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Research article

BP neural network-based analysis of the applicability of NMF in side-step cutting

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A R T I C L E I N F O

Keywords:
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Factorisation method
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A B S T R A C T

Background: Although the spatio-temporal structure of muscle activation in cutting have been studied extensively, including time-varying motor primitives and time-invariant motor modules under various conditions, the factorisation methods suitable for cutting are unclear, and the extent to which each factorisation method loses information about movement during dimensionality reduction is uncertain.
Research question: To clarify the extent to which NMF, PCA and ICA retain information about movement when downscaling, and to explore the factorisation method suitable for cutting.
Methods: The kinematic data during cutting was captured with a Vicon motion capture system, from which the kinematic features of the pelvic centre of mass were calculated. NMF, PCA and ICA were used to obtain muscle synergies based on sEMG of the cutting at different angles, respectively. A back propagation neural network was constructed using temporal component of synergy as input and the kinematics data of pelvic as output. Calculation of the Hurst index using fractal analysis based on the temporal component of muscle synergy.
Results: The quality of sEMG reconstruction is significantly higher with ICA ($P < 0.01$) than with NMF and PCA for the cutting. The NMF reconstruction has a high degree of preservation of movement, whereas the ICA loses movement information about the most of the swing phase, and the PCA loses information related to the change of direction. Hurst index less than 0.5 for all three angles of cutting.
Significance: NMF is suitable for extracting muscle synergies in all directions of cutting. Information related to movement may be lost when using PCA and ICA to extract the synergy of cutting. The high individual variability of muscle synergy in cutting may be responsible for the loss of movement information in muscle synergy.

1. Introduction

Cutting is a common movement in basketball and football, requiring quick braking from a limited distance and rapid propulsion in a specified direction [1]. In recent years, the spatio-temporal regularities of muscle activation (muscle synergy) during cutting have been extensively studied [2,3]. These characteristics are generally obtained using linear decomposition methods based on the sEMG, such as non-negative matrix factorisation(NMF) and principal components analysis (PCA). The selection of factorisation methods often relies on assumptions about the properties of muscle synergies, such as non-negativity, orthogonality and statistical independence [4].

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However, due to the variability in the nature of the synergy in different movements (especially the combined synergies), the same factorisation method does not work equally well in different movements, and the choice of method needs to be based on the movement being studied [5]. Therefore, although the discrepancy between NMF, PCA and ICA has been studied extensively, the results of these studies do not apply to cutting manoeuvre, and the factorisation method that applies to cutting is unclear.

To express the quality of reconstruction of muscle activity before and after dimensionality reduction, the variance accounted for (VAF) is often used as an assessment criterion, which quantifies the percentage of variance in the sEMG signalsaccounted for by the muscle synergy [6]. A larger VAF suggests a better reconstruction of the recorded sEMG. However, using VAF is more controversial in motor control [7]. VAF does not ensure that the synergies can explain the experimental movement but only describes the quality of the reconstruction. In other words, VAF does not establish a link between synergies and movement. In addition, VAF is often calculated as an average indicator across trials, which results in its inability to assess the ability of muscle synergies to rebuild each trial [8–10]. Considering that the musculoskeletal system of the human body is highly non-linear, this further leads to the joint moments generated by the synergies not being realistic [11]. Therefore, there is a need for a new approach to select the factorisation method applied to cutting, one that satisfies the strong non-linearity of the musculoskeletal system but is also able to make a link between motor performance and the muscle synergy.

The pelvis is significantly associated with postural stability of the body during the change of direction (CoD), and therefore the kinematic characteristics of its centre of mass (CM) can describe the adjustment of postural stability by the CNS during cutting [12,13]. Based on the uncontrolled manifold hypothesis [14], this study aimed to build a link between muscle synergy and movement using a back propagation (BP) neural network and to investigate the extent to which the muscle synergy extracted by the three dimensionality reduction algorithms contained information relevant to movement [15]. The extent of information loss in the prediction of muscle synergies extracted according to different factorisation methods is discussed by comparing the differences between actual kinematic features and the predictions of BP neural networks, and which method better retains vital information related to the CoD are investigated to clarify the method applicable to cutting manoeuvre.

