ESTIMATION OF LOWER LIMBS KINETICS FROM LANDMARKS DURING SIDESTEPPING VIA ARTIFICIAL NEURAL NETWORKS

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The purpose of this study was to determine the validity of kinetics estimated from 3D coordinates of landmarks during sidestepping by artificial neural networks (ANN). 71 male college professional soccer athletes performed sidestepping with two directions (left and right) and two cutting angles (45° and 90°) 3times for every task, totally 12 times. Coordinates of reflective markers, ground reaction forces (GRF) and lower limb joint moments were measured. All 18 body landmarks such as joints center were obtained by reflective markers as inputs to estimate GRF and lower joint moments in the ANN whose type was multilayer perceptron. The most of kinetics estimated by ANN showed strong correlation(r>0.9) with measured results. Just few kinetic curves of ANN existed significant differences in a few time points compared to measured results. ANN could accurately estimate kinetics from the coordinates of body landmarks druing sidestepping.

KEYWORDS:kinetic, artificial neural networks, non-laboratory environment.

INTRODUCTION: Kinetics plays an important role in biomechanics, especially in sports injury. However, it's hard to collect kinetic in non-laboratory environment, because of the problem of instrument installation and signal transmission (Oh et al., 2013). As results, many studies selected modelling to estimate kinetics from kinematics. Artificial neural networks (ANN) were recently used to estimate kinetics successfully and get good validity compared by measured results (Mundt et al., 2018). The validity of ANN depends on the inputs mostly, but some inputs can't be obtained in non-laboratory environment. At present, the inputs mainly contained trajectories of anatomically relevant markers (Mundt et al., 2019) and accelerations of body segments (Johnson et al., 2021). However, the ways to obtain inputs above were sometimes infeasible especially in filed. Digitizing videos manually is the most traditional way to get kinematics which could resolve above problem, but it's time costly. In recent years, artificial intelligence (AI) such as Openpose could digitize video automatically to obtain the 2D coordinates of landmarks accurately (Cao et al., 2019), then the 3D trajectories such as joint and segment centres could be obtained from 2D landmarks in different views. Until now, there are few studies explore the validity of kinetics estimated by ANN when coordinates of landmarks as inputs.

The validity analysis of kinetics by ANN is not comprehensively. In the most relevant studies, correlation coefficient r, root mean square error (RMSE) and normalized root mean square error (nRMSE) are used to evaluate the performance of ANN (Mundt et al., 2019). This way just shows total error and fail to analysis the different time points of 1 dimension data such as ground reaction forces (GRF) curves between two methods. Statistical parametric mapping (SPM) could find the significantly different time points of biomechanical curves. So, SPM could be applied to analysis of ANN's validity to find the significant different time points during movement.

Therefore, the purpose of the current study was to determine validity of kinetics estimated by ANN when landmark coordinates as inputs. It was hypothesized that (1) kinetics estimated by ANN would be strongly correlated with measured results and there would be low error between two methods and (2) there would be no significant differences in kinetic curves between ANN's estimation and measured results.

METHODS: 71 male college professional soccer athletes (height=1.78±0.06m, mass=70.5±8.2kg) were recruited. This study was approved by the Ethics Committee of the

Beijing Sport University. Subjects executed sidestepping test with two direction (left and right) and two angle (45° and 90°) of change, total four ways of sidestepping as shown in Figure 1 and three trials per way of sidestepping. The motion was synchronously captured by eight infrared cameras (Motion Analysis Raptor-4, USA ,200Hz) and four forces plates (Kistler 9281CA, Switzerland, 1000Hz). The coordinates of anatomically relevant markers were filtered by butter worth low-pass whose cut-off frequency was 13.3 Hz (Yu et al., 1999) and 3D joint moments were calculated in Visual 3D (Version 2021, C-motion, USA). The stage of sidestepping was defined by vertical GRF with a threshold of 10N and 3D coordinates of markers and kinetics during sidestepping were normalized to 100 points. The GRF and joint moments were normalized by body weight (BW) and product of body weight and body height (BW·BH), respectively.

