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Recurrence analysis discriminates martial art movement patterns

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Abstract We aimed to determine whether the combined application of principal components and recurrence quantification analyses might serve to discriminate both spatial and temporal differences between backwards-forwards movement patterns. Elite ($n = 9$) and nonelite ($n = 9$) martial artists were recorded using motion capture techniques and features of whole-body movement defined at the segment level were investigated by principal components analysis. For both groups of subjects, four movement components explained $> 90\%$ of the variability in the data. Given our interest in temporal patterning, the time series derived from scores for each of the principal components were subsequently subjected to recurrence quantification analysis, participant by participant. For the first movement component, statistically significant differences between groups were detected for the recurrence measure determinism ($p < 0.05$). For the third movement component, statistically significant differences were detected for the recurrence measures laminarity and maxline ($p < 0.01$). Hence use of a combination of principal components and recurrence techniques revealed quantitative differences between movements of the two subject groups, differences that may represent more skilled motor control in the elite group related to the functional importance of these apparently simple movement patterns.

Abbreviations

AP	Anterior–posterior
CoM	Centre of mass
%DET	% Determinism
DIS	Distributed
ENT	Entropy
%LAM	% Laminarity
MAXL	Maxline
ML	Medio-lateral
PCA	Principal components analysis
PM	Principal movement
RP	Recurrence plot
RQA	Recurrence quantification analysis
SEM	Standard error in the mean
V	Vertical

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1 Introduction

Human movements are the consequence of many neural, muscular and skeletal components working together to achieve the desired outcome. Whilst a typical study may involve an investigation of body kinematics, the aim ultimately is to understand the mechanisms underpinning a movement and the neuromuscular strategies and synergies that serve to express the spatial and temporal features of intersegment coordination. The essence of some movements may be captured by the use of simple kinematic techniques applied to, for example, a single limb; in other cases, investigation of the entire set of body segments is required.

Given our interest in whole-body coordination in the movements of martial artists, we adopted the approaches of previous researchers [1–3] for this study and applied principal components analysis (PCA) to the centre of mass coordinates of the set of body segments. This method has conceptual and practical advantages: it reduces a high-dimensional dataset to a lower-dimensional set of independent components that is taken (on the basis of the extent of variation) to represent the more important features of the data structure [4]. Whilst the starting data variables are normally highly correlated, the derived principal components are independent of each other. The contributions of the original variables to a given principal component are represented by their derived coefficients. In our case, these coefficients were related to the centre of mass body segment coordinates, and the set of coefficients indicated the forms and extents of collaboration amongst body segments over the entire time course of a particular principal movement.

It appeared quite unsatisfactory that the temporal dynamics of investigated movements had not been accounted for in deriving coefficient values, though time courses of the derived components were contained in the corresponding unidimensional scores [3]. We, therefore, investigated the temporal structures of these scores by plotting and quantification of recurrences [5].

The recurrence method is a nonlinear approach to analysis that involves unfolding time series data within a multidimensional manifold [6]. It has provided insights into quite a variety of systems and situations from variations in body posture to ecological and climate transitions to metal fracture [6–16]. The steps in recurrence analysis are represented in Fig. 1d–g. Time-dependent signals that have been re-represented in multidimensional space are characterized as the pattern of revisits of the movement trajectory to sub-regions of that space. The revisits are known as *recurrences* and are a fundamental property of dynamical systems [5, 17]. The fundamental equation for the recurrence matrix is provided below and described in detail in Ref. [5]:

$$\boldsymbol{R}_{i,j} = \theta(\varepsilon - \|\overrightarrow{x_i} - \overrightarrow{x_j}\|), \quad i, j = 1, \ldots N, \tag{1}$$

where $\boldsymbol{R}$ is the recurrence matrix, θ is the Heaviside function, ε is a predefined threshold distance, $\|\bullet\|$ is a norm, $\overrightarrow{x_i}$ and $\overrightarrow{x_j}$ are the measured states (represented by m-dimensional state vectors) of the system at times i and j, and N is the number of observed states. Recurrence quantification analysis (RQA) produces a series of measures quantifying the small-scale graphical patterns in a recurrence plot (RP), thereby allowing in-depth description of (in our case) movement patterns, both generally and in relation to athletic performance (Fig. 1f and g) [5, 17]. The RQA measures are presented in Sect. 2 and reviewed in Sect. 4.