2. Methods

2.1. Participants

Power analysis was used to determine the reference sample size, and 21 subjects can ensure that the study has sufficient power to detect differences between task conditions (power = 80 %, $\alpha = 0.05$) [16]. 21 male participants (182.13 $\pm$ 4.12 cm, 74.25 $\pm$ 7.48 kg, 20.73 $\pm$ 3.67 yr) were involved in this study, requiring a history of football, basketball and other ball sports for at least seven years [17]. All subjects self-reported no neuromuscular or musculoskeletal impairments over a 6-month period, and the right leg (cut leg) was the dominant leg. Prior to the formal experiment, the researchers introduced the study protocol to the subjects and asked them to write an informed consent. The experiment was granted approval by the Ethics Review Committee of Beijing Normal University (TY202212088).

2.2. Data collection

In this study, ground reaction force (GRF) data were captured using a Kistler 3D force platform (1000 Hz, 9286AA, Winterthur, Switzerland) embedded in the ground. In addition, a Vicon 3D motion capture system (Oxford, UK) was used to captured kinematic features at a sampling rate of 200Hz. 38 markers attached to key anatomical landmarks on the body were used to track lower limb segments and joints., including feet(6), thigh(10), shank(8), pelvis(6), ankle(4), knee(4). After pre-processing for sEMG acquisition [18,19], the sEMG data of the following muscles were acquired at 2000 Hz using a Delsys sEMG apparatus (Boston, USA): tibialis anterior (TA), vastus lateralis (VL), rectus femoris (RF), tensor fascia latae (TF), external oblique abdominis (EO), rectus abdominis (RA), peroneus longus (LP), soleus (SO), medial head of gastrocnemius (GM), semitendinosus (ST), long head of biceps femoris (BF), gluteus maximus (GA), erector spinae (ES). ,

To prevent fixed running speed affecting the neuromuscular control strategy during cutting, participants were required to try to complete the cut task several times during the warm-up procedure. Participants were required to start with a self-paced velocity [20] at a location 6–7 m from the force platform in the formal experiment and to complete three different angles of cutting (45°, 90° and 135°), with three trials completed for each angle. To increase the precision of identifying the movement stages, the method of Ulrich et al. [21] was used to identify the timing of toe-off accroding to the kinematicsof the reflective marker placed at the second right metatarsal, which was used to identify the start and end of the cutting, while the timing of heel-strike was identified when the GRF >10 N. To further clarify the kinematics during cutting, the stance phase and swing phase of cutting were both normalised to 100 time points.

2.3. Data processing and analysis

The HP filtering (4th-order, 50 Hz), full-wave rectification and LP filtering (4th-order, 20 Hz) were used to preprocess the raw sEMG data to obtain its envelope curve, and amplitude normalisation was performed based on the global peaks of the signal [22].

The biomechanical characteristics of the cutting are similar to those of locomotion, and thus the pelvic CM height characteristics contain information on the CNS modulation of postural stability, so the pelvic CM height calculated by Visual3D (C-Motion, Germantown, MD) is used to describe the postural stability of the cutting [23]. The coordinates of the pelvic CM were estimated based on the coordinates of pelvic Markers obtained by Vicon motion capture system. As the CoD occurs after the pelvis is stabilised, the minimum height of the pelvic CM in the stance is taken as the starting point of CoD, and it is considered that from the start of the CoD point to the end of the stance contains key information about the cutting, which makes the cutting distinct from locomotion. Low-pass filtering of kinematic data with a IIR Butterworth zero-phase filter (4th-order, 20 Hz) [24].

2.3.1. *Extracting muscle synergy*

Muscle activation patterns (sEMG signals after preprocessing) ($\boldsymbol{x}$) can be divided into time-varying temporal structures (motor primitives, $\boldsymbol{P}$) and time-invariant spatial structures (motor modules, $\boldsymbol{M}$)

$$\boldsymbol{x} = \boldsymbol{MP} + \boldsymbol{e} \tag{1}$$

where $\boldsymbol{e}$ represents the relevant error generated during the reconstruction process, The matrix $\boldsymbol{x}$ represents the activity characteristics of the collected muscles (m) at normalised time points (n); $\boldsymbol{M}$ denotes the spatial distribution of $\boldsymbol{r}$ synergies across all acquired muscles; and $\boldsymbol{N}$ denotes the temporal variation of $\boldsymbol{r}$ synergies (Eq. (1)). In order to clarify the reconstruction quality of the three factorisation methods at different numbers of synergy, the range of values for r was determined to be 4–6 based on previous studies of cutting and locomotion [16,22]. The correlation between experimental activation patterns ($\boldsymbol{x}$) and reconstructed muscle activation patterns ($\boldsymbol{V}$) based on $\boldsymbol{MP}$ is commonly used to evaluate factorisation methods:

