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RESEARCH ARTICLE

Two classes of movements in motor control

Elizabeth B. Torres

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Abstract This work investigated whether fundamental differences emerged between segments of complex movement sequences performed at different instructed speeds. To this end, we tested 5 novices and 1 karate expert as they performed beginner's martial arts routines. We found that if one blindly took these segments and separated them according to the variability of trajectory parameters, one could unambiguously group two classes of movements between the same two space regions: one type that remained quite conserved despite speed changes and another type that changed with speed level. These groups corresponded to functionally different movements (strike segments explicitly directed to a set of goals and spontaneously retracting segments supplementing the goals). The curvature of the goal-directed segments remained quite conserved despite speed changes, yet the supplemental movements spanned families of trajectories with different curvature according to the speed. Likewise, the values of the hand's peak velocity across trials were more variable in supplemental segments, and for each participant, there were different statistical signatures of variability between the two movement classes. This dichotomy between coexisting movement classes of our natural actions calls for a theoretical characterization. The present experimental results strongly suggest that two separate sets of principles may govern these movement classes in complex natural behaviors, since under different dynamics the hand did not describe a unique family of trajectories between the same two points in the 3D space.

Keywords Goal-directed movements · Supplemental movements · Speeds · Blind classification · Kinesthetic sense · Martial arts · Maximum velocity

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E. B. Torres (✉)
Psychology Department (Busch Campus), Rutgers University, 152 Frelinghuysen Rd, Piscataway, NJ 08854, USA
e-mail: ebtorres@rci.rutgers.edu
URL: https://sites.google.com/site/blurbaboutmywork/home

E. B. Torres
Cognitive Science, Rutgers University, Piscataway, NJ, USA

E. B. Torres
Computational Biomedicine Imaging and Modeling, Computer Science, Rutgers University, Piscataway, NJ, USA

E. B. Torres
Medical School (Neurology), Indiana University, Bloomington, IN, USA

Introduction

Movement research mainly focuses on goal-oriented behavior; however, a large portion of our everyday natural movements are orchestrated without a deliberate goal in mind and largely without our conscious awareness. This class of movements may go by many names, but here will be referred to as supplemental movements, movements that are collateral to the main goals of a task.

Dancers, musicians, athletes, and their photographers have long been familiar with spontaneous transitional movements that supplement the staged portions of their choreographies (Marey 1874; Marey and Pritchard 1895) yet a thoroughgoing understanding of the contributions of supplemental movements to natural behavior has remained elusive.

Spontaneous movements emerge earlier than goal-directed movements during development. They eventually come to support goal-directed behaviors. By the age of three, the system has made a clear transition from purely spontaneous to goal-directed movements (Smith and Thelen 1993). In fact, one of the telltale markers that there is a neurodevelopmental problem is precisely atypical patterns of spontaneous movements in newborns (Karmel et al. 2010; Karmel and Gardner 2005; Gargner et al. 1990). Upon the early surfacing of goal-directed movements in infants, by the age of four, signatures of mature kinematics (e.g., a unique speed maximum) appear in point to point, reaching movements (Konczak and Dichgans 1997; Berthier and Keen 2006; Konczak and Thelen 1994; von Hofsten and Lindhagen 1979; von Hofsten 1991). These unique features remain stable throughout adulthood (Morasso 1983; Abend et al. 1982) even after recovery from exposure to perturbations of external dynamics (Shadmehr and Mussa-Ivaldi 1994; Conditt and Mussa-Ivaldi 1999), unless a stroke or some neurodegenerative disease affects the individual (Torres et al. 2010, 2011).

We know a great deal about goal-directed behavior, especially about reaching behaviors, but spontaneous transitional movements present in complex sequential behaviors of daily living activities remain largely under-explored. Such movements are an integral part of a possible hierarchical gradient of coexisting modes of control (Fig. 1) whose interrelations seem critical for well-coordinated fluid behavior. The upsetting of the delicate balance among these modes can be readily appreciated in movement disorders such as Parkinson's disease (Redgrave et al. 2010) where the loss of automated control impedes the expression of fluid goal-oriented behaviors. Statistical patterns of variability present in the hand trajectory parameters of such compromised systems have been recently identified in the context of reaching sequences that require the balance between goal-directed and spontaneous transitional movements (Torres et al. 2010, 2011). Yet, how these statistical patterns manifest in complex sequential body movements remains unknown.

The labels of choice to define the proposed hierarchy in Fig. 1 are somewhat arbitrary and arguable, yet they illustrate potential differences in the levels of control. Our question is whether such gradual differences also manifest in the movement variability across repetitions of different movements that map onto different levels of functionality. Specifically, we ask whether changes in speed have different consequences on the trajectories described by staged goal-directed movements than in those described by spontaneous transitional movements that supplement the main goals of a task.

