Predicting Athlete Ground Reaction Forces and Moments from Spatio-temporal Driven CNN Models

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Abstract—The accurate prediction of 3D ground reaction forces and moments (GRF/Ms) outside the laboratory setting would represent a watershed for on-field biomechanical analysis. To extricate the biomechanist’s reliance on ground embedded force plates, this study sought to improve on an earlier Partial Least Squares (PLS) approach by using deep learning to predict 3D GRF/Ms from legacy marker-based motion capture sidestepping trials, ranking multivariate regression of GRF/Ms from five convolutional neural network (CNN) models. In a possible first for biomechanics, tactical feature engineering techniques were used to compress space-time and facilitate fine-tuning from three pre-trained CNNs, from which a model derivative of ImageNet called ‘CaffeNet’ achieved the strongest average correlation to ground truth GRF/Ms $r(F_{mean})$ 0.9881 and $r(M_{mean})$ 0.9715 ($rRMSE$ 4.31 and 7.04 %). These results demonstrate the power of CNN models to facilitate real-world multivariate regression with practical application for spatio-temporal sports analytics.

Index Terms—Biomechanics, Supervised learning, Image motion analysis, Pattern analysis.

I. INTRODUCTION

Conventional methods to generate GRF/Ms data required for the accurate estimation of joint forces and loads are confined to biomechanics laboratories far removed from the sporting field of play. This has been an ongoing frustration for sports biomechanists, who must forego the eco-logical validity of field-based data collections and manage the constraints of synthetic laboratory environments to accurately model musculoskeletal loading parameters (Figure 1) [1], [2]. In the laboratory, biomechanists commonly rely on gold standard marker-based passive retro-reflective systems which utilize high-speed modified video cameras (up to 2,000 Hz) that project strobes of infrared (IR) light onto small spherical retro-reflective markers attached to a participant’s body [1], [3]. The typical error of such systems for dynamic sporting movement is cited at < 2 mm [4]. Alongside motion data, it is common practise to capture synchronized GRF/Ms (shear

Fig. 1. Laboratory motion and force plate data capture overlay. The eight labeled markers used are shown artificially colored and enlarged, and visible through the body. The force plate is highlighted blue, and the ground reaction forces and moments depicted.

forces F_x , and F_y , vertical force F_z , and their corresponding rotation moments M_x , M_y and M_z) as measured by transducers located in the four corners of the force platform (Advanced Mechanical Technology Inc., Watertown, MA, USA).

An increasingly popular approach to on-field data capture is to instrument the player with wearable sensors, with early examples of basic in-shoe pressure sensors and instrumented force shoes [5], [6], [7] evolving to current athletes wearing inertial sensors on multiple body segments [8], [9], [10]. However, the linear modeling applied to the sensor outputs from current wearable devices tends to overfit a particular movement (*e.g.* simple gait), or favor the vertical force (F_z) component only [11].

From a sports injury perspective, rupture of the anterior cruciate ligament (ACL) can be one of the most serious for the community and professional athlete [12], with up to a reported 80 % incidence rate being non-contact in nature, and

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80 % of these events occurring during a sidestep or single-leg landing maneuver [13], [14]. Studies cite elevated knee joint moments (KJMs) as a primary indicator of ACL injury risk [15], [16], and given that the most common approach to estimating KJMs is via inverse dynamics methods that require GRF/Ms input, data of these type are an obvious candidate for further investigation.

Previous computer vision and data science researchers have attempted to estimate GRF/Ms, however studies suffer from poor validation to ground truth data, are not sports related [17], [18], [19], require a full body modeling protocol with multiple inputs [20], or as before, predict only unidirectional GRF components (*e.g.* vertical F_z) [21]. Further, machine learning approaches in biomechanics appear to be limited to simple models and small sample sizes [22], [23], [24], [25].

Prior to this study, our team developed a prototype using a class of supervised multivariate regression, PLS [26], [27], chosen because of its characteristic to perform well with many predictor variables but limited samples. PLS works by projecting to a lower dimensional space where the covariance between predictor and response variables is maximized, and more recently, sparse PLS techniques have emerged which can better deal with multivariate responses when some of the predictor variables are noisy [28].

