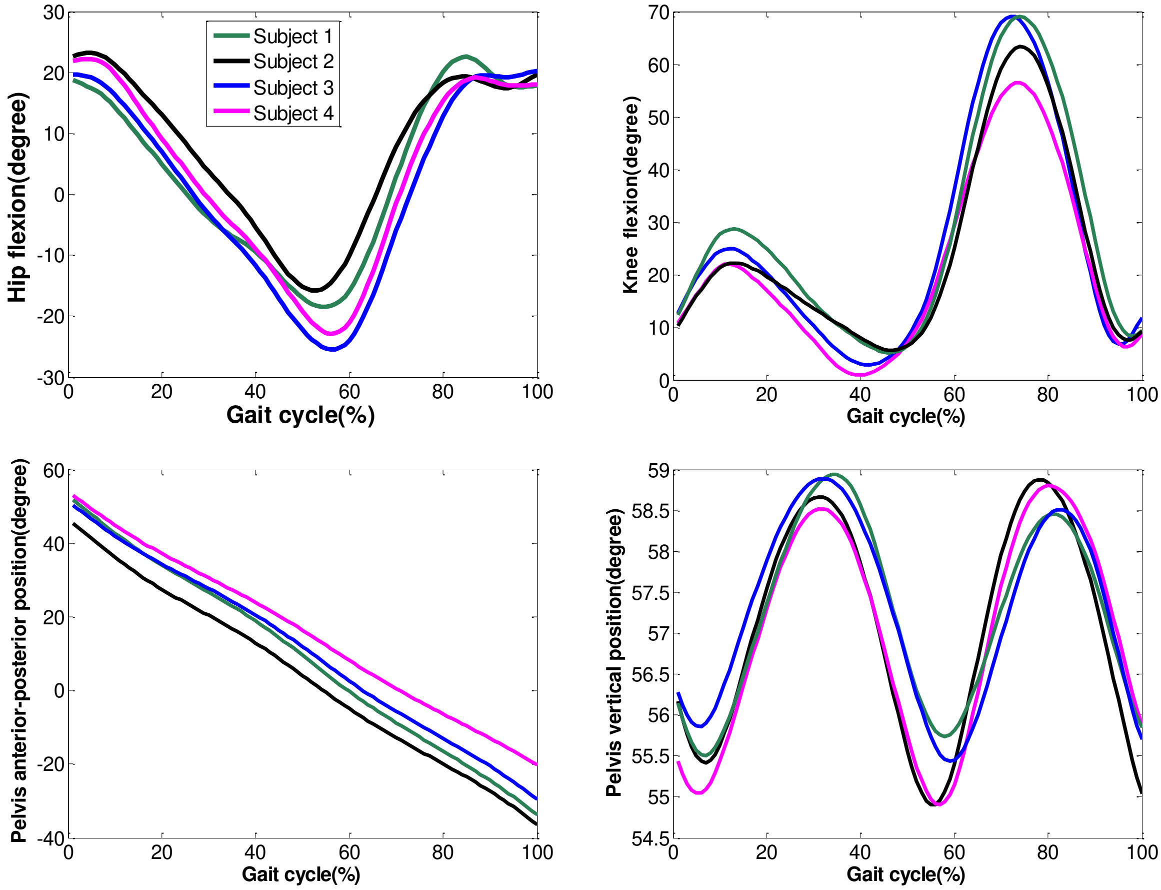

Figure 7 Predicted kinematic waveforms (outputs) corresponding to the knee joint loading patterns adopted from the walking pole rehabilitation strategy (inputs).