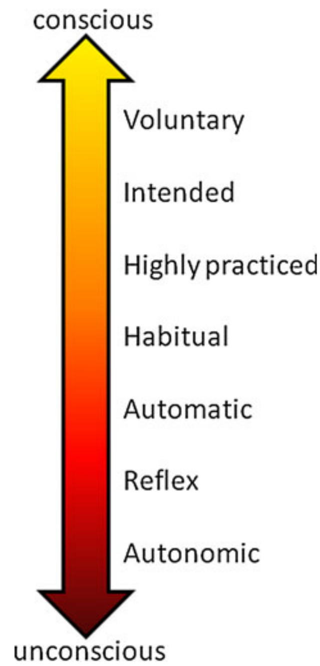

Fig. 1 Simplified schematics of the possible interconnected hierarchy of control modes spanning a continuum from conscious to unconscious processes. A possible corresponding gradient effect of changes in dynamics on the motor variability across these levels is also proposed

Besides the evidence from the developmental and clinical literatures, our quest is partly motivated by previous research on point to point movements of the reaching family which were aimed at a visual target. It has been reported that such goal-directed movements conserved the hand trajectories despite instructed speed changes (Nishikawa et al. 1999), loads applied to the arm (Atkeson and Hollerbach 1985), complex postures (Guigon et al. 2007), and changes in required target orientations (Torres and Zipser 2004) that altered the movement dynamics. The known conservation of goal-directed trajectories contrasts with the unknown outcomes that changes in speed could have on the statistical patterns of variability of supplemental hand trajectories.

In the present work, we investigate possible differences between the effects that changes in dynamics may exert on the variability of hand trajectories described by complex sequential body motions that interleave staged and supplemental movements. To this end, we use segments in movement trajectories described by the hands during the performance of beginner's martial arts routines by a martial arts expert and 5 novice controls (NC). Within these routines, there are strike and retracting movements. Strikes are staged segments corresponding to punches directed toward an imaginary opponent. Retracting segments are transitional untwisting movements co-occurring, as the system overtly focuses on staging another punch with the other hand. First, we establish that across subjects and for each participant (independent of expertise level) given a randomly selected trial it is possible to blindly group movements into two distinct classes and to predict with high accuracy what segment type and technique the trial most likely came from. To further establish specific separable aspects of each class according to the functionality of a movement within a technique, we then evaluate in each participant the statistical patterns of variability of several hand trajectory parameters.

Method

Participants

Performance of a second-degree black-belt martial arts expert (22 years old) was measured on all behavioral tasks in order to serve as a reference for 5 novice participants (ages 19–23 years old). All 6 were undergraduates at Rutgers University. The Rutgers University Institutional Review Board in compliance with the Declaration of Helsinki approved the protocol for the movement studies. Consent for videotaping was obtained from the participants.

Apparatus and behavioral task

The martial arts expert performed simple routines that combined staged movements intended toward an imaginary opponent with transitional incidental segments, as the participant shifted the staged component of the technique from one limb to another. In one experimental block, individual segments of the routine were performed in isolation in the order: Jab, Cross, Hook, and Uppercut. In another block, the four techniques were sequentially combined in the same order into one fluid movement without visible stops (J–C–H–U). In different blocks, isolated and sequential movements were performed at different instructed speeds and under different forms of sensory guidance.

Movements were monitored in real time and captured at 240 Hz using 16 electro-magnetic sensors (Polhemus, Liberty, Colchester, VT) and motion-tracking software (The Motion Monitor, Innovative Sports Training, Inc., Chicago, IL) (see "Appendix" for further details). The output kinematics features of the movement trajectories from both hands were analyzed. Sensors were mounted on the forehead (1), trunk (2), both shoulders (2) (acromial positions), both upper arms (2) (brachial positions), both forearms (2) (antebrachial positions), both hands (2) (on the top, manus position, opposite to the palms), both upper legs (2) (femoral positions), and both lower legs (2) (at the crural positions on the front of the shanks). The 16th sensor was used to digitize the body and render the 3D replica of the subject. This enabled calibration of the rotations and displacements within the range of motions explored. The professional software to digitize, render in 3D, and calibrate the system is provided by the Motion Monitor Sports Inn. Figure 7 shows a 3D replica model of the expert subjects' body and the axes of the 15 sensors. This real-time visualization allowed the experimenters to obtain both real-time feedback during the calibration step as well as a posteriori visual confirmation of the correctness and fluidity of the performance after each block of trials. During performance, participants were not provided with this feedback. For simplicity, we only present data here for the right and left hand, although we also measured the movements of the head, torso, and legs. These data will be reserved for different reports.

