6 Recurrence analysis discriminates martial art movement patterns

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12 Abstract. We aimed to determine whether combined application of principal components and recurrence 13 quantification analyses might serve to discriminate both spatial and temporal differences between backwards-14 forwards movement patterns. Elite (n = 9) and nonelite (n = 9) martial artists were recorded using motion capture 15 techniques and features of whole-body movement defined at segment level were investigated by principal 16 components analysis. For both groups of subjects, four movement components explained > 90% of variability in the 17 data. Given our interest in temporal patterning, the time series derived from scores for each of the principal 18 components were subsequently subjected to recurrence quantification analysis, participant by participant. For the first 19 movement component, statistically significant differences between groups were detected for the recurrence measure 20 determinism (p < 0.05). For the third movement component, statistically significant differences were detected for the 21 recurrence measures laminarity and maxline (p < 0.01). Hence use of a combination of principal components and 22 recurrence techniques revealed quantitative differences between movements of the two subject groups, differences 23 that may represent more skilled motor control in the elite group related to the functional importance of these 24 apparently simple movement patterns.

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33	Abbreviations.	
34		
35	AP	Anterior-posterior
36	CoM	Centre of mass
37	%DET	% Determinism
38	DIS	Distributed
39	ENT	Entropy
40	%LAM	% Laminarity
41	MAXL	Maxline
42	ML	Medio-lateral
43	PCA	Principal components analysis
44	PM	Principal movement
45	RP	Recurrence plot
46	RQ(A)	Recurrence quantification (analysis)
47	SEM	Standard error in the mean
48	V	Vertical
49		

50 **1. Introduction**

Human movements are the consequence of many neural, muscular and skeletal components working together to achieve a desired outcome. Whilst a typical study may involve investigation of body kinematics, the aim ultimately is understanding of 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 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.

57 Given our interest in whole-body coordination in the movements of martial artists, we adopted the 58 approaches of previous researchers [1–3] for this study and applied principal components analysis (PCA) to 59 centre of mass coordinates of the set of body segments. This method has conceptual and practical advantages: it 60 reduces a high-dimensional dataset to a lower-dimensional set of independent components that is taken (on the 61 basis of extent of variation) to represent the more important features of the data structure [4]. Whilst the starting 62 data variables are normally highly correlated, the derived principal components are independent of each other. 63 The contributions of the original variables to a given principal component are represented by their derived 64 coefficients. In our case, these coefficients were related to the centre of mass body segment coordinates, and the 65 set of coefficients indicated the forms and extents of collaboration amongst body segments over the entire time 66 course of a particular principal movement.

67 It appeared quite unsatisfactory that the temporal dynamics of investigated movements had not been 68 accounted for in deriving coefficient values, though time courses of the derived components were contained in 69 the corresponding unidimensional scores [3]. We therefore investigated the temporal structures of these scores 70 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. 1 ((d) to (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 [5]:

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$$\boldsymbol{R}_{i,j} = \theta \left(\varepsilon - \left\| \vec{x_i} - \vec{x_j} \right\| \right), \quad i,j = 1, \dots N,$$
(1)

where **R** is the recurrence matrix, θ is the Heaviside function, ε is a predefined threshold distance, $\|\cdot\|$ is a norm, $\vec{x_i}$ and $\vec{x_j}$ are the measured states (represented by *m*-dimensional state variables) 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. 1(f) and (g)) [5,17]. The RQA measures are presented in the Methods section and reviewed in the Discussion.

