Journal of Human Perfomance and Health 2019; 1 (1): f1-13
Gdansk University of Physical Education and Sport In Gdansk
The Jerzy Kukuczka Academy of Physical Education in Katowice
Faculty of Physical Education and Sport, Charles University in Prague

ORIGINAL

doi: 10.29359/JOHPAH.1.4.06

Neural network based approximation of muscle and joint contact forces during jumping and landing

Daniel J. Cleather[1, 2]

[1] St Mary's University, Waldegrave Road, Twickenham, TW1 4SX, United Kingdom

[2] Institute for Globally Distributed Open Research and Education (IGDORE)

abstract

Background: Musculoskeletal models have been used to estimate the muscle and joint contact forces expressed during movement. One limitation of this approach, however, is that such models are computationally demanding, which limits the possibility of using them for real-time feedback. One solution to this problem is to train a neural network to approximate the performance of the model, and then to use the neural network to give real-time feedback.

Material and methods: In this study, neural networks were trained to approximate the FreeBody musculoskeletal model for jumping and landing tasks.

Results: The neural networks were better able to approximate jumping than landing, which was probably a result of the greater variability in the landing data set used in this study. In addition, a neural network that was based on a reduced set of inputs was also trained to approximate the outputs of FreeBody during a landing task.

Conclusions: These results demonstrate the feasibility of using neural networks to approximate the results of musculoskeletal models in order to provide real-time feedback. In addition, these neural networks could be based upon a reduced set of kinematic variables taken from a 2-dimensional video record, making the implementation of mobile applications a possibility.

Key words: musculoskeletal modelling, FreeBody, machine learning, real-time feedback, biofeedback.

article details

Article statistics: Word count: 4,503; Tables: 2; Figures: 5; References: 23
Received: December 2019; Accepted: December 2019; Published: December 2019

Full-text PDF: http://www.johpah.com

Funding: This research received no specific grant from any funding agency in the public, commercial, or not-for-profit sectors.

Conflict of interests: Author has declared that no competing interest exists.

Corresponding author: Dr Daniel J. Cleather; St Mary's University, Faculty of Sport, Health and Applied Science; Waldegrave Road, Strawberry Hill, Twickenham, TW1 4SX; e-mail: daniel.cleather@stmarys.ac.uk

INTRODUCTION

Disorders of the musculoskeletal system encompass a diverse number of complaints that affect all ages. These range from degenerative diseases like osteoarthritis that can severely compromise the quality of life of the elderly to career-threatening sports injuries experienced by elite athletes. These extremes are all linked on a single mechano-biological spectrum. A large number of musculoskeletal problems are thought to be influenced by the forces experienced by the structures of the human body and hence the stresses on these tissues. For instance, the degeneration of both natural and man-made biological materials is thought to be dependent on the repetitive force loading they experience on a daily basis. Equally, sporting injuries are likely to occur when the force experienced by a particular structure exceeds its failure limit. Consequently, it has been of great interest to biomedical researchers to directly quantify the forces experienced by human tissues (including the loading of bones, ligaments and muscles), both to better understand musculoskeletal disorders, but also to improve the quality of surgical and therapeutic interventions.

The direct measurement of internal tissue forces is an elusive technical challenge. Contemporary approaches to the direct measurement of internal forces tend to be surgically invasive, and are frequently only possible in patients receiving prosthetic joint replacements [1, 2]. Biomedical engineers have therefore been compelled to seek alternative approaches to quantify internal forces. One such method is the use of musculoskeletal modelling techniques. This technology is based upon using measurements of the external kinematics and kinetics during movement to estimate the forces of interest based upon the principles of classical physics and a virtual description of the musculoskeletal system.

There is a growing body of work that has sought to validate the estimates derived from musculoskeletal modelling approaches against more direct measurements [3–5]. These studies demonstrate that musculoskeletal models have the potential to be valuable tools that can provide clinically relevant, subject specific information. However, one problem with musculoskeletal modelling is that it can be highly computationally intensive. The calculation of muscle and joint contact forces for just one movement trial can take anything from a few minutes to several hours depending on the complexity of the problem and the computing resources available. What this means is that real-time calculation of internal forces is not currently feasible using most models, restricting the range of clinical applications.

Neural networks can be used as powerful approximation tools somewhat akin to linear regression. The principle is that a neural network can be “trained” based upon a given data set of input and output variables. The trained network will then be able to give a prediction of the output variables based upon a new set of input variables. In the present case, the input variables would be the experimentally measured external kinematics and kinetics of movement and the output variables would be the estimated internal muscle and joint contact forces. The key advantage of neural networks for the study of internal forces is that, once the network has been trained, the computation of output variables can be very rapid, meaning that real-time prediction of internal forces becomes a possibility.

Only one previous study has sought to train a neural network in the manner described here. Rane et al. [6] trained a neural network to approximate the performance of FreeBody [7], a publicly available musculoskeletal model of the lower limb, using a set of gait data from 156 subjects. Their work provides evidence that neural networks can effectively approximate the performance of musculoskeletal models and do so within a computational time frame that makes real-time prediction of internal forces possible.

One further limitation of musculoskeletal modelling approaches is that the inputs to the model are generally based on the collection of extensive data relating to the mechanics of movement. For instance, the inputs required by the FreeBody musculoskeletal model are the 3 dimensional positions of 18 retro-reflective markers and the location, magnitude and orientation of the resultant ground reaction force (GRF). Much of this detail is necessary to allow the virtual description of the musculoskeletal anatomy to be created. The need for this detail however, means that typical data capture procedures for musculoskeletal models require well-equipped biomechanics facilities, and in particular, the use of motion capture and force plate technologies. This equipment is expensive and often not very portable. This is in turn a considerable barrier to the wider use of musculoskeletal models for the calculation of internal forces. An advantage of neural network based approaches is that there is no necessity to create the virtual model – the prediction is based simply on patterns in the input data. This might mean that neural networks could be trained to give predictions of internal forces based on more readily available input data, increasing the potential range of applications.