Beginner-level martial arts routines were performed which contained 4 individual techniques. Each technique comprised staged and co-occurring incidental segments. The segments performed in the staged mode were aimed at the imaginary opponent. The supplemental, "gluing" segments of the routine were automated transitions supporting the staged segments.

The overtly attended segments staged toward the opponent defined the main goals of the technique and were instructed to be aimed at achieving maximum impact with minimum effort. The expert explicitly instructed how this could be attained with practice and corrections. The staged segments of the techniques were explicitly monitored by both the naïve performers and the instructor. The supplemental segments incidental to each set of goals were unveiled in each isolated technique and were present in similar form within a complete, fluid movement sequence. An important point to keep in mind is that incidental segments can become staged the moment that a participant is deliberately made aware of their existence and explicitly instructed to monitor them. However, without the instruction to monitor the return segments (our participants and expert had no such instruction in these blocks), the default techniques naturally split into these two alternating staged and supplemental modes of control. These two modes can be further distinguished in a dynamics-dependent manner to be made precise later.

Figure 7 describes the four connected segments of the routine: Jab, Cross, Hook, and Uppercut. Each segment had a forward component staged toward an imaginary target (the opponent) and a return component in transition to another forward intended segment. We named these J1 (goal-directed), J2 (collateral), C1–C2, H1–H2, and U1–U2. To better explain each segment, the forward and back trajectories from each technique are shown for 1 trial in Fig. 2, for each hand, in the order in which they flowed.

The participants performed each J1–J2, C1–C2, etc., first in isolation and then in a separate experimental block, they performed them in a fluid sequence. The "Appendix" details each technique.

Each subject attended 8 sessions (4 to perform the routines in isolation and 4 to perform the routines in sequence). Isolated routines included at least 10 trials per speed condition within each form of sensory guidance [imitation, mirror-dark–glowing-lights, mirror-lit-room, simulation, dark and loads (not fully discussed here)]. A minimum of 120 (10 × 2 speeds × 6 sensory conditions) trials per subject were obtained in each session of the isolated and in each of the sequenced performance. These experiments are still ongoing with other subject types.

For each subject, we performed a distributional analyses whereby we fit (using maximum likelihood estimates) the parameters of the Gamma family (shape and scale) to the distribution of peak velocities of the leading hand (left hand opened the Jab in this case). We call this a personalized statistical signature of movement variability for the peak velocity of this technique as each subject moves differently across repeats. Thus, we represent each subject as two points in Gamma parameter (phase) space. One point represents her/his goal-directed Jab signature and the other point represents her/his supplemental Jab signature of variability in the hand's peak velocity across conditions. In each condition, two movement speeds (normal-to-slow and fast) were instructed. Each participant returned several times to the lab for practice and movement recordings.

Behavioral analyses

Determination of the instantaneous speed/acceleration profiles and maxima

To address the three questions above, movement trajectories were decomposed into the goal-directed and supplemental segments according to expert performance of the isolated techniques and of the techniques in sequence (J–C–H–U). Figure 2a, b shows the hand trajectories decomposed into the staged and supplemental segments of each technique in the sequence. Figure 2c, d shows instantaneous speed profiles corresponding to each segment. To construct these profiles, we measured the norm (length) of the velocity vector tangential to the curve described by the movements in each of the 3D hand trajectories of Fig. 2a, b and obtained the instantaneous speed scalar value. Each sub-segment of each technique had a