85 Analysis of movement patterns of taekwondo players has been the subject of various studies aimed at 86 informing coaches on technique development and player performance in competition. Researchers have, for 87 example, investigated intra-limb coordination [18–20], patterns of kicking [21] and impact force characteristics 88 for the most common kicks [22,23]. We extended the investigation of taekwondo movement to the backwards-89 forwards movements that are the basis for development of defensive and attacking actions by a player. We have 90 previously carried out simple kinematic analyses of backwards-forwards movements and have found no 91 differences between nonelite and elite groups of players. We therefore applied the alternative and more elaborate 92 analytical approach presented in this report (PCA followed by RQA) to investigate potential differences in these 93 movements for players of nonelite and elite status. The recurrence method was applied to determine differences 94 in the temporal organization of PCA data. In summary, we asked whether an alternative form of data analysis 95 might discriminate taekwando movement patterns by skill level with the aims of assisting coaching practice and 96 relating taekwando coordination to its underlying neuromuscular control. We postulated differences in 97 coordination patterns between elite and nonelite taekwondo players. Specifically, we hypothesised that RQA 98 measures of principal movements would reveal differences in the temporal structure of coordination between 99 players of different skill level.

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[Insert Fig. 1 about here]

101 **2. Materials and methods**

102 **2.1 Participants and experimental protocol**

Eighteen elite and nonelite taekwondo players were recruited for this study (mean \pm standard error in the mean (SEM); elite (8 males and 1 female; mean \pm SEM; age = 27.0 \pm 0.4 y, mass = 74 \pm 1 kg, height = 1.7 \pm 0.1 m) and nonelite (9 males; age = 35.0 \pm 0.1 y, mass = 86 \pm 3 kg, height = 1.8 \pm 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. 1(a)). The players performed individualized warm-ups for 15 minutes. 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.

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117 **2.2 Data collection and analysis**

118 In order to determine the movement kinematics of the taekwondo player during backwards-forwards 119 movements 12-mm diameter retroreflective markers were placed on the skin over anatomical landmarks (Table 120 A1, Appendix A) and the 3D coordinates of these markers were tracked using a motion capture system (Oqus 3-121 Series, Qualisys AB, Gothenburg, Sweden). Each body segment (15 in total; Table B1, Appendix B) was 122 modelled in line with previously reported standards for tracking the upper [24] and lower [25] extremities, with 123 slight modification to suit this research [20]. Marker trajectories were collected at 300 Hz. The data analysis for 124 backwards-forwards movement had four main steps: (i) prescribing an articulated multi-segment system to 125 obtain centres of mass of each of the body segments (Fig. 1(a); Appendix B); (ii) principal components analysis 126 (PCA) on the centre of mass coordinates of these segments to identify the main movement patterns for 127 backwards-forwards movements (Fig. 1(b) and (c)); (iii) examination of temporal variability using recurrence 128 techniques (RPs and RQA) by analysing the time series formed by the principal component scores (Fig. 1(d) to 129 (g)); (iv) surrogate testing used to assess whether derived recurrence quantification measures were representative 130 of bona fide nonlinear dynamics in the principal component signals, or the product of random noise.

131 Prior to processing for PCA, the first and last 10 s of the centre of mass data were removed to eliminate 132 the influence of transient motions. The submitted data length was 30000 data points (100 s) for each player. 133 Segment masses were quantified as a 30000×45 matrix (frame [rows] × centre of mass [columns]). Each row 134 of the matrix was interpreted as a 45-dimensional posture vector representing the centres of mass at a given point 135 in time. The 45-dimensions represent medio-lateral (ML), antero-posterior (AP) and vertical (V) directions for 136 each of the 15 segments. Representations were cut off after the first four principal components since the summed 137 eigenvalues reached a conventional standard of at least 90% of total variance [2] for both groups. MATLAB 138 software was used for PCA calculations (MATLAB 2013a and Statistics Toolbox 8.1, The MathWorks Inc, 139 Natick, MA, USA). The outputs from PCA are referred to as one-dimensional principal movements (PMs).