The purposes of this study were therefore twofold. Firstly, to replicate the work of Rane and colleagues [6] using the same model but different movements. In particular, to establish the ability of a neural network to approximate FreeBody for jumping and landing – two activities which exhibit much greater force expression. Secondly, to explore the ability of neural network based approaches to provide accurate descriptions of muscle and joint contact forces based upon data sets with a reduced number of input variables.

MATERIAL AND METHOD

experimental approach to the problem

Mechanical data describing jumping and landing was collected using force plate and motion capture technologies. A publicly available musculoskeletal model of the lower limb [7] was used to estimate the muscle and joint contact forces present during these movements. This data was then used to train a number of neural networks. The ability of the neural networks to approximate the outputs of the musculoskeletal model was evaluated.

subjects

Two different data sets were used in this study. The data used in this study has previously been described [8,9], and so only brief details of the data collection procedure are given here. The first data set consisted of 88 vertical jumps performed by 21 men (body mass = 85.0 ±8.9kg, height = 1.75 ±0.09m) and 12 women (body mass = 63.1 ±6.3kg, height = 1.67 ±0.07m). The second data set comprised 165 bilateral landings performed by 23 men (body mass = 81.7 ±12.5kg, height = 1.81 ±0.06m) and 27 women (body mass = 64.7 ±8.0kg, height = 1.67 ±0.06m). All subjects provided informed written consent prior to data collection and the study was approved by the ethics panel of St Mary’s University, Twickenham.

doi: 10.29359/JOHPAH.1.4.06

instrumentations

The data used here was collected during 3 different time periods at 2 different sites. The time history of the position of 18 retro-reflective markers (Table 1 and Figure 1) placed on the pelvis and right lower limb [7] was captured at 200Hz using motion capture technology (Vicon MX System, Vicon Motion Systems Ltd, Oxford, UK; jumping data at site 1: 14 camera array; landing data at site 1: 11 camera array; landing data at site 2: 10 camera array). The GRF was collected synchronously with the kinematic data using force plate technology (jumping and landing at site 1: Kistler 9287BA Plate, 600 × 900 mm, Kistler Instruments Ltd., Hampshire, UK; landing at site 2: Kistler 9286B, 400 × 600 mm). Force data was either collected at 1000Hz and down sampled to 200Hz, or for a minority of subjects, collected at 200Hz.

Table 1. Marker positions used for data capture arranged in order of input to the neural networks. Table is reproduced Cleather and Bull [7] in accordance with the terms of its Creative Commons Attribution Licence

Marker	Location
FCC	Calcaneus
FMT	Tuberosity of the fifth metatarsal
FM2	Head of the second metatarsal
TF	Additional marker placed on the foot
FAM	Apex of the lateral malleolus
TAM	Apex of the medial malleolus
C1, C2, C3	Additional markers placed on the shank segment
FLE	Lateral femoral epicondyle
FME	Medial femoral epicondyle
T1, T2, T3	Additional markers placed on the thigh segment
RASIS	Right anterior superior iliac spine
LASIS	Left anterior superior iliac spine
RPSIS	Right posterior superior iliac spine
LPSIS	Left posterior superior iliac spine

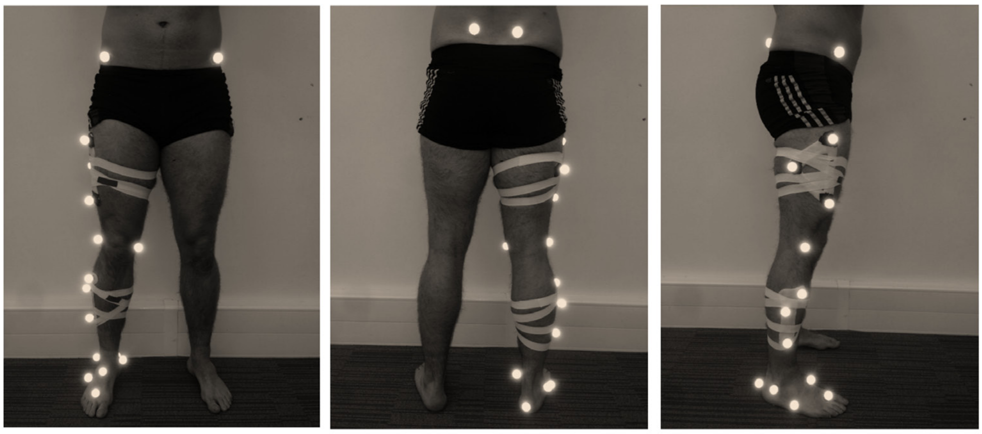

Fig. 1. Position of the 18 retro-reflective markers (also described in Table 1). This image is reproduced from Cleather and Bull [7] in accordance with the terms of its Creative Commons Attribution Licence

procedure

Subjects first performed a standardised warm up (although the warm up differed between the jumping and the landing trials). For the jumping trials they then performed a series of maximum effort vertical jumps with their arms akimbo. Subjects were permitted to take as much recovery as necessary between jumps. For the landing trials, subjects were asked to step off a 30cm box, and to land bilaterally, with 60s rest taken between trials.