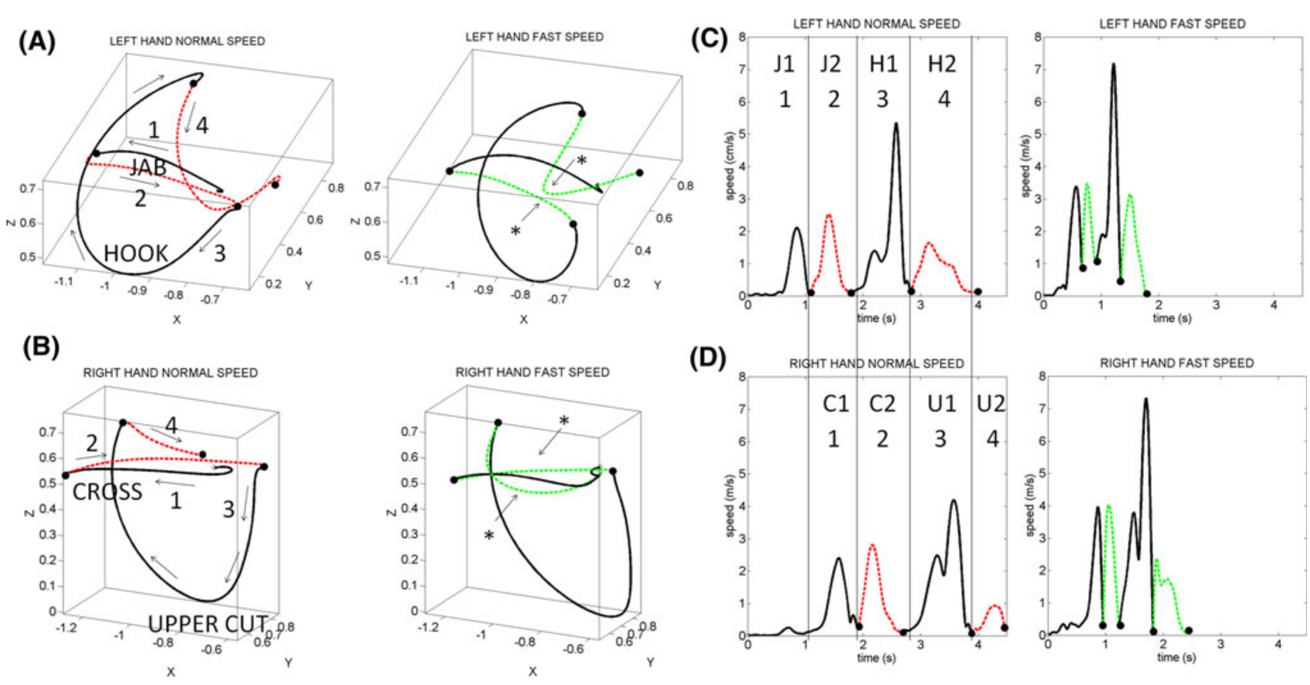

Fig. 2 Methods-Movement trajectory decomposition and speed profiles. **a** Left hand trajectories in a sequenced routine with each dot marking the beginning and the end of a segment. *Solid* segments (1 Jab1 and 3 Hook1) mark the goal-directed segments (forward strikes) intended towards a goal located on an imaginary opponent. *Arrows* mark the directional flow of the movement. *Dashed* traces mark the supplemental transitional segments at normal or fast speed. *Arrows* and *asterisks* mark the differences evoked by the speed in the trajectories of the supplemental segments of each technique. **b** Same as in **a** for the Cross and Uppercut techniques. **c** Instantaneous left hand speed profiles from the fluid sequence labeled in correspondence with the hand trajectories (*dashed* curves are the supplemental segments). **d** The speed profiles from the right hand

maximum value which we determined along with the time at which this value was attained from the technique's movement onset. The hand velocity signaled movement at 5% of the maximum velocity value of the segment. Likewise, the sensors software directly outputs the acceleration vectors in 3D as well as their instantaneous norm to analyze the instantaneous acceleration profiles (not shown). The software also obtains their maximum scalar values for each sub-segment of the technique. Across all repetitions and sensory conditions, we constructed the histograms of these values to investigate the statistical properties of their frequency distributions.

Predicting the type of movement from the hand trajectories

The movement trajectories described by our hands as we move are rich in movement parameters that can be informative of our intentions. This is well known in the literature on gesture and body language. However, spontaneous transitional movements that supplement the staged components of complex movement sequences have not been explored. Using a simple leave-one-out cross-validation algorithm (Quian Quiroga et al. 2006), we can ask—based on the hand trajectory curvature—which technique (Jab, Cross, Hook, or Uppercut) and segment type (strike or retracting) a randomly selected trial most likely came from.

Should any differences existed between striking and retracting modes of the techniques, and since we know that the strike movements are aimed at a goal (or a set of goals) and that the retracting transitional movements are not instructed or aimed at a specific goal, we could map the strikes to goal-directed mode of control and the retracting motions to spontaneous supplemental mode of control. These would roughly correspond in Fig. 1 to intentional versus automatic modes with potentially different gradients in their statistical patterns of variability as the speed changes.

Using a simple linear classifier, we ask whether the supplemental movements are separable from the staged movements for each one of the 4 techniques under study. To this end, we use the hand trajectories' maximum bending. Recall that the trajectory curvature can be related to the bending of the curve that the hand describes in relation to the Euclidean straight line. This scalar quantity can be easily obtained at each point along the hand path, in this case for each technique and movement segment, by projecting each point along the corresponding hand trajectory segment onto the Euclidean straight line and selecting the maximal normal distance.

For each technique type (a total of 4 techniques), 55 trials were used for a total of 220 trials per movement type (a total of 2 movement types). Trials were represented as points in an m-dimensional space, each coordinate corresponding to the parameter of choice [maximum bending (meters)] input to the decoding algorithm for each of the m subjects ($m = 6$, one expert and 5 novices).