Analysis of movement patterns of taekwondo players has been the subject of various studies aimed at informing coaches on technique development and player performance in competition. Researchers have, for example, investigated intra-limb coordination [18–20], patterns of kicking [21] and impact force characteristics for the most common kicks [22, 23]. We extended the investigation of taekwondo movement to the backwards-forwards movements that are the basis for the development of defensive and attacking actions by a player. We have previously carried out simple kinematic analyses of backwards-forwards movements and have found no differences between nonelite and elite groups of players. We, therefore, applied the alternative and more elaborate analytical approach presented in this report (PCA followed by RQA) to investigate potential differences in these movements for players of nonelite and elite status. The recurrence method was applied to determine differences in the temporal organization of PCA data. In summary, we asked whether an alternative form of data analysis might discriminate taekwondo movement patterns by skill level with the aims of assisting coaching practice and relating taekwondo coordination to its underlying neuromuscular control. We postulated differences in coordination patterns between elite and nonelite taekwondo players. Specifically, we hypothesised that RQA measures of principal movements would reveal differences in the temporal structure of coordination between players of different skill level.

2 Materials and methods

2.1 Participants and experimental protocol

Eighteen elite and nonelite taekwondo players were recruited for this study (mean ± standard error in the mean (SEM); elite (8 males and 1 female; age = 27.0 ± 0.4 y, mass = 74 ± 1 kg, height = 1.7 ± 0.1 m) and nonelite (9 males; age = 35.0 ± 0.1 y, mass = 86 ± 3 kg, height = 1.8 ± 0.1 m). The elite taekwondo players had competed at a minimum of A-class international and national levels for at least eight years. The nonelite taekwondo players practised taekwondo at a recreational level and had a maximum of three years' experience. The experimental protocol was given approval by London South Bank University Research Ethics Committee, and all players provided written informed consent prior to taking part in the study.

The stance used during backwards-forwards movement is called *fixed stance*. The legs are split one and a half shoulder widths apart, and the body is turned side-on to the opponent. The front foot is aligned with the player-opponent axis while the back foot is twisted to be approximately perpendicular to that axis. The body weight is shared evenly by the two legs (Fig. 1a). The players performed individualized warm-ups for 15 min. Following this, after a brief rest period, players performed the simplest of backwards-forwards movements over a two-minute period from visual commands, mimicking a competition situation.

2.2 Data collection and analysis

To determine the movement kinematics of the taekwondo player during backwards-forwards movements 12-mm diameter retroreflective markers were placed on the skin over anatomical landmarks (Table A1, Appendix A) and the 3D coordinates of these markers were tracked using a motion capture system (Oqus 3-Series, Qualisys AB, Gothenburg, Sweden). Each body