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141 **2.3 Data processing for recurrence plotting and analysis**

142 The time series obtained by projecting the data onto the intrapersonal principal components were 143 subjected to recurrence plot and recurrence quantification analysis (Fig. 1(d) to (g)). As the name suggests, both 144 recurrence plotting and analysis seek understanding of the temporal structure of a time series in terms of 145 recurring patterns in the data. The data are not, however, examined in their original dimension, rather they are 146 "unfolded" into multiple dimensions. The first step in the process is the selection of a time scale for the analysis 147 (τ) , the second step is derivation of the number of dimensions to be employed (m) and the final step is the setting 148 of a distance criterion (ε , in *m* dimensions) for the revisiting (i.e. recurrence) of a region of phase space along the 149 time-dependent data trajectory. The procedures have been described in detail in [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 consistency of parameter estimation and to detect any changes and transitions in the time series [30]. The data were sectioned in large windows (10000 points), each 33 s long. Adjacent windows were offset by 5000 points yielding a 50% overlap. Five windows were used for 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. 1(f) and (g)) [5,17] and provide insight into 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 [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.

168 The variation of these measures were tested for statistical significance by a surrogate test: (i) Fourier 169 transformation of the signal; (ii) randomization of the transformed phase values (while amplitude values 170 remained constant); and (iii) inverse Fourier transformation [33]. The null hypothesis for this statistical test 171 assumes that the time series was the result of a linear Gaussian stochastic process. The hypothesis test was 172 carried out by computing 150 surrogates on the PM score followed by calculation of %DET, MAXL, ENT and 173 %LAM values for each of the surrogate time series. These were then compared statistically to their original 174 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 175 176 surrogates (Fig. 2), which supports the validity of reporting them as nonlinear measures of the principal 177 movement time series.

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[Insert Fig. 2 about here]

179 **2.4 Statistical analysis**

180 SPSS software (version 21; SPSS Inc, Chicago, IL, USA) was used for calculation of all statistics. The 181 eigenvalues for the first four principal movements (PMs) were normally distributed for both elite and nonelite 182 groups as assessed by Kolmogorov-Smirnov tests (all p > 0.05) and there was homogeneity of variance as 183 evaluated by Levene's test (all p > 0.05). Independent *t*-tests were therefore used to determine the significance of 184 differences between elite and nonelite players. Kolmogorov-Smirnov tests showed that the RQA measurements 185 did not fit normality of distribution (p < 0.05). Therefore, data values were square root transformed and 186 independent t-tests were then carried out to determine the significance of differences between elite and nonelite 187 athletes. The windowing technique served to indicate that RQA measurement values were approximately 188 constant over the trial period (i.e., there was no evidence of player fatigue) so the average of all windows (n = 5)189 for each RQA measurement was used in testing for differences between elite and nonelite groups. The 190 significance level was set at $\alpha = 0.05$.

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192 **3. Results**

Table 1 reports the eigenvalues (mean \pm 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 ($37 \pm 1\%$ versus 46 $\pm 4\%$ 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 ($19 \pm 2\%$ versus $16 \pm 2\%$; p <0.01).

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[Insert Table 1 about here]

199 The eigenvector coefficients shown in Fig. 3 are arranged by group and provide information about the 200 extent to which individual coordinates for body segment masses contribute to the principal movements. 201 Qualitatively, and in contrast to eigenvalue results, there are notable differences between coefficient values for 202 elite and nonelite players. Data are presented for antero-posterior (AP), medio-lateral (ML) and vertical (V) axes 203 of segment displacement. In order to represent something of the character of each of the principal movements we 204 have named them after elite patterns as: PM1AP-V, PM2ML, PM3AP+V and PM4DIS (distributed), "-" and "+" 205 indicating the relative signs of AP and V coordinate contributions. For PM1AP-V coefficients, movement along 206 the AP axis is the main contributor for elite taekwondo performance. In contrast, nonelite backwards-forwards 207 movement performance is characterized less for the AP axis in favour of greater vertical movement. While ML 208 coefficients are differentiated across body segments for elite players, the corresponding components for nonelite 209 are hardly differentiated. The PM2ML coefficient profiles for elite and nonelite taekwondo players are quite 210 similar, with the predominant movement occurring along the ML axis.