One at a time, data from each trial picked at random were used to predict the trajectory parameter from a technique and movement type (chance $P \leq 1/8$, 4 techniques and 2 movement types), based on the parameter distributions derived from all the remaining trials (leave-one-out cross-validation), and were assigned to the class of its nearest neighbor in the m-dimensional space using Euclidean distance (Duda et al. 2001). For assessing statistical significance of the decoding results, a value of 1 was assigned to correctly predicted trials and a value of 0 to the incorrectly predicted ones. The mean of the sequences of correctly and incorrectly classified trials was compared statistically using a non-parametric Wilcoxon rank test (Zar 1996) and represented graphically as confusion matrices. Upon analyses including all 6 participants at once, we then examined each individual separately ($m = 1$) to determine the worst and the best performance.

Statistical analyses of hand trajectories in three dimensions

The Wilk's lambda statistic has the likelihood ratio test $\Lambda = \frac{\det(E)}{\det(E+H)}$ written in terms of the 'within' sum of squares and products matrix E and the 'total' sum of squares and products matrix $(E + H)$. The matrix $E = \sum_{ij} y_{ij} y_{ij}^t - \sum_i^k \frac{1}{n} y_{i.} y_{i.}^t$, where y_{ij} is a sample point and $y_{i.} = \sum_j^n y_{ij}$ is the total sum of the ith sample. The matrix $H = \sum^k \frac{1}{n} y_{i.} y_{i.}^t - \frac{1}{kn} y_{..} y_{..}^t$, where $y_{..} = \sum_i^k \sum_j^n y_{ij}$ is the overall total. This test is similar to the univariate F test. It is a multivariate generalization of the univariate *F-distribution* [and generalizes the *Hotelling's T-square* distribution as the *F-distribution* generalized the Student's *t-distribution* (Mardia et al. 1979)].

We use it in each three-dimensional vector along the hand trajectory. The use of determinants reduces the test statistic Λ to a scalar, making it possible to decide whether the separation of mean vectors is significant. When $\Lambda \leq \Lambda_{\alpha,d,vH,vE}$ (Λ small), the null hypothesis is rejected. In $\Lambda_{\alpha,p,vH,vE}$, α is the level of confidence, d is the number of variables or dimension, $v\mathrm{H} = \mathrm{k} - 1$ and $vE = k(n-1)$ are the degrees of freedom for hypothesis and error, respectively, k is the number of conditions and n the number of trials.

The Wilk's lambda rule rejects the null hypothesis of mean equality for $\Lambda \leq \Lambda^*_{\alpha,d,vH,vE}$, where $\alpha = 0.05$, $d = 3$, and $v_H = 2 - 1$, $v_E = 2(10 - 1)$, are the degrees of freedom for hypothesis and error terms, respectively, for the hand paths. In our case, the number of samples $k = 2$, (slow vs. fast within each control type, goal-directed vs. supplemental). Each block has 10 trials. Thus, the number of points per sample-condition is $n = 10$. $\Lambda^*_{\alpha=0.05,d=3,v_H=1,v_E=18} = 0.803$ (taken from Rencher 1995, Appendix B p. 427). Values of Λ that cannot reject the null hypothesis as such that $\Lambda > \Lambda^*_{\alpha,d,vH,vE}$.

Distributional analysis

The statistical properties of the peak velocity from the hand movement trajectories performing the Jab were obtained and the best distribution family was fitted using maximum likelihood estimation (m.l.e.). The histograms and estimation of bin size used Matlab routines based on well-established algorithms for optimal bin estimation with $W = 3.49\sigma N^{-1/3}$(Scott 1979; Izenman 1991), where W is the width of the bin, σ the SD of the distribution (we used estimated SD s), and N is the number of samples. For each subject, these analyses included between 300 and 400 trials across speed types and sensory conditions for the isolated Jab technique and for the Jab technique embedded in the sequence. In some cases, a small percentage of trials were excluded due to performance error or failure of the system to record. These were less than 5% across the entire data set.

Based on previous results from our work involving human patients (autism and Parkinson's, Jose et al. SNF 2011), (Isenhower et al. 2011a, b; Torres et al. 2010), we used the Gamma probability distribution family to ask whether it adequately captured the broad range of variability patterns in the hand's peak velocity across subjects. The motivation came from our findings that the distributions of this hand trajectory parameter were skewed across a wide range of motor tasks, but the log of the parameter distributes normally with a range of variability across patients and typical controls that span from the exponential to the normal ranges of the log-normal distributions. Various analyses in our previous work assessing different statistical families have revealed best fitting of the Gamma distribution, so we use it here as well.

The Gamma distribution is a two-parameter family of continuous probability distributions. Its probability density function is given by the expression:

$$y = f(x|\alpha, \beta) = \frac{1}{\beta^{\alpha}\Gamma(\alpha)} x^{\alpha-1} \mathrm{e}^{-\frac{x}{\beta}} \quad (1)$$

with shape (α) and scale (β) parameters. If α is a positive real number $\Gamma(\alpha) = \int_0^\infty t^{\alpha-1}\mathrm{e}^{-t}\mathrm{d}t$.