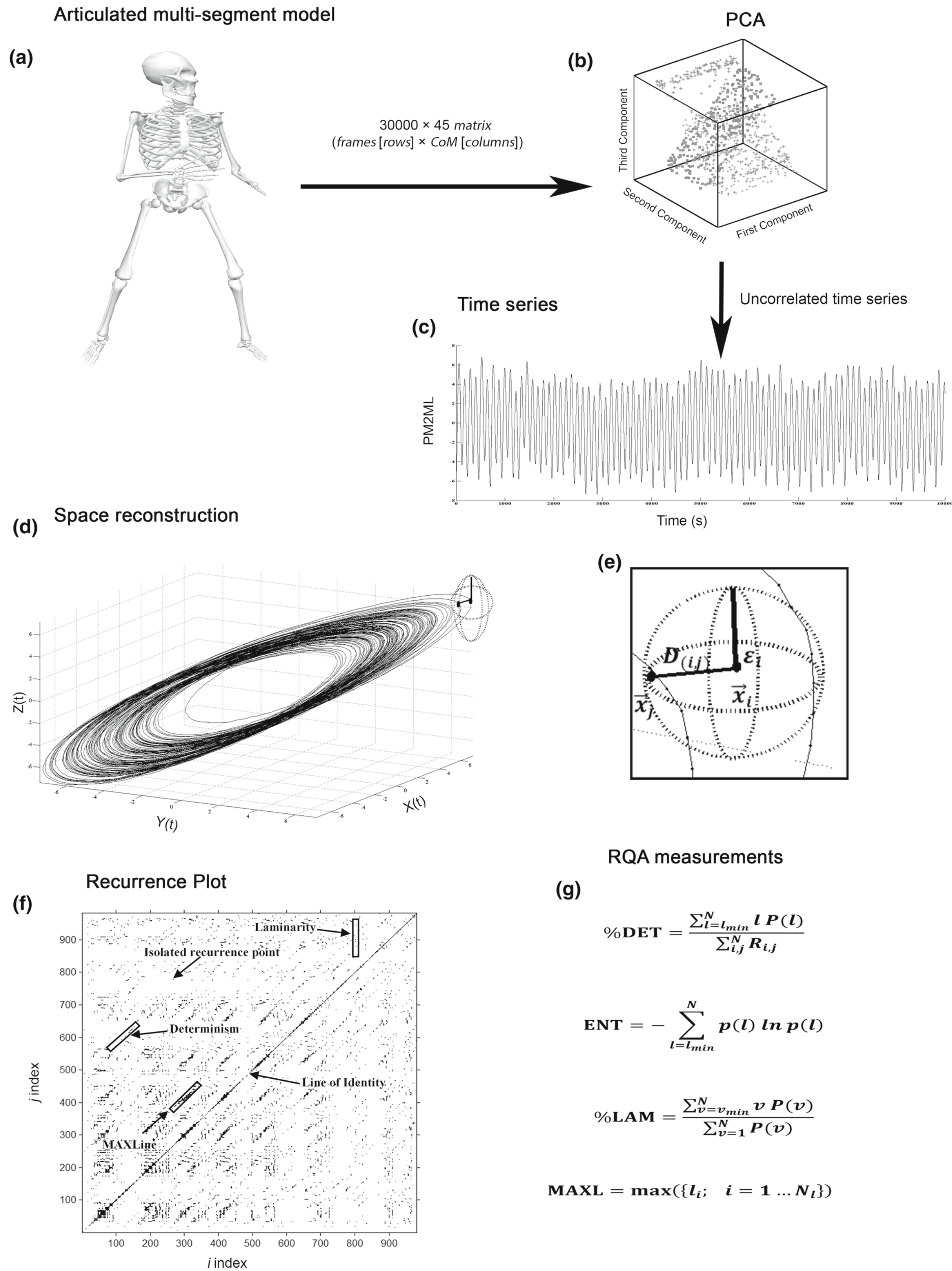

Fig. 1 Graphical presentation of the methods applied to backwards-forwards movement data, illustrated for a single player. **a** Backwards-forwards movement centre of mass displacements obtained from an articulated multi-segment system. **b** Calculation of PCA on the centre of mass displacements of 15 rigid segments. **c** A principal movement (PM) describing the behaviour of the whole body (PM2ML). **d** State space reconstruction in 3D of the structure of a dynamical system for a single PM. **e** Calculation of the radius of the neighbourhood in which recurrent states occur. **f** Recurrence plot of one of the PMs. **g** RQA measures used in this study: determinism (%DET), entropy (ENT), laminarity (%LAM) and maxline (MAXL)

segment (15 in total; Table B1, Appendix B) was modelled in line with previously reported standards for tracking the upper [24] and lower [25] extremities, with slight modifications to suit this research [20]. Marker trajectories were collected at 300 Hz. The data analysis for backwards-forwards movement had four main steps: (i) prescribing an articulated multi-segment system to obtain centres of mass of each of the body segments (Fig. 1a; Appendix B); (ii) principal components analysis (PCA) on the centre of mass coordinates of these segments to identify the main movement patterns for backwards-forwards movements (Fig. 1b and c); (iii) examination of temporal variability using recurrence techniques (RPs and RQA) by analysing the time series formed by the principal component scores (Fig. 1d–g); (iv) surrogate testing used to assess whether derived recurrence quantification measures were representative of bona fide nonlinear dynamics in the principal component signals or the product of random noise.

Prior to processing for PCA, the first and last 10 s of the centre of mass data were removed to eliminate the influence of transient motions. The submitted data length was 30,000 data points (100 s) for each player. Segment masses were quantified as a 30,000 × 45 matrix (frame [*rows*] × centre of mass [*columns*]). Each row of the matrix was interpreted as a 45-dimensional posture vector representing the centres of mass at a given point in time. The 45-dimensions represent mediolateral (ML), antero-posterior (AP) and vertical (V) directions for each of the 15 segments. Representations were cut off after the first four principal components since the summed eigenvalues reached a conventional standard of at least 90% of total variance [2] for both groups. MATLAB software was used for PCA calculations (MATLAB 2013a and Statistics Toolbox 8.1, The MathWorks Inc, Natick, MA, USA). The outputs from PCA are referred to as one-dimensional principal movements (PMs).

2.3 Data processing for recurrence plotting and analysis

The time series obtained by projecting the data onto the intrapersonal principal components were subjected to recurrence plot and recurrence quantification analysis (Fig. 1d–g). As the name suggests, both recurrence plotting and analysis seek understanding of the temporal structure of a time series in terms of recurring patterns in the data. The data are not, however, examined in their original dimension, rather they are "unfolded" into multiple dimensions. The first step in the process is the selection of a time scale for the analysis (τ), the second step is a derivation of the number of dimensions to be employed (m) and the final step is the setting of a distance criterion (ε, in m dimensions) for the revisiting (i.e. recurrence) of a region of phase space along the time-dependent data trajectory. The procedures have been described in detail in Refs. [5, 17].

A time delay of $\tau = 7$ was taken as the time of the first local minimum of the mutual average information function for the time series [26]. The value for the embedding dimension for recurrence analysis was set to 5 according to the false nearest neighbours method [17]. A threshold (ε) value of 10% of the maximum phase space diameter and the Euclidean norm were employed, these being consistent with previous researches using recurrence analysis to evaluate human movement [6, 27–29].