211 For PM3AP+V coefficients, both groups of players make use of movement in all three directions and 212 magnitudes are roughly comparable, though less so for V in the elite group. However, nonelite demonstrate 213 greater differentiation in movement in all three directions across body segments, particularly in the vertical 214 direction. Notable differences in PM4DIS coefficients are comparatively greater utilisation of ML movement in 215 the pelvis and thigh for the elite group (Fig. 3). Overall, the eigenvector coefficients serve to distinguish in detail 216 between patterns of elite and nonelite movement at segment level. (Given the principal focus on recurrence 217 analysis of movements for this paper, a detailed analysis of eigenvector coefficients is not presented. Since the 218 group sizes were comparatively small and some players executed backwards-forwards movements in a markedly 219 idiosyncratic manner a full account of coefficients would take this paper beyond its space allocation.) 220 [Insert Fig. 3 about here]

- 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
- 224 plot, four RQA measures (%DET, ENT, %LAM and MAXL) were derived (Fig. 5).
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[Insert Fig. 4 about here]

226 For %DET (percent determinism, Fig. 5(a)), a significant difference between groups was found for 227 PM1AP-V (p < 0.05). Here, the nonelite athletes demonstrated greater predictability in operating backwards-228 forwards movements (98.4 \pm 1.0% vs 97.5 \pm 1.0%). For ENT (entropy, Fig. 5(b)), there were no significant 229 differences between groups across the four PMs. A significant difference between groups was found for %LAM 230 (percent laminarity, Fig. 5(c)) for PM3AP+V (p < 0.01). Here, the elite athletes demonstrated greater %LAM in 231 their backwards-forwards movements ($69 \pm 8\%$ vs $40 \pm 10\%$). Finally, a significant group difference was found 232 for MAXL (maxline, Fig. 5(d)) for PM3AP+V (p < 0.01) with elite athletes demonstrating greater stability of 233 backwards-forwards movement (1600 ± 300 points vs 430 ± 320 points).

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[Insert Fig. 5 about here]

235 **4. Discussion**

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

238 The PCA approach has various benefits in that the entire movement is described without use of pre-239 selected variables [1,3], rather movement is summarised as a limited set of sub-movements, and the analysis has 240 the capacity to access hidden variables inherent to the movement pattern. The set of PM coefficients provided 241 valuable information about the degree to which individual segment centre of mass coordinates contributed to 242 corresponding component movements and to contrasts between elite and nonelite player groups. The 243 eigenvalues, however, provided only limited insight into movement patterns and inter-group comparisons. To 244 make appropriate use of PCA, it appears important to examine the eigenvector coefficients in order to understand 245 - contextually - the characteristics of each principal movement. This study has taken a somewhat different 246 approach to the application of PCA since previous work has relied more heavily on eigenvalues and scores for 247 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.

258 Movements of the elite group for PM1 anterior-posterior and vertical axes were highly predictable 259 (%DET of 97.5%), though less predictable than those of the nonelite group, and also more stable (higher 260 MAXL), representing an alternative dynamics pattern (higher %LAM) also for PM3 anterior-posterior and 261 vertical axes. This behaviour is reflected in eigenvector coefficients for PM3 anterior-posterior and vertical 262 directions (Fig. 3). For the elite taekwondo players anterior-posterior and vertical movements contributed 263 strongly to PM3 anterior-posterior and +vertical, for medio-lateral less so. The distribution of coefficient values 264 across body segments was also more uniform. In contrast, nonelite players' coefficient contributions to anterior-265 posterior and vertical PM3 were similar for medio-lateral, anterior-posterior and vertical axes, though there was 266 greater coefficient variation across the body than for elites, and values for right and left limbs were not 267 equivalent. This relates to a lower MAXL value and greater variation in time (lower %LAM) for PM3 anterior-268 posterior and vertical axes for nonelite taekwondo players.