By varying the shape and scale parameters, one can go from a Gaussian-like distribution, which we have found in typical-intact systems to the exponential distribution (when $\alpha = 1$) which we have found in the compromised systems. Importantly, the distributions and different parameter values are differentiated solely by the statistical properties of empirical data (i.e., the velocity maximum in this case).

The specific nature of a given statistical distribution allows probabilistic knowledge of what value the random variable (the maximum velocity in our case) will be in the next trial with different levels of certainty—with the exponential (the most random of the distributions) and the Gaussian distribution (needing only two moments to characterize the parameter's behavior) at the extremes. It is in this probabilistic context of certainty and predictability that we have framed our data to objectively assess the individuals' variability within the Gamma parameter (phase) space for the two movement types. Gamma parameters are thus expected to differ between the two types of movements for each participant. Furthermore, the expert's distance between the points corresponding to the 2 movement types in the Gamma phase space is expected to differ more than that of the novices—who are still learning these techniques.

Results

Randomly chosen trials can predict which technique and movement type the trial came from, based on the hand trajectory's maximum bending

The leave-one-out cross-validation procedure revealed that it was possible to accurately predict for a randomly chosen trial not only which technique the trial came from but also, without confusion, whether a given technique segment was from the strike portion or from the retracting portion. Using the maximum bending of the trajectory, the predictive value of the trials was high (0.83 for the strike and 0.99 for the transitional retracting ones).

Figure 3 shows the results in the form of confusion matrices for the group of subjects (A) and for the worst individual performance (B). Rows are actual values from the data sets. Columns are assigned values from the leave-one-out cross-validation algorithm using nearest-neighbor criterion. The 4 upper diagonal values represent the predictability level of each technique within the strike mode. The 4 lower diagonal values represent the same for the transitional retracting segments of each technique. Off-diagonal values within each mode (4-technique quadrant) indicate if there is confusion of one technique with another. Off-diagonal values in the 2-mode quadrants indicate if there is confusion of the type of mode.

Two main results stand out: (1) The retracting movements do a better job at distinguishing the techniques both for the group performance and for the individuals' performance (this is also reflected in Table 1); (2) The strikes of each technique (goal-directed segments) are never confused with the spontaneous retracting segments. Even for the worst individual's decoding performance, the distinction remains (this is shown in Fig. 3a-group performance and 3b-worst individual performance).

Notice that Fig. 3a shows the results from a population analysis including all 6 participants, so it makes a statement about the overall variability in this group of people regarding these techniques and movement types, for the hand trajectories' maximum bending. The same analysis for each individual yielded a result that depended on the level of training. The expert had the highest predictive accuracy of technique-plus-movement type but one subject yielded 0.55 in the strike segments, 0.75 in the spontaneously retracting segments, and 0.65 mean diagonal. These values were still well above chance ($P \leq 1/8$) yet much worse than the expert's (overall diagonal 0.85) and than other subjects who seemed to have learned at a faster rate. These disparate levels of decoding performance were expected. The surprise was how well the decoding algorithm captured the differences in movement types with no confusion between groups of movements even in the worst case (Fig. 3b). Even though the individual techniques within each movement type could be confused in most novices, the two movement types across all techniques were not confused. This clearly established two movement classes which corresponded to the strike and retracting portions of the techniques.

The learning/expertise stages of each individual and of the group were in congruence with the other analyses that we describe next. Table 1 summarizes the results for each individual and for the entire group (last row in the table). The group's variability in the hand trajectories' maximum bending could accurately discern between movement types and technique, albeit with higher accuracy in the technique for the spontaneous transitional segments. In this sense, the spontaneous transitions were far more informative, a point that we expand later with other metrics.

Different effects of the changes in speed on goal-directed versus supplemental segments manifested in expert and novices alike

Given the results from the classifier—which unambiguously separated two groups of movements with different functionality—and that this separation corresponded to the goal-directed strike and the supplemental retracting segments of each technique, we asked whether the instructed speed had differential effects on these two movement classes.