A windowing technique was used to verify the consistency of parameter estimation and to detect any changes and transitions in the time series [30]. The data were sectioned in large windows (10,000 points), each 33 s long. Adjacent windows were offset by 5000 points yielding a 50% overlap. Five windows were used for the recurrence plot and RQA calculations, which employed the Cross Recurrence Plot Toolbox for MATLAB [31].

RQA produces a series of measures of complexity that both quantify the small-scale graphical patterns in an RP (Fig. 1f and g) [5, 17] and provide insight into the dynamical features of a time series. The measures used in this study were as follows. (i) Determinism (%DET) is a measure of the predictability of a data series: higher percentage values indicating higher predictability. (ii) Entropy (ENT) is one quantification of the degree of regular/irregular patterning (the orderliness) in a data series, i.e. higher ENT values are associated with less regular patterns (at least when considering non-periodic signals, see Ref. [32]. (iii) Laminarity (%LAM) gives a measure of states of low variation and persistence (pauses, breaks) in a time series, i.e. %LAM increases with the incidence of states of low variation or high persistence. (iv) Maxline (MAXL) gives a measure of the stability of a system, higher values meaning higher stability or longer persistence.

The variation of these measures was tested for statistical significance by a surrogate test: (i) Fourier transformation of the signal; (ii) randomization of the transformed phase values (while amplitude values remained constant); and (iii) inverse Fourier transformation [33]. The null hypothesis for this statistical test assumes that the time series was the result of a linear Gaussian stochastic process. The hypothesis test was carried out by computing 150 surrogates on the PM score followed by calculation of %DET, MAXL, ENT and %LAM values for each of the surrogate time series. These were then compared statistically to their original counterparts. The null hypothesis was rejected at a level of significance of $\alpha = 0.01$ as proposed by Myers [34]. The RQA measures derived from the original data were significantly different ($p < 0.01$) from those of the surrogates (Fig. 2), which supports the validity of reporting them as nonlinear measures of the principal movement time series.

2.4 Statistical analysis

SPSS software (version 21; SPSS Inc, Chicago, IL, USA) was used for the calculation of all statistics. The eigenvalues for the first four principal movements

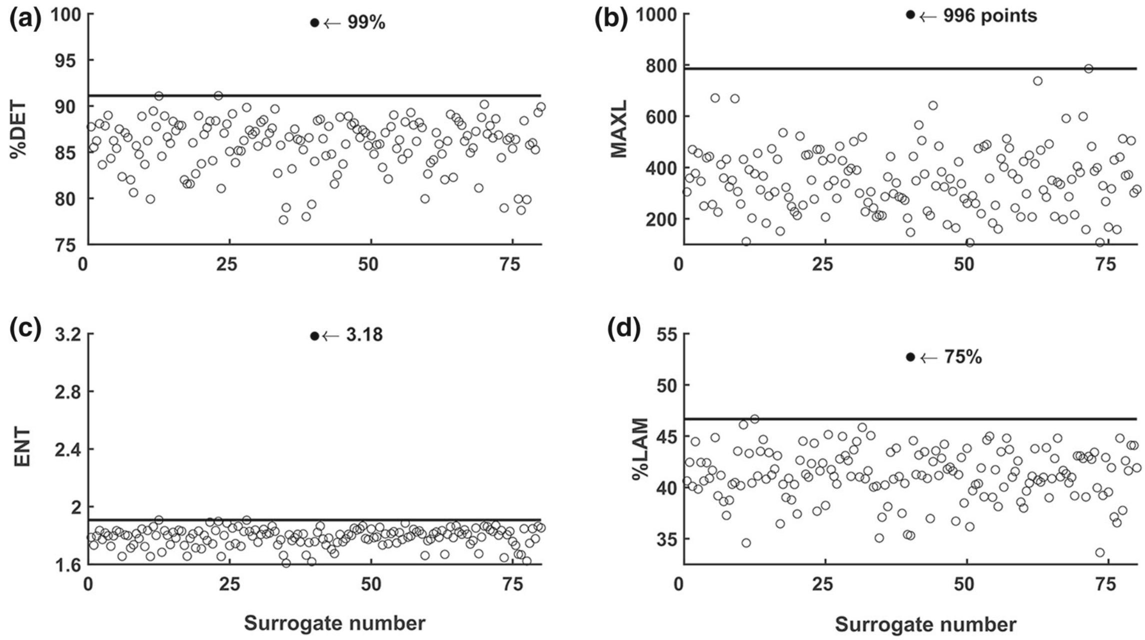

Fig. 2 Outcomes of surrogation analysis for a single PM and a single player. The open circles are surrogate values of %DET (**a**), MAXL (**b**), ENT (**c**) and %LAM (**d**). The solid circles represent the original data. The solid black lines indicate the 99% significance border of the rank order statistics. The RQA measurements for the original data were significantly different from those of the surrogates ($p < 0.01$)