269 The PM3 anterior-posterior and vertical results in particular suggest that elite and nonelite players use 270 different approaches to manage the task variables. This can be related to the controlled/uncontrolled manifold 271 perspective [37]. In this view [37], variables that do not influence task outcome (the uncontrolled manifold) are 272 allowed to fluctuate. For example, in relation to work on shooting, movement of the gun barrel along its axis is 273 not subject to control but movement perpendicular to its axis, having a direct influence on shot outcome, is 274 tightly controlled [38]. Backwards-forwards movements are used by a taekwondo player to gauge distance to an 275 opponent and to mount and escape attacks. A nonelite player may use backwards-forwards movements in a more 276 passive way and be less inclined to arrange their movements as a springboard for attack or for active defence that 277 will involve an immediate counterattack, i.e. their backwards-forwards movements may be tuned less to 278 function. The analysis through combined use of PCA and recurrence analysis allows insights into the relative 279 importance of controlling or failing to control particular movement variables.

280 Whilst statistically significant differences by group were obtained in relation to some RQA measures 281 and principal movements, other data trends are worthy of note. For %DET (Fig. 5(a)), there was a trend of 282 decreased predictability for anterior-posterior and vertical for the movement series PM1 to PM4 (distributed). 283 Entropy values decreased along this series also (Fig. 5(b)). Fluidity of movement, as registered by %LAM, was 284 fairly consistent over principal movements, except for medio-lateral PM2 for which increased transitioning was 285 apparent in the movements of both groups (Fig. 5(c)). Finally, the stability of movement (MAXL, Fig. 5(d)) 286 remained consistent across the series of principal movements, except for medio-lateral PM2 where instability 287 was apparent in the movement of both groups. Across the set of RQA measurements, medio-lateral PM2 is 288 distinctive.

289 Limitations to our study and report are acknowledged. Whilst a body of data was collected under 290 carefully controlled conditions, experimentation was modest in scope in that each of the groups had only nine 291 participants. Comparisons therefore had limited statistical power. Assignment to groups was based somewhat 292 arbitrarily on taekwondo experience: some "nonelite" individuals may have executed backwards-forwards 293 movements in an elite manner despite their more limited experience. In addition, comparatively large variation 294 between the movement patterns of players was evident both from differences in RP patterns (Fig. 4) and from 295 comparatively large SEM values (Fig. 5), and this naturally made statistical significance more difficult to 296 achieve.

297 We report, according to conventional standards, the discrimination of movement patterns between our 298 elite and nonelite groups. There is group-level generality but also player individuality in the movements 299 recorded. In some cases, elite variation was greater than nonelite and in some cases it was less. One can therefore 300 put forward alternative views, namely that large elite variation was functional and derived from experience and 301 that large nonelite variation was a result of lack of control and lack of experience. Variation in backwards-302 forwards movements within subject groups may simply be a representation of the individuality of solution to a 303 movement "problem", functional or not. Nevertheless, statistically significant group-level differences were 304 noted. A straightforward interpretation is that elite players have refined these relatively simple movements 305 through extended training and competition experience. PCA, through the sets of coefficient values, revealed 306 qualitative differences between elite and nonelite backwards-forwards movements. The combination of PCA and 307 RQA revealed quantitative differences in temporal variation in the principal movements. Given the availability 308 of motion capture, coordination assessments of individual athletes may be carried out and these methods may be 309 of assistance to coaches in analysing movements of their athletes.

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368 Figure Captions

369 Fig. 1 Graphical presentation of the methods applied to backwards-forwards movement data, illustrated for a

370 single player. (a) Backwards-forwards movement centre of mass displacements obtained from an articulated

371 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).

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 represents 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).

Fig. 3 Eigenvector coefficients from PCA for body segment masses for the backwards-forwards movement task.

- 381 Lightly shaded, open and darkly shaded bars represent ML, AP and V movements respectively. Columns 382 represent average values over the player group; error bars are corresponding \pm SEMs. The masses are reported in 383 order from head to foot.
- **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.

386 Fig. 5 Results of RQA measurement for the first four PMs for the backwards-forwards movement task for elite

- 387 (filled square) and nonelite (open square) taekwondo players. (a) %DET, (b) ENT, (c) %LAM and (d) MAXL
- 388 for PM scores averaged with over the five data windows (± SEM). ^x indicates a significant difference between

389 elite and nonelite values on square-root-transformed data.