Across participants—despite levels of expertise—the trajectories from the supplemental (retracting) segments incidental to each technique divided into different families of trajectories according to the instructed speed. The trajectories from the supplemental segments changed their curvature with the speed. By marked contrast, the goal-directed trajectories maintained their geometric features despite different speeds. This result was congruent with the decoder, which for each individual and also as a group

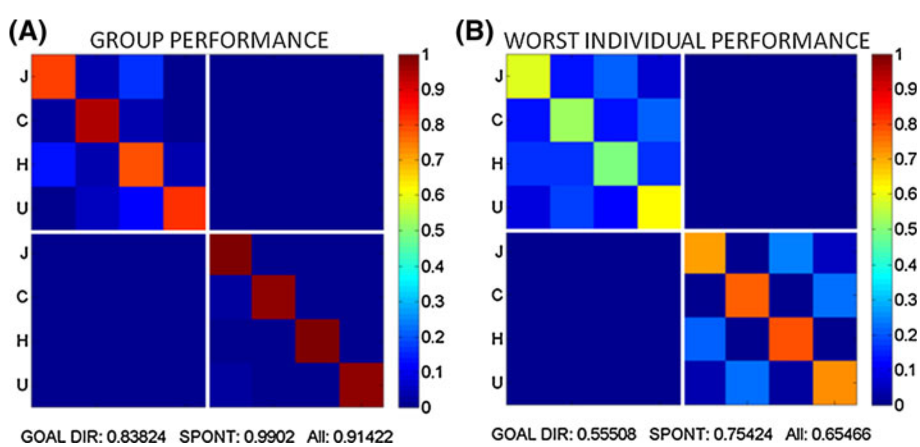

Fig. 3 Randomly chosen trial accurately predicts the technique and the movement type from the hand trajectory's bending. **a** Group prediction from 6 participants (5 novices and the expert) is accurate for both the technique and movement type. Notice that spontaneous supplemental movements in each technique are better predicted than goal-directed ones. **b** Worst individual performance (well above chance, 1/8 from 4 techniques and 2 movement types) still does not confuse the two movement types at all. *Rows* are actual values while columns are assigned values from the leave-one-out cross-validation

Table 1 Individual and ensemble decoding results using leave-one-out cross-validation with nearest-neighbor criterion

	Movement functionality		Diagonal
	Goal-dir	Supplem	
Expert	0.75	0.85	0.93
Novice 1	0.73	0.78	0.83
Novice 2	0.70	0.80	0.89
Novice 3	0.61	0.59	0.66
Novice 4	0.55	0.65	0.75
Novice 5	0.69	0.69	0.70
Ensemble	0.83	0.91	0.99

showed better predictive value for the spontaneous transitions interleaving the goal-directed strikes.

Figure 4 shows the speed profiles (a-left hand, b-right hand) and the corresponding 3D trajectories (c-left; d-right hand) from the expert performance of the full fluid sequence across 20 trials. Notice in C and D examples of the supplemental spontaneous trajectories from the Hook (H2) and from the Uppercut (U2) as the system transitioned to other staged technique with the opposite hand. These trajectories dramatically changed with the speed and grouped into different families of curves even though they were preceded by the goal-directed curves, the strike segments of each technique that had preserved their geometric features (bending and orientation) despite speed changes.

Figure 5 shows the performance of a typical novice. Notice that as in the expert, the effects of speed were different in the staged segments (the trajectories are more conserved) than in the supplemental segments of the technique (the trajectories changed), albeit with more variability than the expert's motions. In each technique for the novice in Fig. 5a–d, the trajectories from the goal-directed segments remained similar despite changes in speed ($\Lambda > \Lambda^*$) for each point along the path, but the corresponding supplemental trajectories split according to speed type ($\Lambda \ll \Lambda^*$) (Rencher 1995)—*Wilks* Λ test, $\alpha = 0.05$). This was the case particularly for the highly curved movements (Hook and Uppercut). As in the expert performance, the novices' performance conserved the goal-directed curves but the supplemental trajectories changed according to speed type. These effects were congruent across subjects and consistent in other parameters of the hand trajectories—as described later.

The decoder's blind distinction between strike and retracting motions of each technique had a correspondence with the effects of instructed speed on the hand trajectories of each movement type. The supplemental motions of each technique had systematically higher predictive value across subjects and for the group—since different families of trajectories for each technique emerged with changes in speed. Their patterns of variability not only changed significantly, they actually split into different families of trajectories.

In the strike segments specifically aimed at a set of goals, the decoder's prediction showed more confusion for each subjects and for the group than the supplemental segments. In the goal-directed trajectories, there was more conservation and less variability. In this sense, their bending patterns across speeds were less informative. Next, we examine the temporal coverings of these curves and assess the statistical patterns of variability of the maximum hand velocity along each technique's segment.