The success by Johnson *et al.* [27] of the initial PLS study encourages further investigation employing deep learning techniques, in particular CNN variants under frameworks such as Caffe (Convolutional Architecture for Fast Feature Embedding), TensorFlow and Torch [29], [30], [31]. The origins of many current deep learning approaches can be traced to recent ImageNet Large Scale Visual Recognition Challenges, and hence their strength in computer vision feature classification [32], [33]. Despite the fact motion capture is, by definition, spatio-temporal in nature, fine-tuning of existing image-based models such as AlexNet, CaffeNet, and GoogLeNet provides an opportunity to leverage training at scale, only needing to re-train selected higher-level components [34].

The contribution of this study is to investigate if pre-trained CNN models can be transferred to improve 3D GRF/M predictions beyond what was achieved by PLS, using a subset of marker trajectories extracted from legacy motion capture sidestepping trials. The accuracy and validity of the approach was assessed by comparing mean alignment between GRF/Ms derived from ground truth force plate data against those predicted by a series of new models, ranked by CNN method. It was hypothesized that fine-tuning of a pre-trained CNN model would outperform previous PLS accuracy results, particularly in the case of GRMs which demonstrate greater noise and non-linearity.

II. METHODS

A. Design and setup

This study was made possible by access to the motion capture trial archive of The University of Western Australia (UWA), in which data capture sessions were carried out in multiple laboratories over a 17-year period from 2001–2017 (Figure 2). No new data capture was undertaken. Most research

in the laboratory is sport-based, therefore all data included in this study was drawn from a young healthy athletic population aged between 16–35 years. Over this period, the number and type of infrared video cameras have changed (12–20 Vicon type MCam2, MX13, and T40S cameras; Oxford Metrics, Oxford, UK), as has the software to drive them (Workstation v4.6 to Nexus v2.5). However, selecting force platforms by specific types, as defined by the ‘coordinate 3D’ *c3d* file format (Motion Lab Systems, Baton Rouge, LA), meant the imported analog GRF/M data structures remained consistent. The force platforms in these laboratories are subject to annual calibration testing [35], therefore the source ground truth data was expected to contain a systematic error of the order GRF 1.4 % and GRM 1.6 %. The customized full-body UWA marker set has also evolved during this time to range from 24–67 markers. Pilot research revealed that a subset of only eight of these passive retro-reflective markers (C7; sacrum SACR; plus hallux MT1, calcaneus CAL, and lateral ankle malleolus LMAL of each foot) were required to maximize trial inclusion, relevance to the sidestep movement input, and GRF/M data output (Figure 1) [36].

B. Data preparation

The total *c3d* file archive at the time of this study contained 433,186 trials. Under UWA ethics approval RA/4/1/8415, processing of this data was conducted using MATLAB R2017b (MathWorks, Natick, MA) in conjunction with the Biomechanical ToolKit 0.3 [37], Python 2.7 (Python Software Foundation, Beaverton, OR) and R 3.4.3 [38], running on Ubuntu v16.04 (Canonical, London, UK). Desktop PC hardware included a Core i7 4GHz CPU, 32GB RAM, and NVIDIA Titan X GPU (NVIDIA Corporation, Santa Clara, CA).

The data preparation phase was designed to avoid gaps or errors from the motion capture marker trajectories and force plate analog channels contaminating CNN model training [4], [35]. The eight nominated marker trajectories were required to be contiguous and labeled (Figures 3 & *fig_tbme_supp*), and force plate channel data fully present, both for one complete stance phase that was defined by foot-strike (FS) to toe-off (TO) of the right stance limb. FS and TO were automatically determined in accordance with previously published biomechanical methods [39], [40], [41] (calibrated F_z rising above 20 N for 0.025 s, and subsequently falling below 10 N), which facilitated stance phase normalization by cubic spline interpolation. The PLS prototype was used to inform specific inclusion time-bases. Consequently, trajectory data was scaled from minus 66 % before FS to TO (125 samples) and force plate data minus 16 % before FS to TO (700 samples). Despite its smaller time-base, the larger number of force plate scaled samples reflected its higher relative data capture frequency compared with marker trajectories. Experimentally derived filters were used to eject duplicate and invalid capture samples (based upon marker trajectories z , x for relevant calcaneus markers; GRF/Ms F_z and M_z), regardless of earlier filtering (raw or processed analog outputs), whether the movement was planned or unplanned, FS technique, stepping crossover or regular. Movement trials passing all tests were admitted to the