data analysis

In order to generate the training and test data for this study, a publicly available model of the lower limb (FreeBody) was used to estimate the muscle and joint contact forces exhibited during jumping and landing from the motion capture and force plate data. The development and testing of FreeBody has been previously described in great detail [5, 7, 10–17] and so only a brief sketch of the model is provided here. In short, the equations of motion of a chain of 5 rigid segments representing the pelvis and right lower limb are posed using wrench notation. The equations are parameterised using the kinematic and kinetic data, a scaled musculoskeletal geometry taken from the cadaveric study of Klein Horsman and colleagues [18] and the anthropometry of de Leva [19]. The unknowns within the equations of motion are 193 muscle, ligament and joint contact forces. As there are only 22 equations of motion this is an indeterminate problem which is then solved using an optimization approach. In particular, the solution that minimises the sum of the maximum muscle stresses cubed and the ligament forces relative to their failure limit cubed is found [12, 20, 21] using the optimization toolbox of GNU Octave (https://www.gnu.org/software/octave/).

statistical analysis

For this study the software package Neural Designer (version 4.2.0, Artificial Intelligence Techniques Ltd., Spain) was used to construct and train all neural networks. The same architecture was employed for all networks in order to facilitate comparison of the results (although the number of inputs differed for the third network as described below). In particular, the neural network comprised a scaling layer, 2 perceptron layers, an unscaling layer and a bounding layer (Fig. 2).

The neurons in the first (or hidden) perceptron layer were activated based upon a hyperbolic tangent function whereas those in the second (output) perceptron layer used a linear activation function. The loss index was calculated based upon the normalised squared error with the addition of a regularisation term. The optimization was performed using the quasi-Newton method.

Three neural networks were trained. Each network was trained using the motion capture and force plate data as inputs and the muscle and joint contact forces predicted by FreeBody as the training targets. The input variables were the 3 dimensional coordinates of the 18 markers in the order given in Table 1 (54 variables), the GRF (3 variables) and the centre of pressure (2 variables). The outputs were 40 muscle and tendon forces, 5 joint reaction forces and the tibiofemoral mediolateral load share (all shown in Table 2). The inputs and force predictions for each frame were taken to be separate instances that were used as training data. Firstly, a neural network was trained using the vertical jump data. This comprised 9,999 instances taken from 64 jumps. A second neural network was trained using the landing data and there were 4,397 instances taken from 96 landings. Finally, a third neural network was trained based upon a reduced number of inputs consisting of 2 dimensional kinematic data only. This comprised the frontal plane coordinates for the markers of the second and fifth metatarsals,

Journal of Human Performance and Health 2019; 1 (1): f1-13
doi: 10.29359/JOHPAH.1.4.06

the lateral and medial malleoli, the lateral and medial epicondyles, and the right and left anterior iliac spines (16 variables in total). A 17th variable was added which simply provided the body weight of the subjects. The training data for this final neural network consisted of 5,962 instances taken from 133 landings. The training data set for each neural network was split into training (60% of the instances), validation (20%) and test (20%) groups for use within Neural Designer.

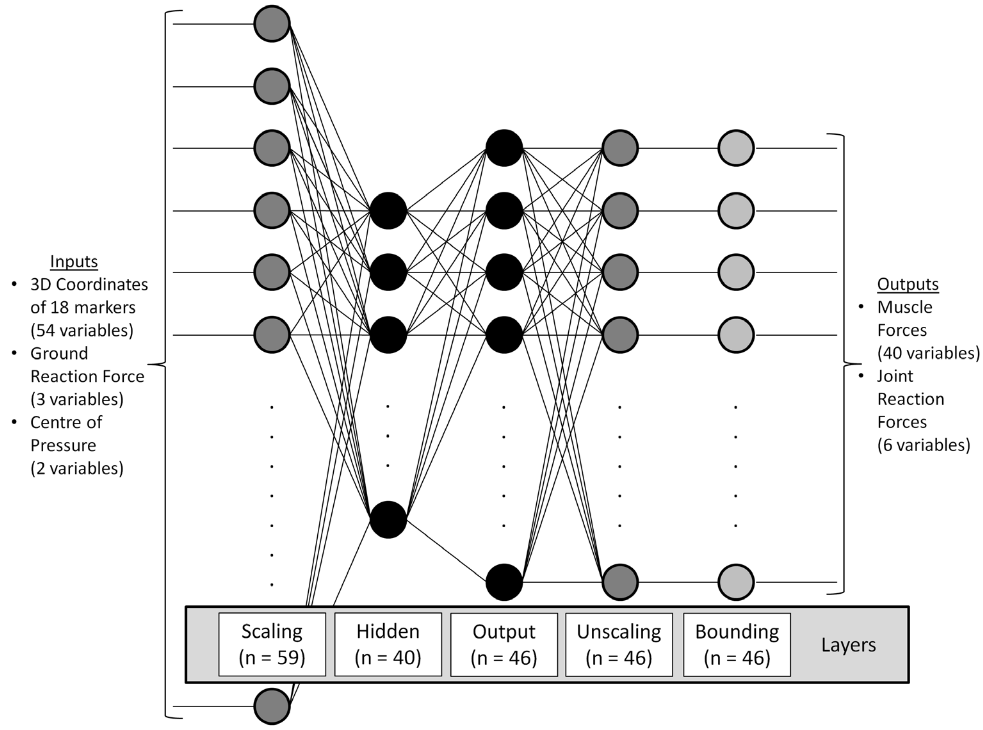

Fig. 2. Neural network architecture

After training, each of the three neural networks was then deployed as an .m file – these .m files are available as supplementary material to this article, and can be run in either MATLAB® (MathWorks®, 1 Apple Hill Drive, Natick, MA, USA) or GNU Octave. The performance of each neural network was then evaluated using a separate test data set, whereby the approximations given by the neural network were compared to the predictions generated by FreeBody. For jumping, the test data set consisted of 3,878 instances taken from 24 jumps, for landing there were 1,565 instances representing 37 landings and for the kinematic only landing there were 1,351 instances taken from 32 landings. The deployed neural networks were "subject exposed" to the secondary test data set – that is, the training data set included a jump or landing trial from each of the subjects in the test data set [6].