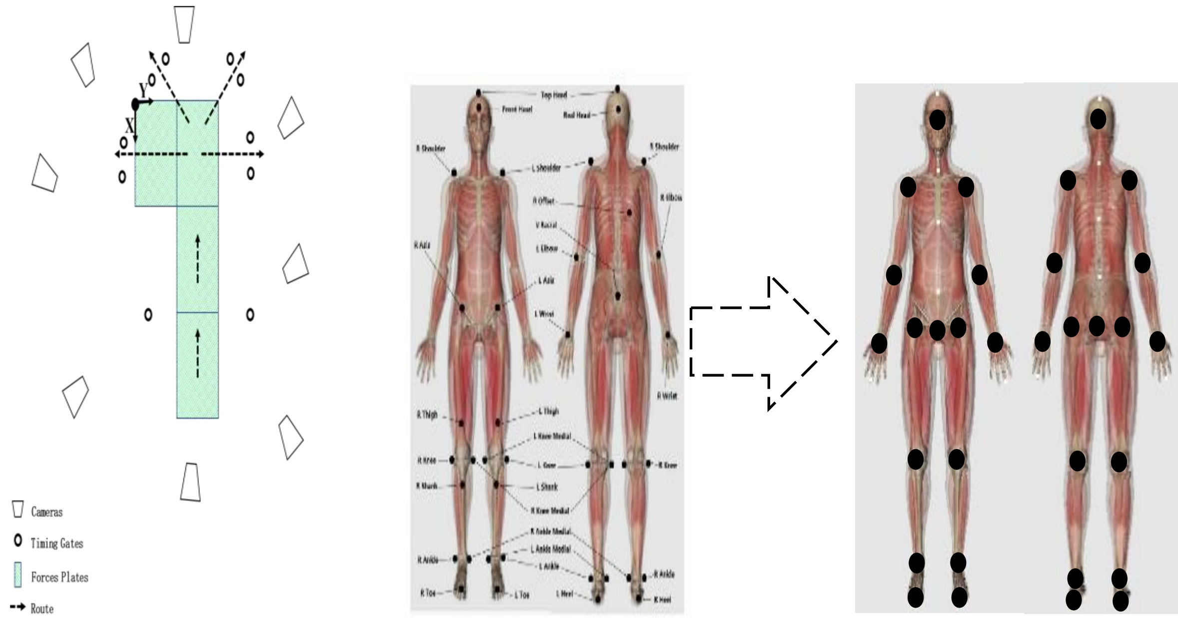

Figure 1: Setup of laboratory and placement of reflective markers and landmarks.

The 18 body landmarks were obtained by transforming the 29 anatomically relevant markers, as shown in Figure 1. The inputs were 3D coordinates of body landmarks (100x18x3) and the outputs were GRF and joint moments of stance lower limb(100x4x3). All subjects were randomly assigned into one of the training, validation and test set which the number was 61,6,4 respectively and all trials of one subject were in corresponding set. So there was no subject whose trials were in different sets. Finally, the number of training, validation and test set was 732,72,48 respectively. The ANN in this study was multilayer perceptron and its best hyperparameters were defined by grid search.The loss function in ANN was Mean Square Error (MSE) and 10-fold cross validation was used to reduce risk of overfitting. When the MSE of validation set stop decreasing more than time 10 epochs, ANN complete training. The final hyperparameter were as follows: learning rate (0.01), active function (LeakyRelu), optimizer (SGD), batch size (64), layers and nodes (3000-2500-1000).

Pearson correlation coefficient, RMSE and nRMSE which was normalized by dividing the range of measured results were used to evaluate the performance of ANN. The SPM was used to analysis significant differences of kinetic curves during sidestepping.

RESULTS: The performance of ANN was shown in Table 1, which showed most of kinetics was strongly correlated with measured results. About error, GRF showed low error, however a few joint moments showed large error (nRMSE>20%). The SPM showed there were few significant time points in anterior-posterior (10-11%, p=0.013;93-95, p=0.015) and vertical GRF (5-12%, p<0.001) and adduction-abduction (99-100%, p=0.015) and internal-external rotation (1%, p=0.017) moments of hip during sidestepping, and rest of kinetic curves didn't show significant differences between ANN and measured results.

Table 2: Performance of ANN.

		correlation coefficient (r)	RMSE	nRMSE (%)
	Anterior-Posterior	0.967±0.015	0.0791±0.0215	11.19±2.84
GRF	Lateral-Medial	0.940±0.028	0.0718±0.0398	13.49±5.20
	Vertical	0.957±0.022	0.2712±0.0747	11.52±3.46
	Flexion-Extension	0.938±0.030	0.0649±0.0269	13.92±5.55
Hip	Adduction-Abduction	0.883±0.056	0.0880±0.0456	19.01±7.5
	Internal-External Rotation	0.824±0.084	0.0476±0.035	21.46±11.96
	Flexion-Extension	0.942±0.032	0.0393±0.0238	14.97±6.74
Knee	Adduction-Abduction	0.862±0.081	0.0434±0.0203	18.23±9.28
	Internal-External Rotation	0.820±0.112	0.0253±0.0122	25.49±18.47
	Flexion-Extension	0.929±0.049	0.0215±0.0083	18.59±8.34
Ankle	Adduction-Abduction	0.838±0.129	0.0171±0.0081	24.17±10.94
	Internal-External Rotation	0.925±0.066	0.0231±0.0107	14.70±6.96