Fig. 2. Study overall design.

Fig. 3. Training-set eight marker trajectories, sidestep left movement type (off right limb), combined 1,884 predictor samples.

data-set using predictor X and response y array formats typical of multivariate regression [28]. For information only, the final proportions of data-set participants were male 59.1 %, female 40.9 %, height 1.77 ± 0.098 m, and mass 73.9 ± 14.5 kg.

C. Feature engineering and model training

A number of CNN regression models were trained from a random shuffle and split of the data-set using a single fold (training:test). An 80:20 split was used for all methods except GoogLeNet for which a 90:10 ratio was required due to resource limits. Within time constraints, but to check for overfitting [42], one model was tested over 5-folds whereby each member of the data-set was a participant of each of the five test-sets only once. The single movement type sidestep left was selected, both for its task complexity (*i.e.* non-planar) but also due to its relevance to knee injury. The total number of sidestep left trials from the archive which were successfully admitted to the data-set was 2,355, which translated to a training-set of 1,884 and a test-set of 471 samples. The large drop-off from the original archive was dominated by incomplete marker labels (85.5 %).

A prototype had earlier been developed using a number of PLS variants, in which R-spls Sparse SIMPLS was demonstrated as the strongest PLS method for this data and is included here for comparison [28], [27].

CNN network learning speed is increased when the data structures follow a funnel topology, with more input predictor features than those of the output response. Due to its analog technology, and higher sensitivity requirements, force plate data is captured at a higher frequency than motion trajectory data which resulted in more output response features than predictor inputs. Therefore, a variety of dimensionality reduction protocols were assessed including Principal Component Analysis (PCA), Fast Fourier Transform (FFT), and PLS [43], [44]. PCA with tuning threshold t 0.999 was selected for its

compression accuracy with this data type, which for example with CaffeNet translated to 113 internal components and a ceiling of $r(F_{mean})$ 0.9997 and $r(M_{mean})$ 0.9979.

To be presented to the CNN for fine-tuning, the training-set input marker trajectories were converted from their native spatio-temporal state to a corresponding set of static images [45], [46] (Figure 4). The coordinates of each marker (x, y, z) were mapped to the image additive color model (R, G, B), the eight markers to the image width, and the 125 samples to the image height. CaffeNet for example requires input images to have dimensions 227×227 pixels, and the resultant 8×125 image was warped to suit the particular CNN model using cubic spline interpolation. By freezing space and time, fine-tuning could be achieved from CNN models pre-trained on image data at scale, which means the new models were able to learn despite the relatively low sample sizes and without the complexity of Long-Term Short Memory (LSTM) layers. Fine-tuning networks were selected based on their performance and proximity of original training to the current investigation, therefore those trained on the ImageNet classification problem such as AlexNet, CaffeNet and GoogLeNet were apparent candidates (*e.g.* CaffeNet having been trained on 1.3 million ImageNet images and 1,000 object classifications). Because of its deeper layers relative to available hardware resources, it was necessary to throttle GoogLeNet via smaller batch sizes, and a 90:10 training:test split, processing limitations which prohibited investigation of additional dense networks. Waveform output (rather than the more common object classification) was achieved by replacing the last SoftMax loss with Euclidean loss thereby turning the classifier into a multivariate regression network [47], [48]. All fine-tuning was carried out with the network output reduced via PCA. Additionally, for CaffeNet, the training-set output GRF/M data was deinterlaced into its component waveforms ($F_x, F_y, F_z, M_x, M_y, M_z$), and the training process executed six times.