Linear regression was used to compare the approximations from the neural network to the predictions from FreeBody. The neural network was assumed to be approximating FreeBody well if the correlation coefficient and the gradient of the line of best fit were between 0.9 and 1.0, and if the intercept of the line of best fit was between 0.0 and 0.1. Finally, the muscle and joint reaction forces for both the neural network approximations and the FreeBody predictions were time normalised and then spline interpolated in order to calculate mean composite curves for the entire cohort.

RESULTS

The outputs of the neural network for jumping were generally highly correlated with the FreeBody estimates (r = 0.492 – 0.986, mean r = 0.893) and for 11 of the 46 variables the neural network approximated FreeBody well (Table 2). Only 4 variables did not correlate highly, and of these, 2 were variables where the predicted maximum muscle forces were negligible. In contrast, for landing, although there was still a generally high level of correlation between the neural network and FreeBody (r = 0.491 – 0.929, mean r = 0.810), no variable was considered to be approximating FreeBody well. For the neural network that was based upon landing kinematic data only, only 16 variables exhibited a high level of correlation (r > 0.7) between the neural network and FreeBody (r = 0.160 – 0.846, mean r = 0.642). The differences between neural network approximations and FreeBody predictions for one of the best performing variables (vastus lateralis) are presented in Fig. 3.

Table 2. Comparison of neural network approximations to FreeBody predictions of muscle and joint contact forces during vertical jumping and landing. Forces are listed in the order that they are output from the neural network

Muscle or joint	Jumping				Landing			Landing (Reduced)		
	R	*m*	*c*	Max	*r*	*m*	*c*	*r*	*m*	*c*
Adductor Brevis	0.872	0.761	0.003	0.47	0.859	0.824	0.023	0.667†	0.512	0.042
Adductor Longus	0.876	0.763	0.006	1.08	0.883	0.861	0.041	0.689†	0.524	0.076
Adductor Magnus	0.952	0.870	0.038	1.65	0.873	0.829	0.123	0.640†	0.553	0.279
Biceps Femoris Long Head	0.947	0.863	0.073	2.18	0.889	0.809	0.061	0.663†	0.463	0.187
Biceps Femoris Short Head	0.874	0.761	0.004	0.61	0.762	0.652	0.022	0.659†	0.466	0.025
Extensor Digitorum Longus	0.824	0.664	0.008	0.38	0.491†	0.474	0.043	0.365†	0.313	0.062
Extensor Hallucis Longus	0.908	0.795	0.006	0.24	0.597†	0.532	0.032	0.539†	0.354	0.041
Flexor Digitorum Longus	0.957	0.898	0.006	0.20	0.798	0.790	0.023	0.642†	0.628	0.039
Flexor Hallucis Longus	0.962*	0.950	0.034	1.51	0.792	0.799	0.130	0.767	0.572	0.167
Gastrocnemius	0.755	0.582	0.053	1.69	0.675†	0.493	0.156	0.202†	0.074	0.213
Gemellus	0.982*	0.945	0.006	0.62	0.852	0.687	0.017	0.740	0.599	0.026
Gluteus Maximus	0.969*	0.926	0.071	4.63	0.860	0.750	0.182	0.639†	0.548	0.312
Gluteus Medius	0.950*	0.930	0.036	2.09	0.838	0.728	0.204	0.604†	0.400	0.357
Gluteus Minimus	0.862	0.675	0.012	0.47	0.791	0.615	0.054	0.644†	0.399	0.076
Gracilis	0.866	0.771	0.001	0.25	0.833	0.850	0.010	0.704	0.656	0.015
Iliacus	0.882	0.743	0.005	0.60	0.849	0.750	0.060	0.715	0.499	0.074
Obturator Externus	0.848	0.667	0.026	0.59	0.868	0.807	0.061	0.619†	0.548	0.153
Obturator Internus	0.985*	0.960	0.026	2.03	0.862	0.680	0.079	0.782	0.628	0.114
Pectineus	0.881	0.766	0.002	0.26	0.861	0.811	0.014	0.686†	0.511	0.024
Peroneus Brevis	0.954	0.883	0.023	1.42	0.757	0.647	0.090	0.687†	0.569	0.109
Peroneus Longus	0.954	0.883	0.032	1.87	0.746	0.650	0.133	0.650†	0.543	0.171
Peroneus Tertius	0.934	0.833	0.005	0.24	0.522†	0.442	0.039	0.474†	0.378	0.048
Piriformis	0.986*	0.970	0.009	0.65	0.896	0.739	0.022	0.846	0.657	0.027
Plantaris	0.620†	0.328	0.000	0.02	0.638†	0.471	0.002	0.160†	0.073	0.003
Popliteus	0.857	0.610	0.007	0.25	0.626†	0.521	0.010	0.449†	0.302	0.014
Psoas Minor	0.879	0.753	0.000	0.03	0.852	0.793	0.001	0.686†	0.501	0.002
Psoas Major	0.882	0.742	0.005	0.61	0.864	0.783	0.056	0.729	0.520	0.072
Quadratis Lumborum	0.978*	0.937	0.015	1.17	0.907	0.746	0.028	0.795	0.706	0.050
Rectus Femoris	0.888	0.762	0.060	1.67	0.858	0.773	0.173	0.646†	0.466	0.370
Sartorius	0.492†	0.266	0.003	0.18	0.842	0.732	0.030	0.601†	0.514	0.059
Semimembranosus	0.942	0.835	0.034	1.36	0.882	0.821	0.047	0.589†	0.397	0.119
Semitendinosus	0.846	0.706	0.030	1.02	0.892	0.865	0.030	0.551†	0.398	0.115
Soleus	0.940	0.921	0.214	8.20	0.795	0.719	0.640	0.557†	0.451	1.490
Tensor Fascia Latae	0.736	0.511	0.013	0.44	0.858	0.758	0.033	0.702	0.474	0.060