(PMs) were normally distributed for both elite and nonelite groups as assessed by Kolmogorov–Smirnov tests (all $p > 0.05$) and there was homogeneity of variance as evaluated by Levene's test (all $p > 0.05$). Independent t-tests were therefore used to determine the significance of differences between elite and nonelite players. Kolmogorov–Smirnov tests showed that the RQA measurements did not fit the normality of distribution ($p < 0.05$). Therefore, data values were square root transformed and independent t-tests were then carried out to determine the significance of differences between elite and nonelite athletes. The windowing technique served to indicate that RQA measurement values were approximately constant over the trial period (i.e., there was no evidence of player fatigue) so the average of all windows ($n = 5$) for each RQA measurement was used in testing for differences between elite and nonelite groups. The significance level was set at $\alpha = 0.05$.

3 Results

Table 1 reports the eigenvalues (mean ± SEM) for the backwards-forwards movement task. The contribution of the first component to overall variability was less for elite players as compared with nonelite (37 ± 1% versus 46 ± 4%, respectively) with greater elite contributions to the second to fourth components. The only significant difference between elite and nonelite athletes was found for the third component (19 ± 2% versus 16 ± 2%; $p < 0.01$).

The eigenvector coefficients shown in Fig. 3 are arranged by group and provide information about the extent to which individual coordinates for body segment masses contribute to the principal movements. Qualitatively, and in contrast to eigenvalue results, there are notable differences between coefficient values for elite and nonelite players. Data are presented for antero-posterior (AP), medio-lateral (ML) and vertical (V) axes of segment displacement. To represent something of the character of each of the principal movements we have named them after elite patterns as: PM1AP-V, PM2ML, PM3AP+V and PM4DIS (distributed), "-"and "+" indicating the relative signs of AP and V coordinate contributions. For PM1AP-V coefficients, movement along the AP axis is the main contributor for elite taekwondo performance. In contrast, nonelite backwards-forwards movement performance is characterized less for the AP axis in favour of greater vertical movement. While ML coefficients are differentiated across body segments for elite players, the corresponding components for nonelite are hardly differentiated. The PM2ML coefficient profiles for elite and nonelite taekwondo players are quite similar, with the predominant movement occurring along the ML axis.

For PM3AP+V coefficients, both groups of players make use of movement in all three directions and magnitudes are roughly comparable, though less so for V in the elite group. However, nonelite demonstrate greater differentiation in movement in all three directions across body segments, particularly in the vertical direction. Notable differences in PM4DIS coefficients

Table 1 Eigenvalues of the first four principal movements for backwards-forwards movements for elite and nonelite taekwondo players

	First (PM1AP-V)	Second (PM2ML)	Third (PM3AP+V)	Fourth (PM4DIS)
Elite	37 (± 1)* %	27 (± 1)%	19 (± 2)%	7 (± 1)%
Nonelite	46 (± 4)%	25 (± 1)%	16 (± 2)%	6 (± 1)%
$p^{\#}$	0.087	0.91	0.0040	0.36