Fig. 4. CNN fine-tune training (CaffeNet shown), input marker trajectories converted to static images, output GRF/Ms 6-way deinterlaced PCA reduced.

TABLE I
REGRESSION MODEL PERFORMANCE INVESTIGATION, MARKER-BASED MOTION CAPTURE TO GRF/M¹

Regression model	F_x $r \ (rRMSE \ %)$	F_y $r \ (rRMSE \ %)$	F_z $r \ (rRMSE \ %)$	M_x $r \ (rRMSE \ %)$	M_y $r \ (rRMSE \ %)$	M_z $r \ (rRMSE \ %)$	F_{mean} $r \ (rRMSE \ %)$	M_{mean} $r \ (rRMSE \ %)$
1. R-spls Sparse SIMPLS	0.9656 (8.16)	0.9793 (6.13)	0.9868 (6.35)	0.9281 (13.31)	0.9120 (11.44)	0.9238 (13.62)	0.9772 (6.88)	0.9213 (12.79)
2. CaffeNet	0.9770 (5.68)	0.9914 (4.19)	0.9927 (3.94)	0.9802 (8.23)	0.9629 (8.44)	0.9688 (6.52)	0.9870 (4.60)	0.9706 (7.73)
3. AlexNet	0.9762 (5.76)	0.9907 (4.43)	0.9920 (4.16)	0.9788 (8.50)	0.9591 (8.89)	0.9673 (6.95)	0.9863 (4.78)	0.9684 (8.11)
4. GoogLeNet, single 90:10 fold	0.9617 (8.89)	0.9762 (7.24)	0.9820 (7.19)	0.9398 (12.97)	0.9321 (12.23)	0.9514 (9.89)	0.9733 (7.77)	0.9411 (11.70)
5. CaffeNet, 6-way deinterlaced	0.9804 (5.18)	0.9911 (3.94)	0.9927 (3.82)	0.9764 (7.68)	0.9673 (7.37)	0.9709 (6.06)	0.9881 (4.31)	0.9715 (7.04)
6. CaffeNet, 6-way deinterlaced 5-fold	0.9770 (5.69)	0.9864 (4.18)	0.9913 (4.08)	0.9754 (7.59)	0.9694 (7.22)	0.9714 (6.20)	0.9849 (4.65)	0.9720 (7.00)

¹Movement type sidestep left, data-set 2,355 samples, single 80:20 fold unless stated.

All CNN outputs reduced by PCA.

Fig. 5. Learning curve (training loss), CaffeNet, 6-way deinterlaced, six models F_x , F_y , F_z , M_x , M_y , and M_z .

III. RESULTS AND DISCUSSION

The validity of this approach was tested by comparing the difference in accuracy between the ground truth 3D GRF/Ms recorded from the force plate with those predicted by each CNN regression model. To allow comparisons with the literature, two methods of agreement were used, that of correlation coefficient r and relative root mean squared error $rRMSE$ [49]. The mean of the average correlations (or errors) for F_x , F_y , and F_z , F_{mean} and similarly for M_x , M_y , and M_z , M_{mean} allowed for ranking of CNN methods using pairs of numbers (Table I).

The prototype using R-spls Sparse SIMPLS [27] had achieved an average of $r(F_{mean})$ 0.9772 and $r(M_{mean})$ 0.9213 ($rRMSE$ 6.88 and 12.79 %). The closest maximum in the literature using a comparable approach is that of Oh *et al.* [24] who reported $r(F_{mean})$ 0.9647 and $r(M_{mean})$ 0.8987 using a single hidden layer neural network and 48 samples, but for a more simple movement (gait analysis).