$$\boldsymbol{x} \approx \boldsymbol{V} = \boldsymbol{MP} \tag{2}$$

In NMF, the components M_i and P_i of $\boldsymbol{M}$ and $\boldsymbol{P}$ are assumed to be non-negative. This non-negativity is not only consistent with the physiological significance of muscle activation, but also allows the optimisation problem to be convective, making sure that the result is a global minimum rather than a local minimum. Iterative updating using the EM algorithm to improve the fit of $\boldsymbol{V}$ to $\boldsymbol{x}$ (Eq. (2)). Within 20 iterations, the iterations were closed when the update of R^2 was less than 0.01 % [25]. In PCA, the component P_i of $\boldsymbol{P}$ is assumed to be orthogonal, and the covariance of P_i is minimised while retaining as much of the original information as possible. Since PCA utilises the data's second-order statistics (variance and covariance), it is more suitable for non-linear data with Gaussianity and low noise [26]. ICA uses higher order moments (kurtosis) to deal with non-Gaussianity in the data, which makes the basis vectors P_i all independent of each other. The VAF was used to assess the reconstruction quality (Eq. (3)) of these three factorisation methods when synergies were 4, 5 and 6, respectively:

$$VAF = 100\% \times \left(1 - \frac{\|x - V\|^2}{\|x - \bar{x}\|^2}\right) \tag{3}$$

As the order of synergies extracted by NMF, ICA and PCA during cutting was not the same as the actual activation order, the centre of activity (CoA) was used to identify the order of synergy activation during the movement phase. The value of CoA during the cutting was computed based on circular statistics using a vector angle (1st triangular moment) in polar coordinates (the direction of the polar coordinates indicates the stage of cutting (Eq. (4)), the polar angle θ changes between 0 and 360°) pointing to the centre of mass of this circular distribution [27]:

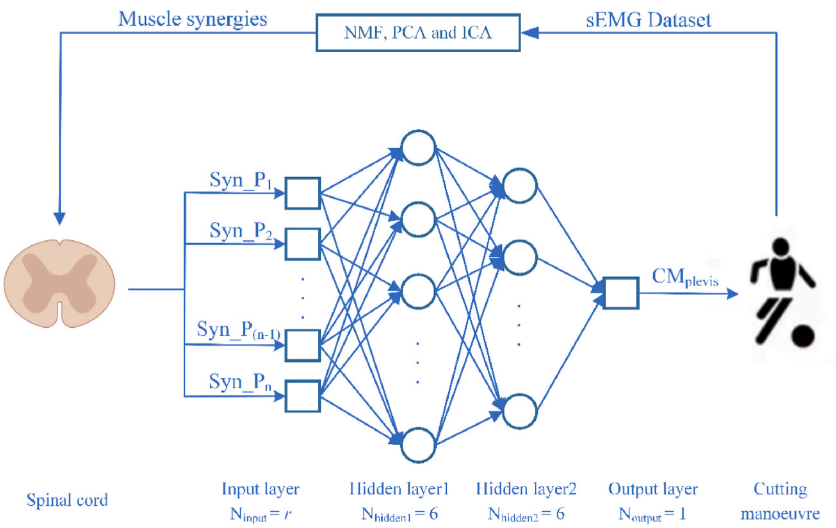

Fig. 1. Establishing the relationship between muscle synergy and movement based on BP network.

$$\begin{cases} A = \sum_{t=1}^{p} (\cos\theta_t \times P_t) \\ B = \sum_{t=1}^{p} (\sin\theta_t \times P_t) \\ CoA = \arctan(B/\mathrm{A}) \end{cases} \tag{4}$$

where p is the normalised data points in the cutting task and P is the time structure of each synergy.

2.3.2. Neural network construction

Considering the strong non-linearity of the human musculoskeletal system, this study employs a BP neural network to establish the connection between synergies and movement (the pelvic CM height) [28], as shown in Fig. 1.