Table 2 – continued

Muscle or joint	Jumping				Landing			Landing (Reduced)		
	R	*m*	*c*	Max	*r*	*m*	*c*	*r*	*m*	*c*
Tibialis Anterior	0.651†	0.406	0.024	1.54	0.710	0.740	0.119	0.576†	0.410	0.239
Tibialis Posterior	0.927	0.860	0.050	1.50	0.830	0.768	0.166	0.731	0.756	0.243
Vastus Intermedius	0.980*	0.952	0.021	2.52	0.929	0.837	0.076	0.841	0.787	0.120
Vastus Lateralis	0.963*	0.955	0.067	5.00	0.925	0.842	0.267	0.834	0.801	0.413
Vastus Medialis	0.983*	0.963	0.040	4.79	0.918	0.803	0.153	0.830	0.749	0.214
Patellar Tendon	0.980*	0.968	0.054	5.92	0.900	0.837	0.498	0.744	0.690	0.977
Ankle JRF	0.969	0.970	0.157	10.02	0.820	0.812	0.880	0.737	0.631	1.992
Lateral Tibiofemoral JRF	0.913	0.931	0.103	4.43	0.816	0.842	0.401	0.677†	0.735	0.929
Medial Tibiofemoral JRF	0.920	0.834	0.296	8.71	0.748	0.696	1.060	0.451†	0.383	2.120
Hip JRF	0.978	0.951	0.163	11.29	0.804	0.772	1.100	0.572†	0.441	2.554
Patellofemoral JRF	0.984*	0.984	0.073	13.59	0.922	0.842	0.636	0.815	0.790	0.942
Mediolateral Load Share	0.766	0.674	0.201	0.98	0.767	0.724	0.164	0.635†	0.555	0.239
Mean	0.893	0.797	0.046		0.810	0.733	0.178	0.642	0.520	0.347

Notes: landing (reduced) = neural network based upon 2 dimensional kinematic data only; r = correlation coefficient; m = gradient of line of best fit; c = intercept of line of best fit; Max = maximum value of force prediction from FreeBody; * = neural network approximating the FreeBody predictions well (0.9 < r < 1.0, 0.9 < m < 1.0 and 0.0 < c < 0.1); † = neural network approximation not highly correlated with the FreeBody predictions (r < 0.7)

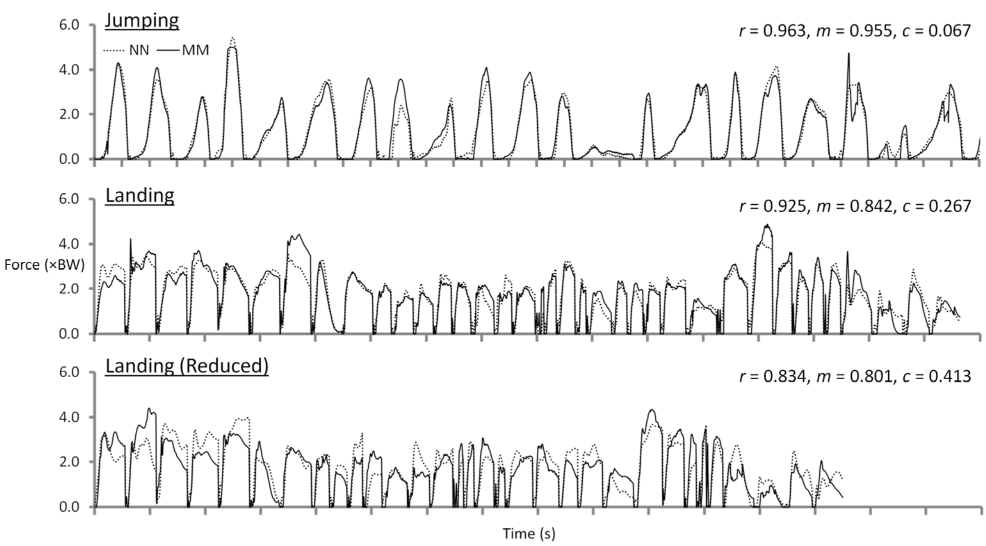

Fig. 3. Comparison of neural network approximations to FreeBody predictions of vastus lateralis muscle force during jumping and landing (multiple trials are shown)

Notes: landing (reduced) = neural network based upon 2 dimensional kinematic data only; r = correlation coefficient; m = gradient of line of best fit; c = intercept of line of best fit; NN = neural network; MM = musculoskeletal model (FreeBody)

When considered at a cohort rather than an individual level, the mean values for the jumping and landing neural networks showed a close agreement with the FreeBody predictions (Fig. 4). In contrast, the kinematics only approximation of landing did not show the same high level of agreement, although there was still a reasonable degree of qualitative similarity (Fig. 5).