Fine-tuning of the selected pre-trained CNN models was investigated, first by training from six output vectors presented as interlaced waveforms and the single resultant array reduced by PCA. Here, CaffeNet proved the most successful with $r(F_{mean})$ 0.9873 and $r(M_{mean})$ 0.9704 (shown bolded in Table I, $rRMSE$ 4.60 and 7.73 %), with AlexNet in close proximity $r(F_{mean})$ 0.9864 and $r(M_{mean})$ 0.9685 ($rRMSE$ 4.78, 8.11 %). This ranking was expected given CaffeNet was designed to improve on AlexNet (by its reversal of the pooling and normalization layers). GoogLeNet came third in this analysis $r(F_{mean})$ 0.9733, $r(M_{mean})$ 0.9367 ($rRMSE$ 7.77, 11.70 %), however possibly unthrottled with additional GPU resources, it may return improved results on those presented here. All the fine-tune models achieved significant improvement on the ground reaction moments $r(M_{mean})$ when compared to R-spls Sparse SIMPLS (CaffeNet +5.4 %), illustrating the characteristic of CNNs to achieve stronger relationships in data with greater noise and non-linearity

compared with PLS and thus supporting the hypothesis.

The CaffeNet network was further analyzed. Deinterlacing the six output GRF/M waveforms and running PCA (with the same threshold t) and models for six iterations, resulted in further improved average correlations $r(F_{mean})$ 0.9880 and $r(M_{mean})$ 0.9715 (shown bolded, $rRMSE$ 4.31 and 7.04 %). Each model was run for 5,000 iterations although the learning curve illustrates the majority of training loss is removed by 2,500 iterations (Figure 5). The training-set, test-set mean, and test-set sample with the corresponding maximum $r(F_{mean})$ are shown (Figure 6). Finally, the CaffeNet PCA deinterlaced method was cross-validated over five k-folds. The similarity of the 5-fold results $r(F_{mean})$ 0.9849, $r(M_{mean})$ 0.9720 ($rRMSE$ 4.65, 7.00 %) with the earlier single-fold experiment indicated overfitting had been avoided.

A limitation of this approach is that despite data preparation best efforts, the method relied on the integrity of the original motion capture and force plate calibration and data capture in order to train an accurate CNN model. In all models investigated, PLS included, the strongest agreement with ground truth was demonstrated in the vertical (F_z) explained by the influence of mass and corresponding greater deviation on which to associate.

IV. CONCLUSIONS

Using the Caffe deep learning framework, multivariate regression of marker-based motion capture to 3D ground reaction forces and moments was compared via five CNN pre-trained models, each tested with sidestep left, this movement type being the most prevalent in the investigation's 17-year data archive. Tactical feature engineering techniques were used to compress spatio-temporal data and thus allow fine-tuning from three pre-trained CNNs (CaffeNet, AlexNet, and GoogLeNet). By leveraging the big data of the ImageNet database, the authors were able to deliver ground-breaking results from only 2,355 original data capture trials. This should encourage researchers who may think they do not have enough data for deep learning. For this movement-to-GRF/M application, this magnitude of trials could readily be captured with one sports team over a single training season.

The CaffeNet pre-trained CNN model, using dimensionality reduced and deinterlaced outputs, achieved the strongest average correlation to ground truth GRF/Ms with $r(F_{mean})$ 0.9881 and $r(M_{mean})$ 0.9715 ($rRMSE$ 4.31 and 7.04 %). The success of using CNN models to predict GRF/M output for a dynamically complex task advances the project beyond the earlier limitations of PLS and already offers the possibility of use-cases for biomechanical analysis where a force plate is undesirable (or unavailable). Driving the CNN model using marker-based motion capture is simply a necessary first step. Subsequent research using kinematics derived from wearable sensors (or even 2D video) will finally unlock the potential to liberate biomechanists from laboratory constraints and make accurate multidimensional in-game player analyses a reality.

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Fig. 6. Left, training-set force plate output F_x , F_y , F_z , M_x , M_y , and M_z , 1,884 samples versus stance phase. Middle and right, test-set ground-truth GRF/Ms (blue, ticks) and predicted response (red), using CaffeNet, 6-way deinterlaced. Middle, min/max range and mean predicted response; right, individual sample with the strongest $r(F_{mean})$.

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