Since the higher the number of synergies, the more sEMG information it contains, the motor primitives (Syn_P_i) obtained by the three factorisation methods at six synergies were selected as the input to the network, and the output was the pelvic CM height. There are initially 5 to 20 nodes in the two hidden layers.The node configuration with the lowest mean of mean square error (MSE) was found by performing a ten-fold cross-validation of each combination. To avoid network dependence on a certain factorisation method, mini-batch gradient descent based on a mixture of the three factorisation methods was used for training. The learning rate of the network is set to 0.01, and the threshold is that the absolute partial derivative of the error function is less than 0.01 in ten-fold cross-validation [29]. The predictive performance of muscle synergies extracted by the three dimensionality reduction algorithms was assessed using R^2, MSE and MAE (mean absolute error), respectively.

2.3.3. Fractal analysis

Although it has been shown that there is a large similarity in synergies between subjects in locomotion, cutting as a non-rhythmic movement may have some variability in synergies between individuals [30]. To clarify the degree of similarity of muscle synergies across different subjects in the cutting manoeuvre, a fractal analysis of the muscle synergy extracted by the best predictive factorisation method was further performed, and the Hurst index (H) was computed using the rescaled range analysis [31]. Fractal analysis is able to explore and identify the timing of changes in the characteristics of more complex systems and thus describe the natural complexity of such systems. Fractal analysis therefore facilitates the quantification of system patterns and the identification of situations when there is a deviation from the normal sequence of system. (H further quantifies the dependence of these deviations on time) [32]. If H is less than 0.5, this indicates a higher degree of oscillation of the motor primitives across the time series and a poorer similarity of muscle synergies characteristics across participants, while the opposite indicates a higher degree of similarity of muscle synergies characteristics across participants and similar synergy characteristics of cutting to ordinary locomotion.

2.4. Statistics

Normal distribution test was performed using SW test. Sphericity assumption test was performed using Mauchly sphericity test. Based on one-dimensional statistical parametric plotting (SPM1d), kinematic characteristics were compared based on one-way RMANOVA with Bonferroni when cutting at different angles, and paired t-tests were used to compared the difference between predicted and actual values of pelvic CM height.The level of significance was set at 0.05.

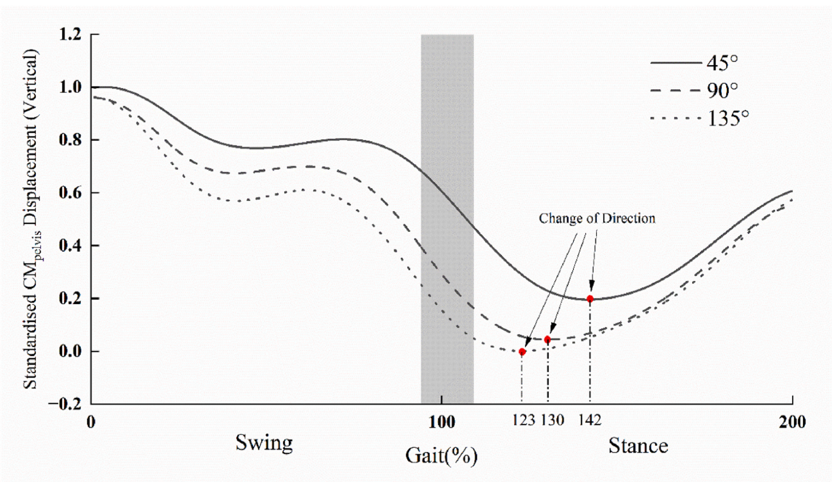

Fig. 2. The characteristics of the pelvic CM height at different angles (squares shaded indicate significant differences).

3. Results

3.1. The kinematic features of the pelvic CM

Fig. 2 shows the kinematic features of the pelvic CM during cutting. Near the moment of heel-strike (90%–109 %; shaded part), the height of the pelvic CM was significantly lower at 135° compared to 45° ($P < 0.02$). The pelvic CM of the 135° reaches the CoD point earliest after heel-strike, while the pelvic CM of the 45° reaches the CoD point only near the mid-stance, and its amplitude is relatively weak, indicating that the 45° cut has a lower demand for stability and is closer to locomotion.

3.2. VAF characteristics of three factorisation methods

Fig. 3 shows the VAF at 4, 5 and 6 synergies extracted by each of the three factorisation methods. The VAF for all three methods increased significantly ($P < 0.01$) as the numbers of synergy increased. The VAF of PCA at four synergies was significantly lower ($P < 0.01$), indicating poorer quality of reconstruction. The reconstruction quality of ICA at 45° and 90° was significantly higher than the remaining two methods ($P < 0.01$) when synergies were 5. When the number of synergies was 6, the reconstruction quality of ICA was significantly higher than that of PCA and NMF at all three angles ($P < 0.01$).