* ± SEM; # independent samples t-test

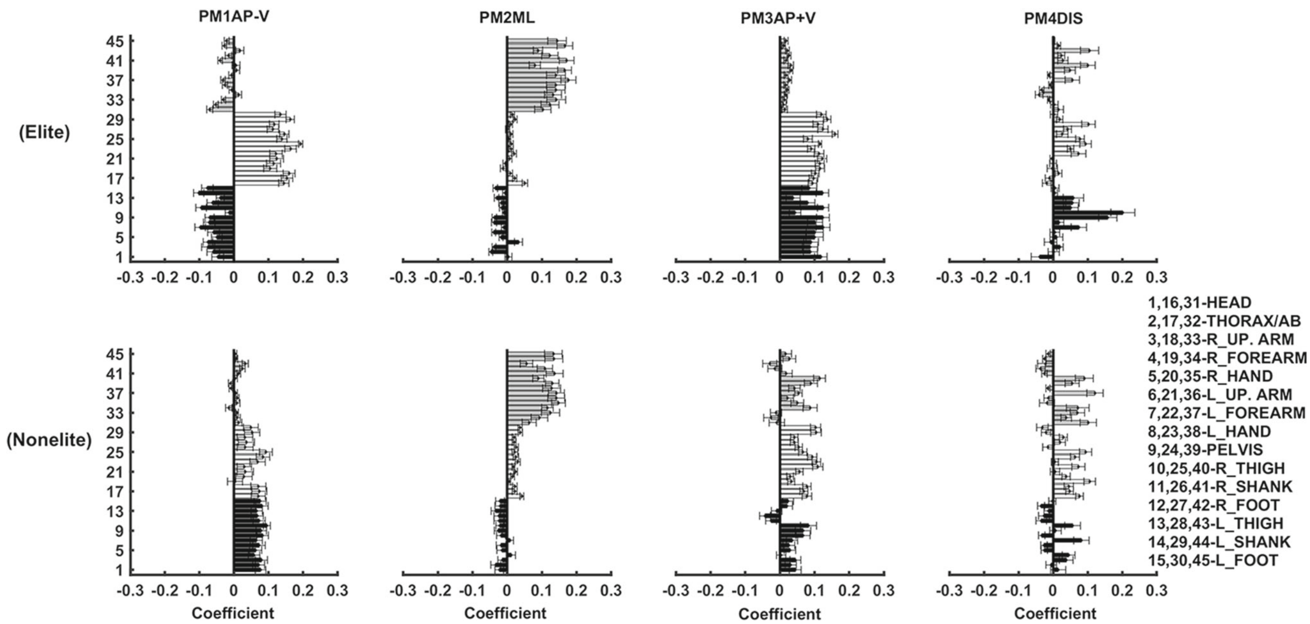

Fig. 3 Eigenvector coefficients from PCA for body segment masses for the backwards-forwards movement task. Lightly shaded, open and darkly shaded bars represent ML, AP and V movements, respectively. Columns represent average values over the player group; error bars are corresponding ± SEMs. The masses are reported in order from head to foot

are comparatively greater utilisation of ML movement in the pelvis and thigh for the elite group (Fig. 3). Overall, the eigenvector coefficients serve to distinguish in detail between patterns of elite and nonelite movement at the segment level. (Given the principal focus on recurrence analysis of movements for this paper, a detailed analysis of eigenvector coefficients is not presented. Since the group sizes were comparatively small and some players executed backwards-forwards movements in a markedly idiosyncratic manner a full account of coefficients would take this paper beyond its space allocation.)

Examples of backwards-forwards movement recurrence plots for each of the four PMs from an elite and nonelite player are illustrated in Fig. 4. Between players and PMs, a variety of recurrence plot typologies were demonstrated. These included homogenous, single isolated, drift and disrupted patterns [5]. For each recurrence plot, four RQA measures (%DET, ENT, %LAM and MAXL) were derived (Fig. 5).

For %DET (percent determinism, Fig. 5a), a significant difference between groups was found for PM1AP-V ($p < 0.05$). Here, the nonelite athletes demonstrated greater predictability in operating backwards-forwards movements (98.4 ± 1.0% vs 97.5 ± 1.0%). For ENT (entropy, Fig. 5b), there were no significant differences between groups across the four PMs. A significant difference between groups was found for %LAM (percent laminarity, Fig. 5c) for PM3AP+V ($p < 0.01$). Here, the elite athletes demonstrated greater %LAM in their backwards-forwards movements (69 ± 8% vs 40 ± 10%). Finally, a significant group difference was found for MAXL (maxline, Fig. 5d) for PM3AP+V ($p < 0.01$) with elite athletes demonstrating greater stability of backwards-forwards movement (1600 ± 300 points vs 430 ± 320 points).

4 Discussion

We sought and identified group-wide differences in the spatial and temporal structures of backwards-forwards movements of our taekwondo martial artists.

The PCA approach has various benefits in that the entire movement is described without the use of preselected variables [1, 3], rather movement is summarised as a limited set of sub-movements, and the analysis