390

391 Table Captions

392 Table 1 Eigenvalues of the first four principal movements for backwards-forwards movements for elite and393 nonelite taekwondo players.



398 Fig. 2



401 Fig. 3







404 Fig. 4











Table 1

	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

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Appendix

Recurrence analysis discriminates martial art movement patterns

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444 APPENDIX A.

445 Marker definition

Table A1 Marker definition and tracking set up.

Segment	Labels	Numbers	Definition	Tracking	Description
Hand	TMJ	2	✓	√	Temporomandibular Joint
Head	BHD	2	\checkmark	\checkmark	Back Head
	IC	2	\checkmark	\checkmark	Iliac Crest
	AC	2	\checkmark	\checkmark	Acromion
	C7	1	\checkmark	✓	Seventh Cervical Vertebra
	SSN	1	\checkmark	\checkmark	Suprasternal Notch
Thorax	XIPH	1	✓	✓	Xiphoid Process
Потах	T10	1	\checkmark	\checkmark	Tenth Thoracic Vertebra
	СР	2	✓ ✓		Coracoid Process
	AA	2	<u>√</u>		Angulus Acromialis
	AI	2	<u>√</u>	✓	Angulus Inferior
	TS	2	<u>√</u>	\checkmark	Trigonum Spinae Scapulae
	LHEC	2	<u>√</u>		Lateral Epicondyle of the Humerus
	MHEC	2	\checkmark		Medial Epicondyle of the Humerus
Upper arm	UAI	2		<u>✓</u>	Upper arm 1
	UA2	2		<u>✓</u>	Upper arm 2
	UA3	2	1	√	Upper arm 3
	RSP	2	√	✓	Radial Styloid Process
Forearm	USP	2	V	✓	Ulnar Styloid Process
	FAI	2		v	Forearm 1
	FA2	2		×	Forearm 2
IIaad	FA3	2		•	Forearm 3
Hand	CARP3	2	V	•	Anterior Superior Ilies Spins
Pelvis	ASIS	2	• •	• •	Anterior Superior Iliac Spine
		2	• •	v	Lateral Epicondule of the Femure
	MEC	2			Madial Epicondyle of the Femur
	THI1	2	•	1	Thigh 1
Thigh	THI2	2		· ·	Thigh 2
	THI2	2		· ·	Thigh 2
	THI4	2		· •	Thigh 4
	LMAL	2	✓		I ateral Malleolus
	MMAL	2	\checkmark		Medial Malleolus
	SHK1	2		\checkmark	Shank 1
Shank	SHK2	2		✓	Shank 2
	SHK3	2		✓	Shank 3
	SHK4	2		✓	Shank 4
	MET1D	2	✓		First Metatarsal
	MET5D	2	\checkmark		Fifth Metatarsal
	CAL	2	✓		Calcaneus
Foot	FOT1	2		✓	Foot 1
	FOT2	2		\checkmark	Foot 2
	FOT3	2		\checkmark	Foot 3
Individual marker		48	46	26	
Cluster marker		34		34	_
Total		82	46	60	-

449 APPENDIX B.

450 Multi-segment model

451 Each player was represented as an articulated multi-segment system with 15 rigid segments (head, thorax, upper 452 arms, forearms, hands, pelvis, thighs, shanks and feet; see anatomical coordinate system below). The inverse 453 kinematics technique was applied to the model with specific joint constraints (Table A2). Upper extremity and 454 lower extremity inverse kinematic linkages were created, which started at the pelvis segment for the lower 455 extremity, and at the thorax segment for the upper extremity. For each joint, a set of constraints was enforced, 456 where segments could rotate with three degrees of freedom, but not translate with respect to the adjacent 457 segment. The centre of masses of the segments were measured from the global coordinate system. Visual3D 458 software (C-Motion Inc, Germantown, MD, USA) was used to build the articulated multi-segment system and 459 for centre of mass calculations.