Figure 8

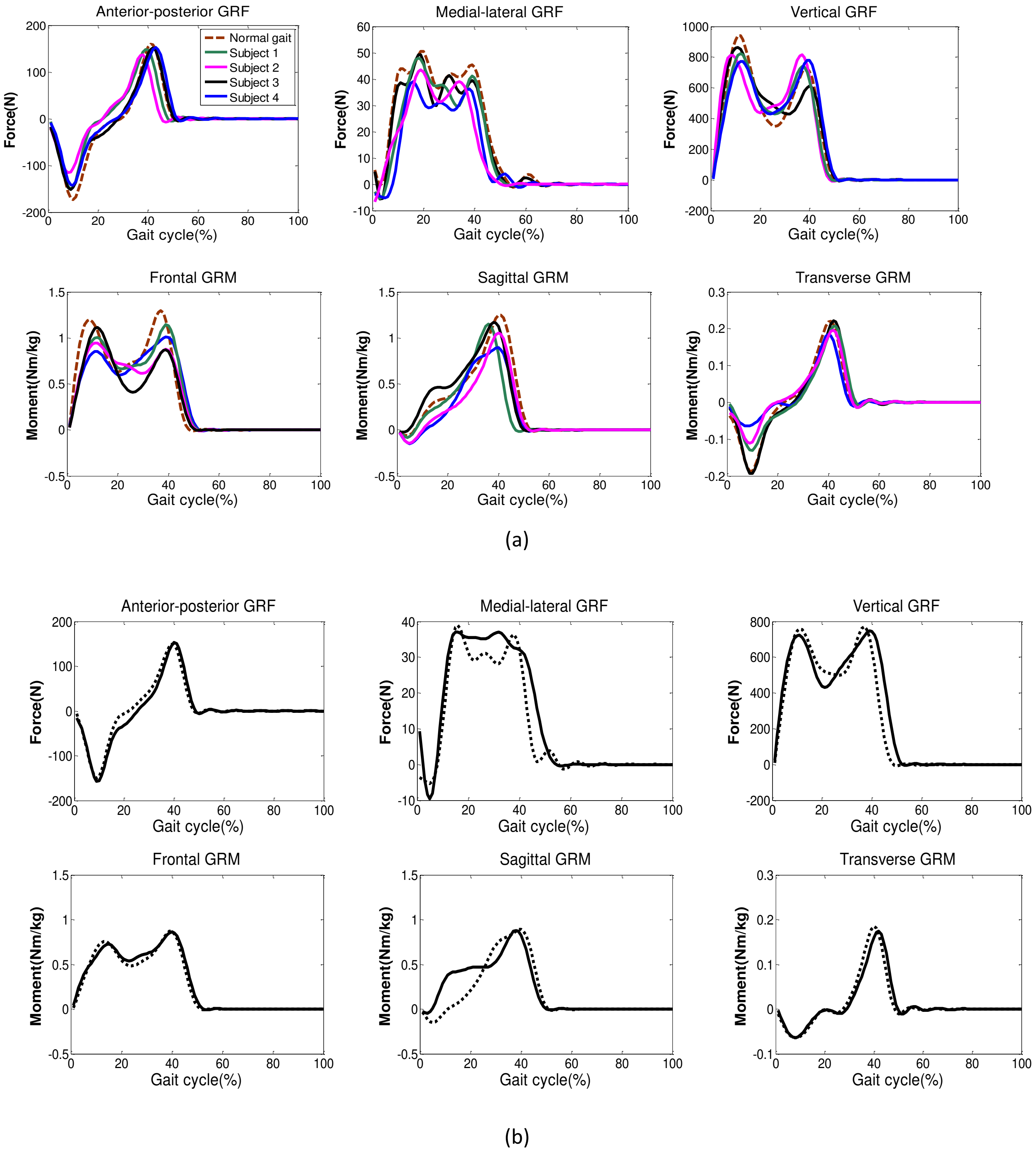

Figure 8 (a) Updated ground reaction force and moment profiles corresponding to the medial thrust-based predicted kinematics, (b) FFANN-based updated GRF&M was compared versus the corresponding experimental measurements of medial thrust pattern for subject 3 as an example.