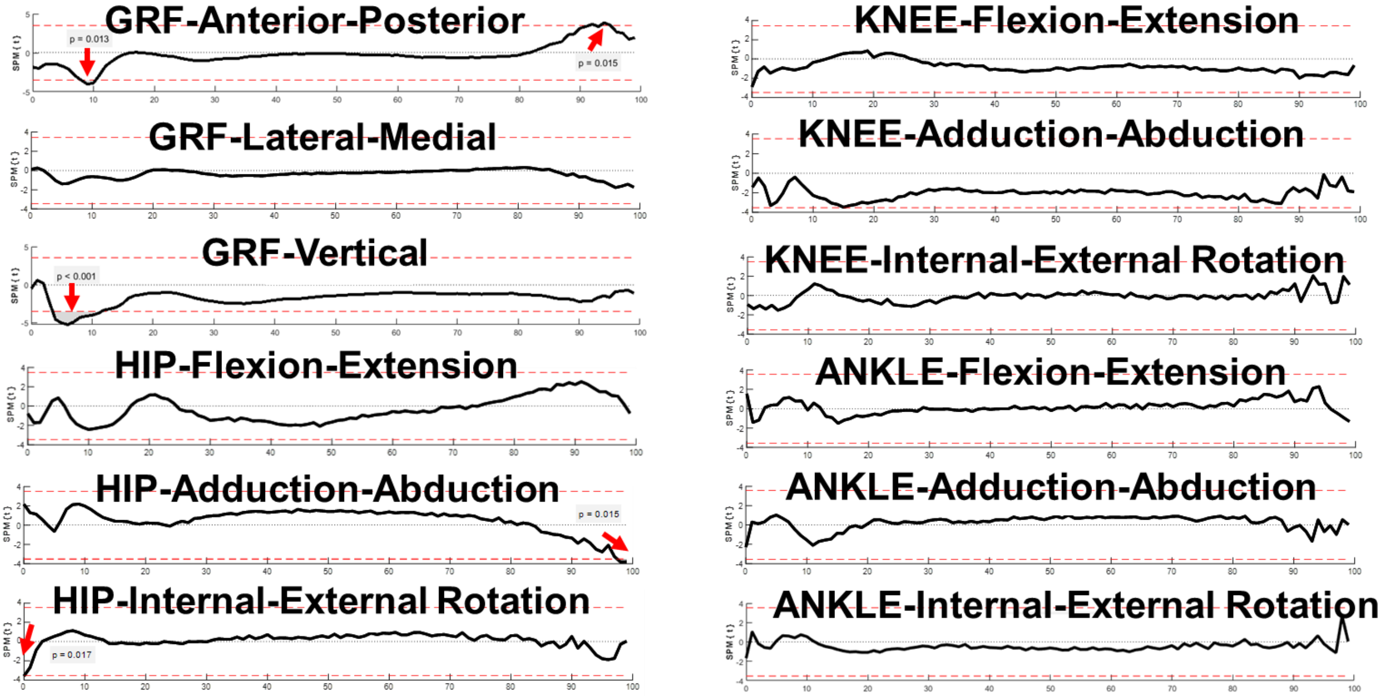

Figure 2: Results of SPM analysis.

DISCUSSION: The results in current study partially support hypothesis (1) that kinetics estimated by ANN would be strongly correlated with measured results and there would be low error between two methods. The GRF and flexion-extension moments of lower joints show strongly correlation and low error with measured results, which indicate body landmark contained enough information to estimate kinetics accurately in sidestepping by ANN. The results in this study are consistent with some previous relevant studies whose inputs were reflective markers' coordinates and accelerations (Johnson et al., 2021; Mundt et al., 2019), what's more, the number of body landmark in inputs was smaller than reflective marker in Mundt et al. (2019). Therefore, the ANN in this study is simpler and more convenient, and it's easier to apply in practise. Although the results in this study are a little inferior than other relevant studies about running and walking (Mundt et al., 2018), the reasons may be the characteristic of movements. Compared to walking and running, sidestepping showed more variability between subjects, which might make this task more difficult to estimate. Furthermore, there are four different tasks of sidestepping in data set which would increase

variance between trials. This hypothesis is supported by the higher accuracy found in those motion directions showing less variance (Fohrmann et al., 2020).
The results in current study partially support hypothesis (2) that there would be no significant differences in kinetic curves between two ANN's estimation and measured results. SPM shows that significant differences just exist few time points in GRF and hip moments, and it indicates coordinates of body landmarks could be used to estimate kinetic curves accurately during sidestepping by ANN. ANN mainly overestimate the first peak GRF in braking and vertical direction. Some previous studies found similar result in running (Komaris et al., 2019). This may be interpreted by the angle of direction change. Compared to 45° sidestepping, subjects may show higher braking GRF in 90° sidestepping and higher variance makes it overestimate. Although few time points exist significant error, the result of ANN in current study still could be used once the time points which need be used are not contain those time points above.
The main limitation of the current study is that the body landmarks are get from anatomical reflective markers, as results, the influence of error which is produced during AI digitizing automatically on estimation validity of ANN is not clear. Further studies are warranted to determine validity of kinetics estimated by ANN from the body landmarks digitized by AI.

CONCLUSION: The findings of this study indicates that ANN could accurately estimate kinetics from the coordinates of body landmarks. The most of kinetic curves estimated by ANN could be used to further analysis. Researchers could obtain kinetics from body landmarks in non-laboratory environment via ANN.

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