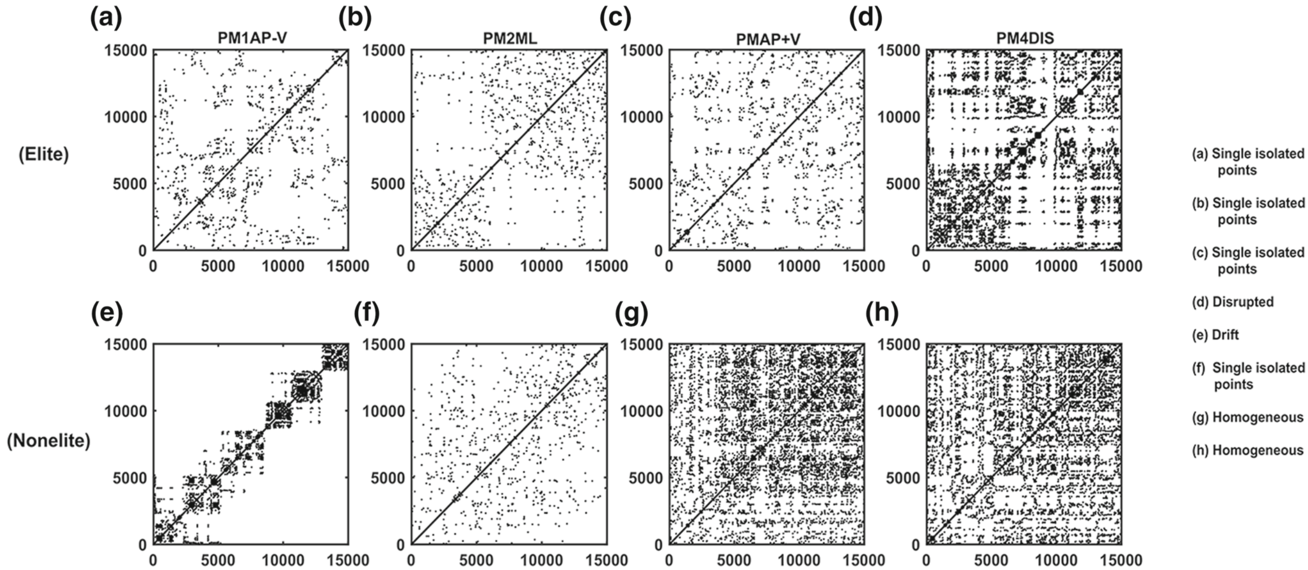

Fig. 4 Recurrence plots from representative elite and nonelite players for the first four PMs for the backwards-forwards movement task. Norm = Euclid; Delay = 7; Embedding dimension = 5; Threshold = 0.1. The horizontal and vertical axes represent samples taken at intervals of 3.3 ms

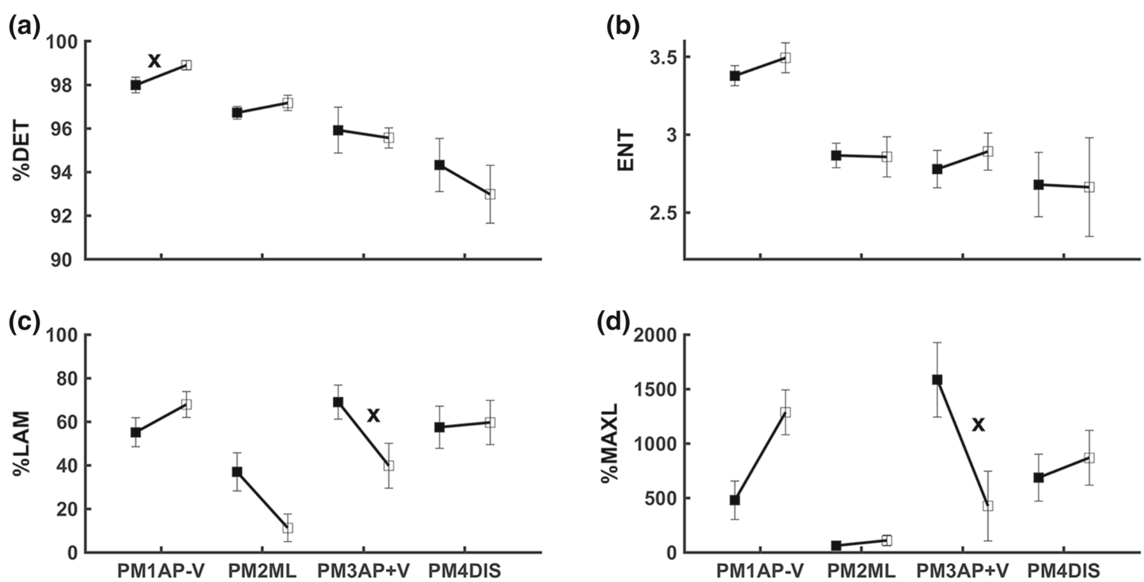

Fig. 5 Results of RQA measurement for the first four PMs for the backwards-forwards movement task for elite (filled square) and nonelite (open square) taekwondo players. **a** %DET, **b** ENT, **c** %LAM and **d** MAXL for PM scores averaged over the five data windows (± SEM). ˣ indicates a significant difference between elite and nonelite values on square-root-transformed data

has the capacity to access hidden variables inherent to the movement pattern. The set of PM coefficients provided valuable information about the degree to which individual segment centre of mass coordinates contributed to corresponding component movements and to contrasts between elite and nonelite player groups. The eigenvalues, however, provided only limited insight into movement patterns and inter-group comparisons. To make appropriate use of PCA, it appears important to examine the eigenvector coefficients to understand—contextually—the characteristics of each principal movement. This study has taken a somewhat different approach to the application of PCA since previous work has relied more heavily on eigenvalues and scores for interpretation [4, 35, 36].