3.3. BP network prediction parameters for three factorisation methods

The BP network prediction parameters for the three factorisation methods are shown in Table 1. The prediction performance (R^2) of all three methods decreased significantly ($P < 0.01$) as the angle increased. Although the VAF of ICA was higher in all three angles, its R^2 was significantly lower than the other two methods ($P < 0.01$) and the MAE and MSE were significantly larger ($P < 0.01$).

3.4. Differences between BP network prediction and experiments

Fig. 4 shows the difference between predicted and actual pelvic kinematic features at different cutting angles. Differences between NMF-based predictions and experimental kinematic characteristics occurred mainly in the initial swing phase (1%–20 %, $P < 0.05$); similarly, differences between PCA-based predictions and experimental kinematic features also occurred in the initial swing phase (1%–25 %, P < 0.05). The ICA-based predictions differed more from the experimental kinematic characteristics and occurred in the most part of swing (1%–38 %; 56%–88 %; $P < 0.002$).

When the angle was 90°, the NMF-based predictions differed less from the experimental kinematic profile (1%–18 %; $P < 0.05$); the PCA-based predictions lost some of the key information about the cutting (171%–184 %; $P < 0.05$); and the ICA-based predictions differed more from the experimental kinematic profile (1%–80 %; $P < 0.001$). The results at 135° are similar to those at 90°: differences between PCA-based predictions and experimental kinematic characteristics occurred in areas containing key information (175%–187 %; $P < 0.05$), whereas NMF (1%–19 %; P < 0.05) and ICA focused on the early part of the swing phase (1%–30 %; $P < 0.05$).

3.5. Fractal analysis

The R/S curves of muscle synergy based on NMF at different angles are shown in Fig. 5. The H for all three curves was less than 0.5 [31], indicating that the activation of muscle synergy in the three angles had anti-persistent behaviour and were less similar.

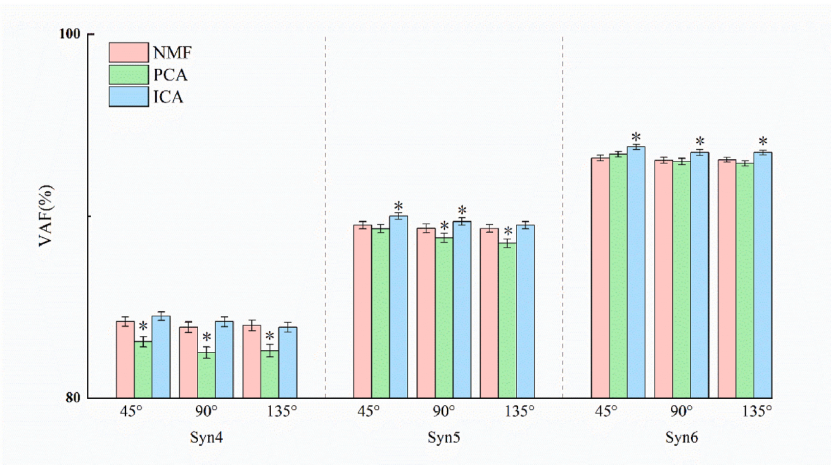

Fig. 3. VAF characteristics of the three factorisation methods at three muscle synergy numbers (* indicates that the method is significantly different from the other two methods).

Table 1
Prediction measures for three methods.

	45°Cut (Mean ± SD)			90°Cut (Mean ± SD)			135°Cut (Mean ± SD)		
	NMF	PCA	ICA[a]	NMF	PCA	ICA[a]	NMF	PCA	ICA[a]
R^2	0.77 ± 0.07	0.78 ± 0.05	0.46 ± 0.13	0.72 ± 0.09	0.73 ± 0.07	0.41 ± 0.14	0.66 ± 0.08	0.63 ± 0.07	0.46 ± 0.07
MAE	0.13 ± 0.01	0.12 ± 0.02	0.2 ± 0.02	0.14 ± 0.01	0.13 ± 0.01	0.21 ± 0.03	0.14 ± 0.02	0.15 ± 0.02	0.19 ± 0.02
MSE	0.02 ± 0.01	0.02 ± 0.01	0.05 ± 0.01	0.03 ± 0.01	0.03 ± 0.01	0.06 ± 0.01	0.03 ± 0.01	0.03 ± 0.01	0.05 ± 0.01

Note.
[a] represents a significant difference between this method and the other two methods.