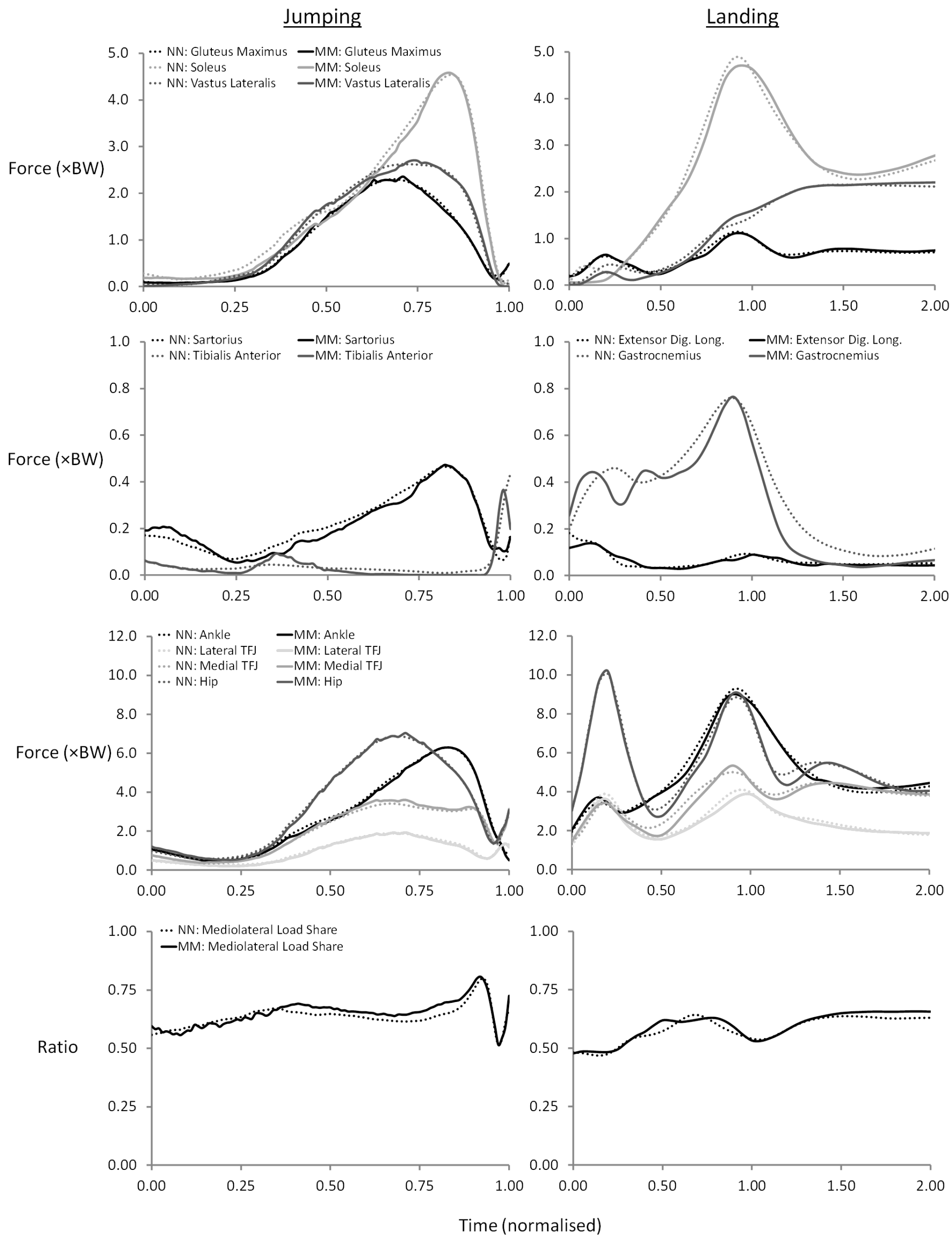

Fig. 4. Mean muscle and joint contact forces calculated during vertical jumping and landing

Notes: NN = neural network; MM = musculoskeletal model (FreeBody), BW = body weight

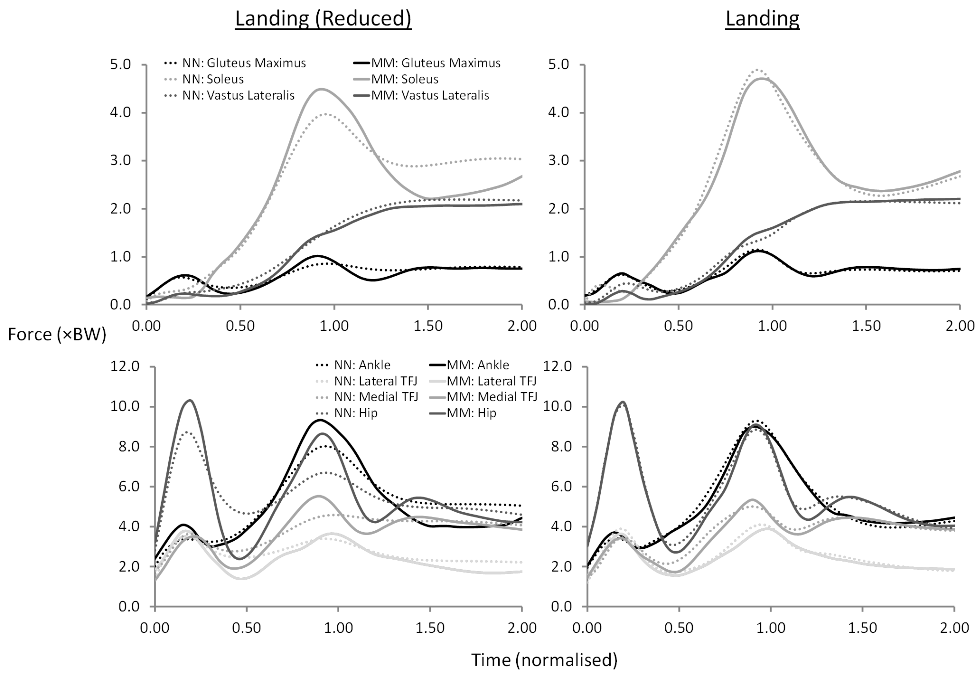

Fig. 5. Mean muscle and joint contact forces calculated during landing for the neural network based on the complete input set and the kinematics only input set (reduced)

Notes: NN = neural network; MM = musculoskeletal model (FreeBody), BW = body weight

DISCUSSION

The first aim of this study was to evaluate the ability of a neural network to approximate the muscle and joint contact force estimates of FreeBody during jumping and landing. The results of this study confirm the findings of Rane and colleagues in suggesting that neural networks that have been trained on the calculations from musculoskeletal models show a good level of agreement with the underlying model.