Table DI Ta	natomiea eooramate system and myerse kmemates for each ood y segmer	16.	
Segments	Coordinate systems x, y and z	IK constraint	IK unconstraint
Head	Origin: Midpoint between R_AC and L_AC		
	x: Oriented from L_AC to R_TMJ pointing right	Trovalation	Detetion
1.	y: Perpendicular to x in the plane defined by L_AC to R_AC and midpoint between R_BHD and L_BHD	Iranslation	Rotation
E	r: Perpendicular to both a and a pointing upwards	x, y, z	x, y, 2
Thorax/Ab	Origin: Waist joint - midpoint between R IC and L IC		
E			Rotation
80	x: Oriented from L_IC to R_IC pointing right		x, y, z
5.5	y: Perpendicular to \mathbf{x} in the plane defined by R_IC, L_IC and		
₩ <u>₿</u> ₩	midpoint between R_AC and L_AC		Translation
T T	z: Perpendicular to both x and y pointing upwards		<i>x, y, z</i>
Upper arm	Origin: Shoulder joint centre (SJC)		
6	z. Oriented from elbow joint centre (EIC) to shoulder joint centre		
1	(SJC) pointing upwards	Translation	Rotation
	\mathbf{x} : Perpendicular to \mathbf{z} in the plane defined by LHEC, MHEC and SJC	x, y, z	x, y, z
	pointing right	-	
0	y: Perpendicular to both x and z pointing forwards		
Forearm	Origin: EJC - midpoint between LHEC and MHEC		
69.	z: Oriented from midpoint between RSP and USP to FIC pointing	Translation	Rotation
M	upwards	x, y, z	<i>x</i> , <i>v</i> , <i>z</i>
	\mathbf{x} : Perpendicular to \mathbf{z} in the plane defined by RSP, USP and EJC		
	pointing right		
	y: Perpendicular to both x and z pointing forwards		
Hand	Origin: CARP3		
Sicto.	z. Oriented from CARP3 to midpoint between RSP and USP pointing	Translation	Rotation
1997	upwards	x, y, z	<i>x</i> , <i>v</i> , <i>z</i>
2123	\mathbf{x} : Perpendicular to \mathbf{z} in the plane defined by CARP3 and midpoint		
2896	between RSP and USP pointing right		
Ŋ	y: Perpendicular to both x and z pointing forwards		
Pelvis	Origin: Midpoint between R_ASIS and L_ASIS		Detection
	Orighted from L ASIS to D ASIS pointing right		Kotation
	*: Perpendicular to x in the plane defined by R ASIS I ASIS and		х, у, Z
	the midpoint between R PSIS and L PSIS		Translation
	z: Perpendicular to both x and y pointing upwards		x, y, z
Thigh	Origin: Hip joint centre (HJC)		
	z: Oriented from midpoint between LEC and MEC (KJC) to HJC	T 1.1	D i i
1	pointing upwards	Iranslation	Rotation
	<i>x</i> . Perpendicular to <i>z</i> in the plane defined by LEC, MEC and HJC pointing right	x, y, z	x, y, 2
	\mathbf{v} : Perpendicular to both \mathbf{x} and \mathbf{z} pointing forwards		
Shank	Origin: Knee joint (midpoint between LEC and MEC)		
	z: Oriented from midpoint between LMAL and MMAL to KJC	Translation	Rotation
	pointing upwards	x, y, z	x, y, z
	KIC pointing right		
	v: Perpendicular to both x and z pointing forward		
Foot	Origin: Ankle joint (midpoint between LMAL and MMAL)		
<u>i</u> (11.	z: Oriented from midpoint between LMAL and MMAL to midpoint	Translation	Potetion
D	* Perpendicular to z in the plane defined by I MAI MMAI		r v 7
1	MET1D and MET5D pointing right	л, y, 2	л, <i>у</i> , 2
9	v: Perpendicular to both x and z pointing forward		

Table B1 Anatomical coordinate system and inverse kinematics for each body segment.