Figure 9

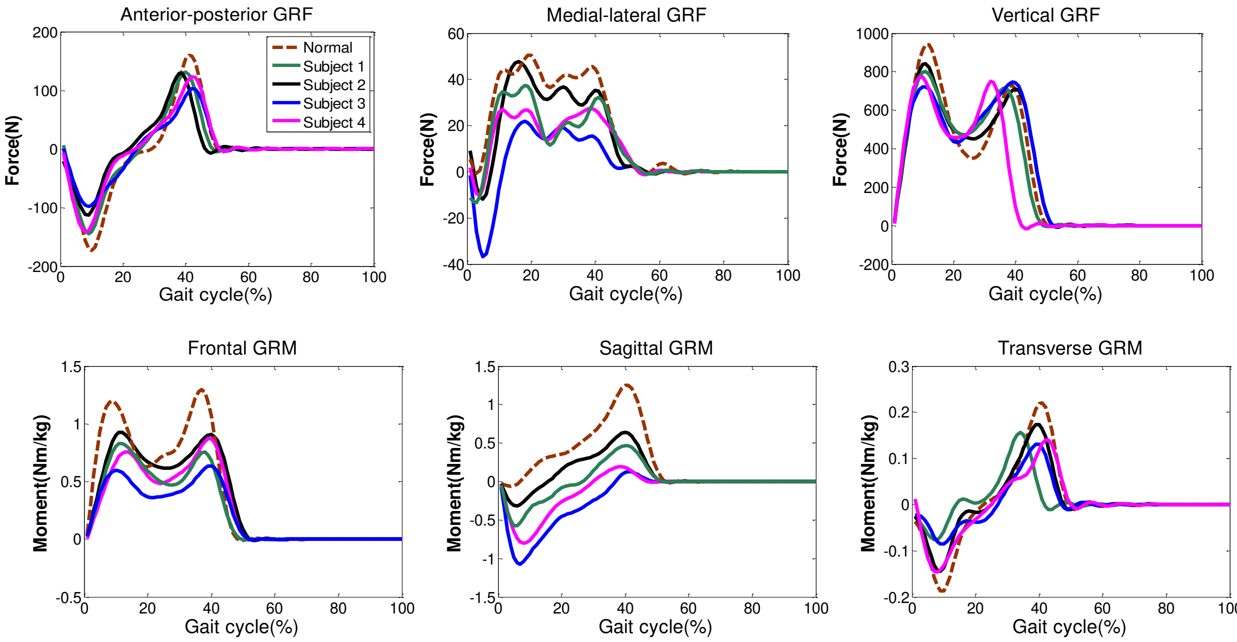

Figure 9 Updated ground reaction force and moment profiles corresponding to the walking pole-based predicted kinematics.