The neural network for jumping was able to better approximate FreeBody than the neural network for landing. This seems likely to be due to the fact that there was more variability in both the inputs and outputs of the landing data set in comparison to the jump data. Evidence for this can be found in our recent principal component analyses of larger jumping and landing data sets from which the data in this study was drawn. In particular, for jumping, only 3 principal components were required to describe 90% of the variability in the 3-dimensional inter-segmental joint moments (which can be taken to be a proxy for the input data set) and 4 principal components to describe 90% of the variability in the muscle forces calculated by FreeBody [22]. In contrast, for landing, 4 principal components were needed for the moments and 6 for the muscle forces [23]. Whether this difference in variability is a function of the particular populations studied, or fundamentally inherent to differences in the tasks themselves is unclear, although I have argued that the latter is more probable [23]. In any case, the relatively poorer performance for landing does not mean that neural networks show less promise for this task, but rather that it may be necessary to use a larger training data set when trying to approximate data sets (or movements) with more variability.

The criteria used to assess the degree of fit between the two approaches in this study were quite stringent. In order to be assessed as approximating the data well the neural network needed to be able to match the FreeBody outputs extremely closely for all individuals. This can be clearly seen by comparing the jumping and landing graphs in Figure 3. Although the predictions for landing are close for most individuals there are some individuals where they differ. This is not the case for jumping. When the individual predictions are combined into cohort level data however, the performance of the two approaches is much closer. For instance, in Figure 4, the third and fourth graphs present the cohort level data for muscles where the individual predictions from the neural network were not highly correlated with the estimates from the musculoskeletal model (for jumping, sartorius and tibialis anterior; for landing, extensor digitorum longus and gastrocnemius). This is evidence that the neural network is a robust approach when applied at the cohort level.

In interpreting these results it should be noted that the approximation task in question was quite demanding and could be simplified by only seeking to approximate a subset of the output variables. In addition, the size of the training data set was relatively small. For these reasons these results should be considered to indicate a lower bound for the performance of neural networks in approximating the performance of musculoskeletal models in jumping and landing tasks. It seems likely that if the input data sets, network architecture and output variables are optimised (and in the case of outputs reduced) to focus on answering a particular question, that the fidelity of the approximation will be much greater. Similarly, the use of larger training data sets that are optimised for the question in hand will also likely deliver considerable improvements in performance. When these results are considered in this light this study provides strong evidence that neural networks are a realistic and feasible approach to the real-time prediction of subject specific muscle and joint contact forces.

It is important to remember that the neural networks used in this study approximated the outputs of FreeBody, a musculoskeletal model. The predictions given by the neural network are thus only as good as the underlying model itself. The neural network could be approximating FreeBody with 100% accuracy, but this would not necessarily mean that its outputs were close to the physiological reality. This study does not, therefore, sound a death knell for research in musculoskeletal modelling, but rather the contrary. What this work and the study of Rane et al. [6] suggest is a clearer potential pathway towards a clinically relevant, real-time tool. That is, that musculoskeletal modelling technology is used to create large training data sets, and that optimised neural networks are then deployed to approximate the performance of these models. This makes the clinical use of the outputs of musculoskeletal models more realistic, and thus should serve as motivation for musculoskeletal modellers to redouble their efforts in trying to build and validate models that are able to provide subject specific estimates that are close to physiological reality.

The second aim of this study was to explore the ability of a neural network to approximate FreeBody based upon a reduced number of input variables. Clearly, the approximations that are based on the reduced inputs are not as good as those based on the full data set. However, for some of the output variables the correlations for the individual level data are still high (Table 2) and the predictions at the cohort level are a reasonable approximation of the musculoskeletal model (Fig. 5).

CONCLUSIONS

In reducing the variables for the input data set I was trying to imitate the variables that could potentially be mined from a simple, 2-dimensional, frontal plane, video image. In doing so, I was attempting to test the feasibility of using the video record taken from one camera to generate predictions of muscle and joint contact forces. Again, in performing this analysis, I chose the more demanding test by working with the more variable landing data set. I would thus again suggest that these results are reflective of a lower bound for the performance on this type of task. Similarly, when the number of output variables were reduced it was possible to find neural networks that could closely approximate the training data. However, these solutions over-fit the data, and then the performance on the test data set was poorer. However, this does suggest the possibility of creating neural networks with much better performance if a larger training data set is used.

Given these limitations, these results demonstrate the feasibility of calculating muscle and joint contact forces from just one 2-dimensional video camera. Future research should focus on establishing the aspects of the video record that are most effective to use in approximating the performance of the underlying musculoskeletal model. It is worth noting that input variables for the neural network do not need to be the same as, or even a subset of, those used for the musculoskeletal model. Such work represents a viable pathway to the development of a mobile application that could provide real-time feedback during movement.