4. Discussion

From a kinematic point of view, the adjustment of the pelvic CM to the change in cut-angle occurs before the change of direction (end-swing). According to Cesari et al. [33], this anticipatory adjustment will only be characterised in athletes with more cutting experience, mainly in terms of anticipatory postural changes in the hip and knee, which is a key factor in maintaining postural stability (low variability) during large angle cutting. Thus, the key information of the cutting occurs not only during the period from CoD point to the end-stance but should also include approximately 10 % of the period before and after heel-strike, which together constitute the uniqueness of the cutting.

From the VAF perspective alone, ICA is more suitable for cutting than PCA and NMF, as its reconstruction quality is higher at all three kinds of synergy compared to PCA and NMF. It should be noted, however, that VAF does not evaluate the extent to which key motion information is retained in the reconstructed data but only provides an observation of how well the reconstructed data fit the original sEMG data [6]. This study found that when predicting movement based on the reconstructed data, the prediction of ICA was significantly lower than that of NMF and PCA, and the error was relatively large, indicating that despite the high VAF of the reconstructed data of ICA, it contained less information on movement and could not recover the actual movement better. When the number of synergies was low, the differences between the different factorisation methods were greater, suggesting that the choice of method should be more focused when the number of synergies is low. In cutting studies, PCA should not be chosen as a suitable method if the number of synergies is lower.

Furthermore, although the VAF of the reconstructed data from the NMF is low compared to the ICA, it contains all of the key information about the cutting, and the loss of kinematic information is all concentrated in the initial swing, which does not affect the recovery of the actual movement. In contrast, the ICA loses most of the information about the swing, and its predicted motor performance differs more from the actual ones; the PCA loses the key information about the change of direction when predicting 90° and 135° cuts, and therefore its extracted synergies may lead to some errors when applied to the motor control study of cutting.

The study also found that synergies in cutting were less similar across subjects, contrary to the findings of Rabbi et al. [34] on locomotion. This suggests that although the cut resembles a variant of running in terms of motor performance, its synergies characteristics are closer to voluntary movement rather than rhythmic movements, i.e. has significant individual differences, which may be one of the reasons for the large discrepancy between the actual values and predictions [35].

In summary, NMF is more suitable for cutting, and its reconstructed motor primitives contain all the key information about the change of direction. However, this does not mean that PCA and ICA are of low value for application; the choice of factorisation method relies heavily on assumptions about the nature of the synergy. The orthogonality and independence assumptions of PCA and ICA may favour the extraction of non-task-specific synergies [36], which, despite the relatively poor motor performance predicted on the basis of these synergies, may have a very important role in motor production.

Data availability statement

The data that support the finding of this study are available on request from the corresponding author. The data are not publicly available due to privacy or ethical restrictions.

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CRediT authorship contribution statement

Zhengye Pan: Writing – review & editing, Writing – original draft, Validation, Software, Project administration, Methodology, Data curation, Conceptualization. **Lushuai Liu:** Data curation. **Xingman Li:** Data curation. **Yunchao Ma:** Writing – review & editing, Supervision, Resources, Funding acquisition, Conceptualization.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to