Whilst PCA produces time series for movement components (the scores), it does not access the temporal structure of the components. For this purpose, we employed recurrence plots and recurrence quantification analysis to identify facets of the movement components that describe predictability, uncertainty, states of stability and low variation. We were, thus, able to gain insight into the movement patterns in some depth and identify ways in which the elite and nonelite groups differed in their execution of backwards-forwards movements. A primary concern in relation to RQA relates to the source of data variation. That is, is the variation in a time series deterministic or is it the result of random noise? To this end we used the Fourier transform surrogates to establish the existence of nonlinear dynamics underlying our experimental data (Fig. 2). We confirmed nonlinearity in our data set, leading us to conclude that the observed player responses do in fact reflect variation in movement due to neuromuscular control.

Movements of the elite group for PM1 anterior–posterior and vertical axes were highly predictable (%DET of 97.5%), though less predictable than those of the nonelite group, and also more stable (higher MAXL), representing an alternative dynamics pattern (higher %LAM) also for PM3 anterior–posterior and vertical axes. This behaviour is reflected in eigenvector coefficients for PM3 anterior–posterior and vertical directions (Fig. 3). For the elite taekwondo players anterior–posterior and vertical movements contributed strongly to PM3 anterior–posterior and vertical, for medio-lateral less so. The distribution of coefficient values across body segments was also more uniform. In contrast, nonelite players' coefficient contributions to anterior–posterior and vertical PM3 were similar for medio-lateral, anterior–posterior and vertical axes, though there was greater coefficient variation across the body than for elites, and values for right and left limbs were not equivalent. This relates to a lower MAXL value and greater variation in time (lower %LAM) for PM3 anterior–posterior and vertical axes for nonelite taekwondo players.

The PM3 anterior–posterior and vertical results in particular suggest that elite and nonelite players use different approaches to manage the task variables. This can be related to the controlled/uncontrolled manifold perspective [37]. In this view [37], variables that do not influence task outcome (the uncontrolled manifold) are allowed to fluctuate. For example, in relation to work on shooting, movement of the gun barrel along its axis is not subject to control but movement perpendicular to its axis, having a direct influence on the shot outcome, is tightly controlled [38]. Backwards-forwards movements are used by a taekwondo player to gauge the distance to an opponent and to mount and escape attacks. A nonelite player may use backwards-forwards movements in a more passive way and be less inclined to arrange their movements as a springboard for attack or for an active defence that will involve an immediate counterattack, i.e. their backwards-forwards movements may be tuned less to function. The analysis through combined use of PCA and recurrence analysis allows insights into the relative importance of controlling or failing to control particular movement variables.

Whilst statistically significant differences by group were obtained in relation to some RQA measures and principal movements, other data trends are worthy of note. For %DET (Fig. 5a), there was a trend of decreased predictability for anterior–posterior and vertical for the movement series PM1 to PM4 (distributed). Entropy values decreased along this series also (Fig. 5b). Fluidity of movement, as registered by %LAM, was fairly consistent over principal movements, except for medio-lateral PM2 for which increased transitioning was apparent in the movements of both groups (Fig. 5c). Finally, the stability of movement (MAXL, Fig. 5d) remained consistent across the series of principal movements, except for medio-lateral PM2 where instability was apparent in the movement of both groups. Across the set of RQA measurements, medio-lateral PM2 is distinctive.

Limitations to our study and report are acknowledged. Whilst a body of data was collected under carefully controlled conditions, experimentation was modest in scope in that each of the groups had only nine participants. Comparisons, therefore, had limited statistical power. Assignment to groups was based somewhat arbitrarily on taekwondo experience: some "nonelite" individuals may have executed backwards-forwards movements in an elite manner despite their more limited experience. In addition, comparatively large variation between the movement patterns of players was evident both from differences in RP patterns (Fig. 4) and from comparatively large SEM values (Fig. 5), and this naturally made statistical significance more difficult to achieve.

We report, according to conventional standards, the discrimination of movement patterns between our elite and nonelite groups. There is group-level generality but also player individuality in the movements recorded. In some cases, elite variation was greater than nonelite and in some cases it was less. One can therefore put forward alternative views, namely that large elite variation was functional and derived from experience and that large nonelite variation was a result of lack of control and lack of experience. Variation in backwards-forwards movements within subject groups may simply be a representation of the individuality of the solution to a movement "problem", functional or not. Nevertheless, statistically significant group-level differences were noted. A straightforward interpretation is that elite players have refined these relatively simple movements through extended training and competition experience. PCA, through the sets of coefficient values, revealed qualitative differences between elite and nonelite backwards-forwards movements. The combination of PCA and RQA revealed quantitative differences in temporal variation in the principal movements. Given the availability of motion capture, coordination assessments of individual athletes may be carried out and these methods may be of assistance to coaches in analysing the movements of their athletes.

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