REFERENCES

[1] D'Lima DD, Steklov N, Patil S, et al. The Mark Coventry Award in vivo knee forces during recreation and exercise after knee arthroplasty. Clin Orthop. 2008;466:2605-2611. https://doi.org/10.1007/s11999-008-0345-x

[2] Fleming BC, Beynnon BD. In vivo measurement of ligament/tendon strains and forces: A review. Ann Biomed Eng. 2004;32:318-328. https://doi.org/10.1023/B:ABME.0000017542.75080.86

[3] Fregly BJ, Besier TF, Lloyd DG, et al. Grand challenge competition to predict in vivo knee loads. J Orthop Res. 2012;30:503-513. https://doi.org/10.1002/jor.22023

[4] Kinney AL, Besier TF, D'Lima DD, et al. Update on Grand Challenge Competition to Predict in Vivo Knee Loads. J. Biomech. Eng. 2013;135:021012-021012-021014. https://doi.org/10.1115/1.4023255

[5] Ding Z, Nolte D, Kit Tsang C, et al. In vivo knee contact force prediction using patient-specific musculoskeletal geometry in a segment-based computational model. J Biomech Eng. 2016;138:021018-021018. https://doi.org/10.1115/1.4032412

[6] Rane L, Ding Z, McGregor AH, et al. Deep Learning for Musculoskeletal Force Prediction. Ann Biomed Eng. 2019;47:778-789. https://doi.org/10.1007/s10439-018-02190-0

[7] Cleather DJ, Bull AMJ. The development of a segment-based musculoskeletal model of the lower limb: introducing FreeBody. R Soc Open Sci. 2015;2:140449. https://doi.org/10.1098/rsos.140449

[8] Cushion EJ, Warmenhoven J, North J, et al. Principal component analysis reveals the proximal to distal pattern in vertical jumping is governed by two functional degrees of freedom. Front Bioeng Biotechnol. 2019;7:193. https://doi.org/10.3389/fbioe.2019.00193

[9] Cleather DJ, Czasche MB. Knee forces during landing in men and women. J Hum Kinet. 2019;68:177-192. https://doi.org/10.2478/hukin-2019-0065

[10] Cleather DJ, Goodwin JE, Bull AMJ. An optimization approach to inverse dynamics provides insight as to the function of the biarticular muscles during vertical jumping. Ann Biomed Eng. 2011;39:147-160. https://doi.org/10.1007/s10439-010-0161-9

[11] Cleather DJ, Goodwin JE, Bull AMJ. Erratum to: An optimization approach to inverse dynamics provides insight as to the function of the biarticular muscles during vertical jumping. Ann Biomed Eng. 2011;39:2476-2478. https://doi.org/10.1007/s10439-011-0340-3

[12] Cleather DJ, Bull AMJ. An optimization-based simultaneous approach to the determination of muscular, ligamentous, and joint contact forces provides insight into musculoligamentous interaction. Ann Biomed Eng. 2011;39:1925-1934. https://doi.org/10.1007/s10439-011-0303-8

[13] Cleather DJ, Bull AMJ. Lower-extremity musculoskeletal geometry affects the calculation of patellofemoral forces in vertical jumping and weightlifting. Proc Inst Mech Eng [H]. 2010;224:1073-1083. https://doi.org/10.1243/09544119JEIM731

[14] Price PDB, Gissane C, Cleather DJ. Reliability and minimal detectable change values for predictions of knee forces during gait and stair ascent derived from the FreeBody musculoskeletal model of the lower limb. Front Bioeng Biotechnol. 2017;5:74. https://doi.org/10.3389/fbioe.2017.00074

[15] Southgate DF, Cleather DJ, Weinert-Aplin RA, et al. The sensitivity of a lower limb model to axial rotation offsets and muscle bounds at the knee. Proc Inst Mech Eng [H]. 2012;226:660-669. https://doi.org/10.1177/0954411912439284

[16] Cleather DJ, Bull AMJ. Influence of inverse dynamics methods on the calculation of inter-segmental moments in vertical jumping and weightlifting. Biomed Eng OnLine. 2010;9:74. https://doi.org/10.1186/1475-925X-9-74

[17] Cleather DJ, Bull AMJ. Knee and hip joint forces: Sensitivity to the degrees of freedom classification at the knee. Proc. Inst. Mech. Eng. [H]. 2011;225:621-626. https://doi.org/10.1177/0954411911399975

[18] lein Horsman MD, Koopman HFJM, van der Helm FCT, et al. Morphological muscle and joint parameters for musculoskeletal modelling of the lower extremity. Clin Biomech. 2007;22:239-247. https://doi.org/10.1016/j.clinbiomech.2006.10.003

[19] de Leva P. Adjustments to Zatsiorsky - Seluyanov's segment inertia parameters. J Biomech. 1996;29:1223-1230. https://doi.org/10.1016/0021-9290(95)00178-6

[20] Crowninshield RD, Brand RA. A physiologically based criterion of muscle force prediction in locomotion. J Biomech. 1981;14:793-801. https://doi.org/10.1016/0021-9290(81)90035-X

[21] Raikova RT. Investigation of the influence of the elbow joint reaction on the predicted muscle forces using different optimization functions. J Musculoskelet Res. 2009;12:31-43. https://doi.org/10.1142/S021895770900216X

[22] Cleather D, Cushion E. Muscular coordination during vertical jumping. 2019 [cited 2019 Nov 7]; Available from: https://osf.io/preprints/sportrxiv/68mnd/.

[23] Cleather DJ. Principal component analysis of landing strategies with a medially or laterally loaded tibiofemoral joint. SportRxiv; 2019.

Cite this article as:

Cleather DJ.
Neural network based approximation of muscle and joint contact forces during jumping and landing
J Hum Perform Health. 2019;1(1):f1-13
doi: 10.29359/JOHPAH.1.4.06