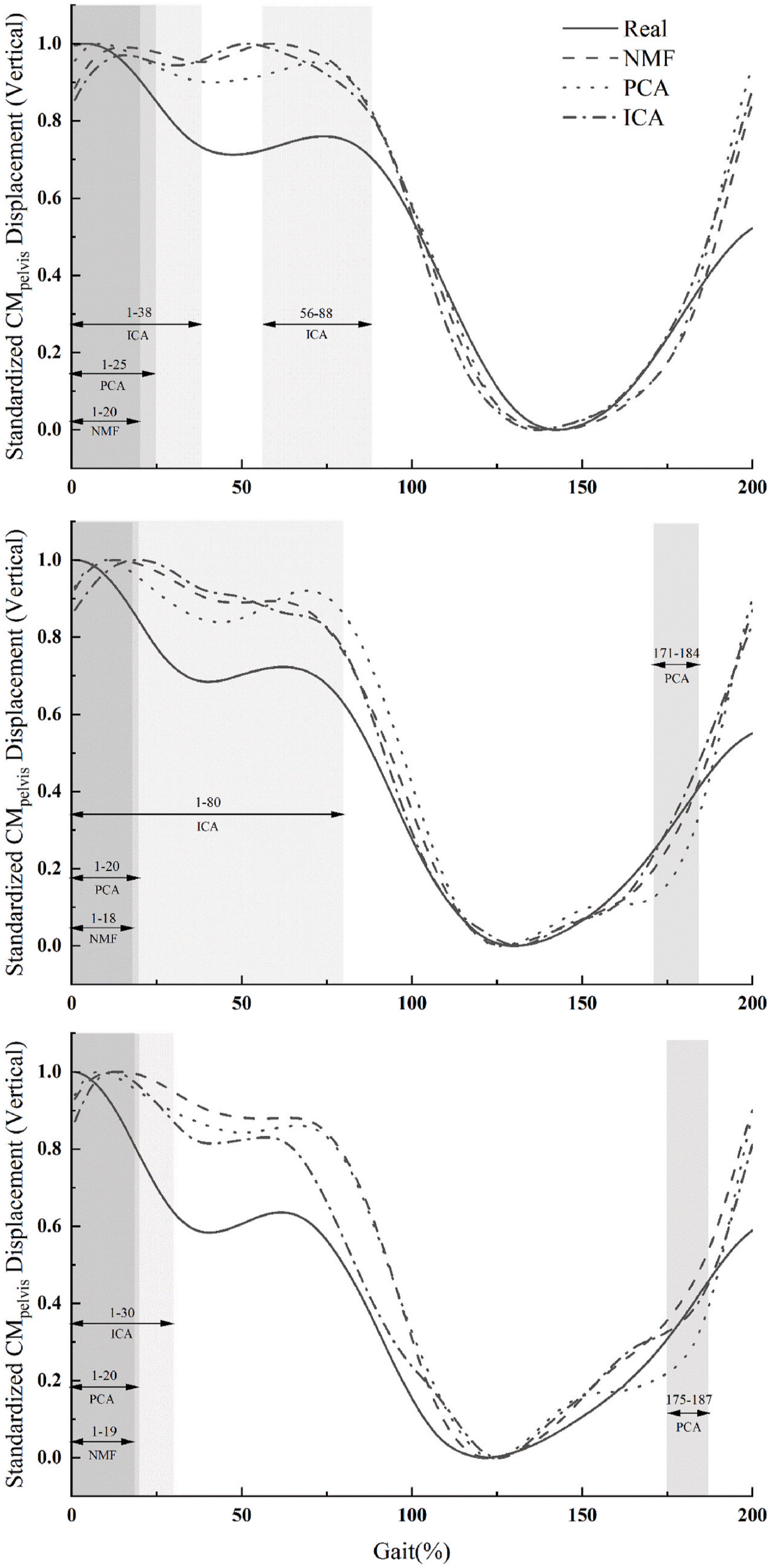

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Fig. 4. Predicted versus experimental characteristics of the pelvic CM (shaded areas are where the predicted curve differs significantly from the experimental curve for each factorisation method)(From top to bottom:45°, 90° and 135°).

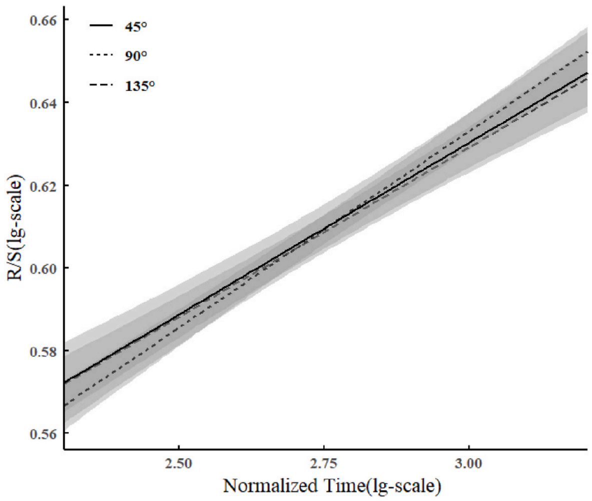

Fig. 5. R/S curves (Mean ± SD) of muscle synergy based on NMF at different angles.

influence the work reported in this paper.

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