Figure 10

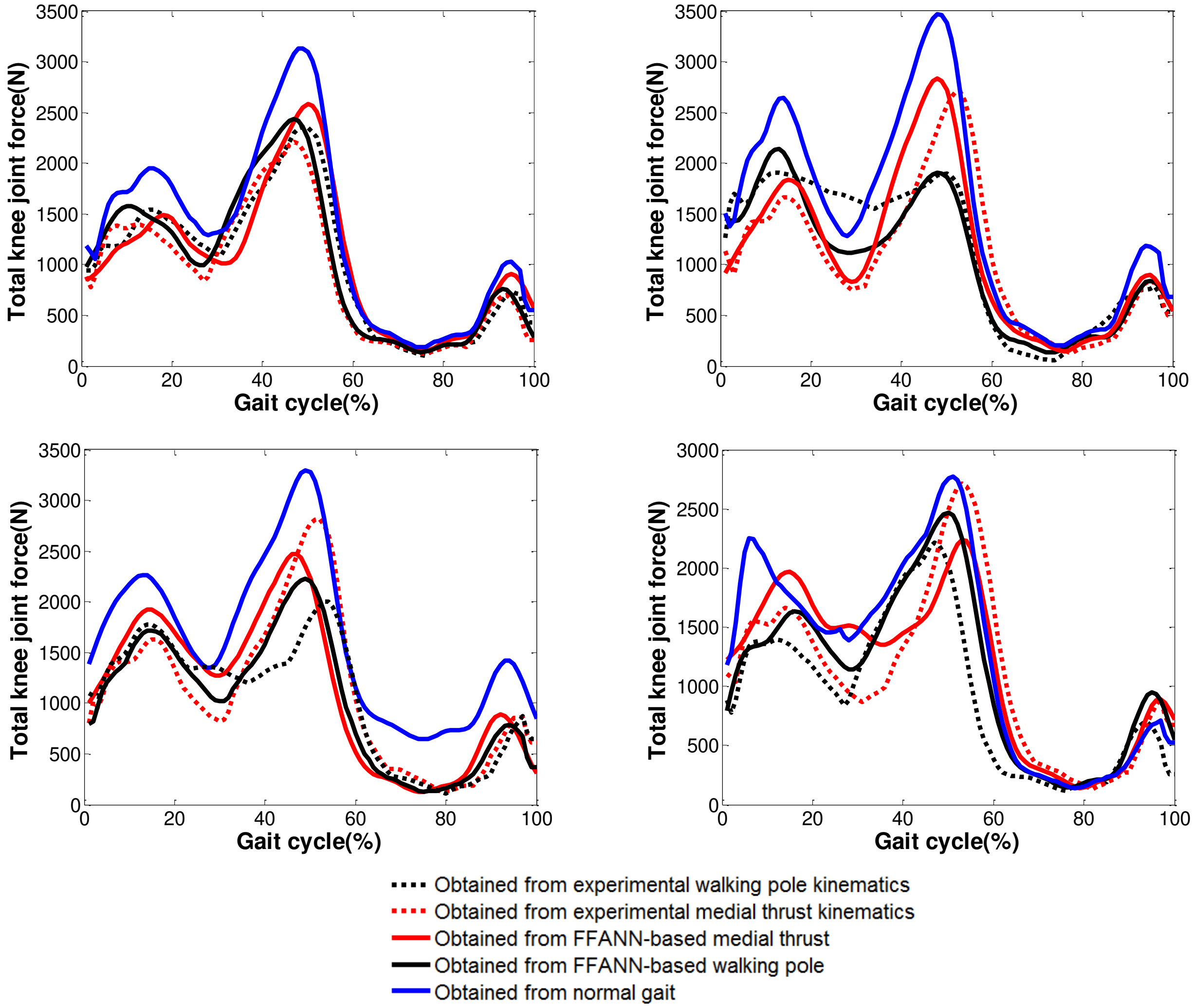

Figure 10 Both medial thrust-based predicted kinematics and walking pole-based predicted kinematics could decrease the knee joint loading compared to the normal gait pattern

Figure 11

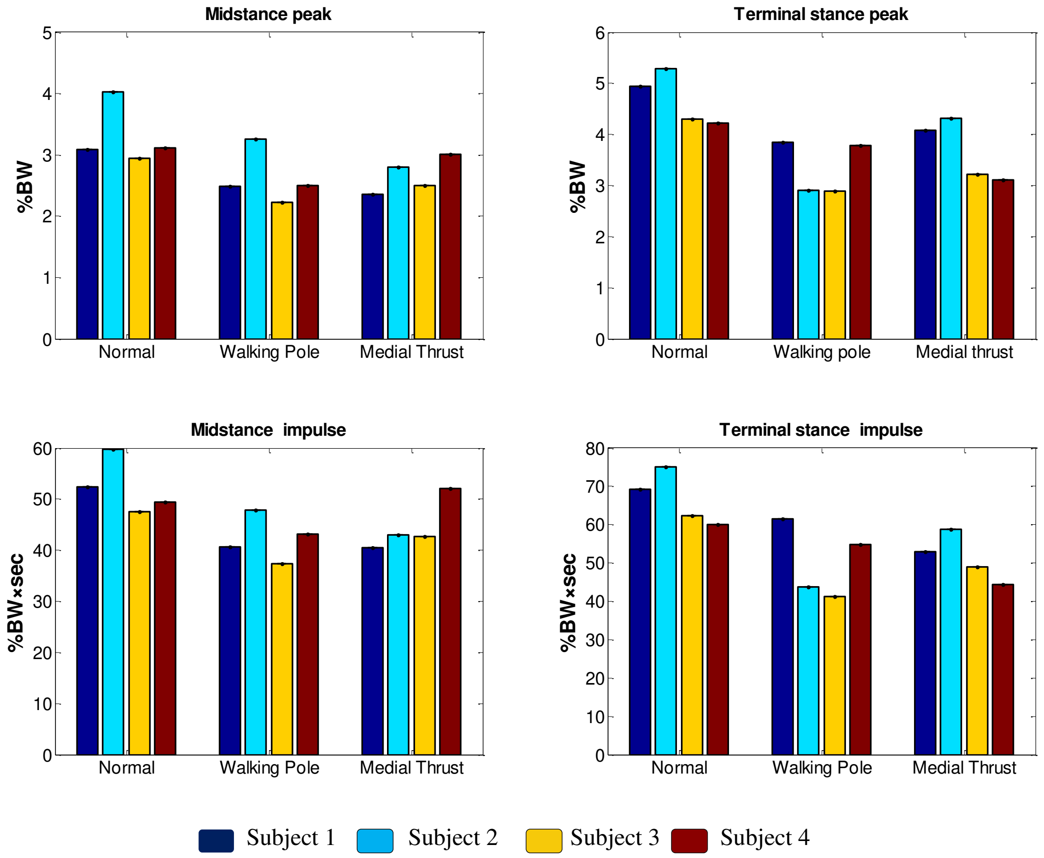

Figure 11 Both medial thrust-based kinematics and walking pole-based kinematics could decrease knee joint loadings in terms of the peak and angular impulse values in the midstance and terminal stance phases.

Supplementary data

Click here to download Supplementary data: Appendix.docx