Skewed distributions of the peak velocity values from the hand trajectories

The distributions of the maximal speed values across repetitions and techniques were skewed across subjects with different degrees of skew well fitted by the continuous 2-parameter Gamma family (Fig. 6). In both goal-directed and supplemental cases, taking the logarithm of the peak velocity turned the distributions normal (Fig. 6a, b insets for expert and representative novice). Across novices, the hand speed ranged between 0.97 and 7.91 m s^{-1} in the goal-directed segments and between 0.60 and 4.96 m s^{-1} in the supplemental segments incidental to the main techniques. The expert motions were significantly faster (up to 9 m s^{-1}). They also differed between staged and supplemental movements in the Gamma parameter (phase) space. This is shown across all subjects in Fig. 6c with the power fit, goodness of fit values reported in the figure caption (absolute value of the exponent for goal-directed 0.93 was below 1, but above 1 (1.64) for supplemental motions and maximal separation between the 2 m.l.e. sets of parameters for the expert). The goodness of fit was best in the supplemental movements as well. These results were congruent with the decoder's and with the different patterns of trajectory variability for the two movement types of each technique.

Discussion and conclusions

This work investigated patterns of movement variability during the performance of complex beginner's martial arts routines. First, we showed that across repeats of these complex sequences and for this group of participants, one could randomly choose a trial and predict with high accuracy the type of technique and segment functionality that the randomly chosen trial most likely came from. Based on the maximum bending of the hand trajectory, a simple linear classifier did not confuse which strike and technique a blindly chosen trial came from. These

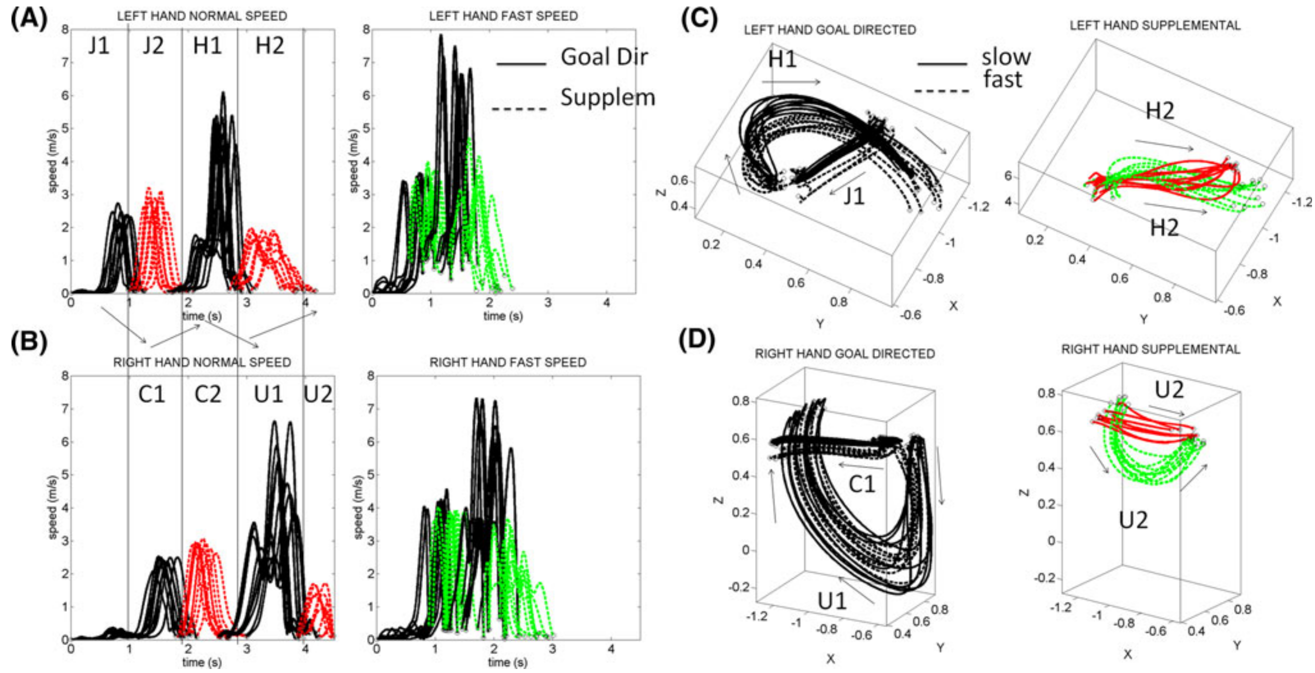

Fig. 4 Different effects of speed changes on the supplemental and staged movement trajectories: Expert performance of a fluid sequential full set of techniques. **a, b** The instantaneous speed profiles from all 10 trials performed at the slow instructed speed from the left hand alternating between staged and supplemental segments of each technique. The technique segment is indicated for each hand speed. *Arrows* indicate the alternating order and mark the simultaneous performance of an intended (staged) and a supplemental segment. **c** All trajectories from the staged segments of the left hand at the fast and the slow speeds grouped to show their similarity in space. Contrast the left hand trajectories from the supplemental segment of the Hook back which changed their spatial properties and the region in space as a function of speed. Faster movements were more curved on the way to the body and also changed the curve space orientation. **d** Staged trajectories for the staged segments in the Cross and Hook techniques performed by the right hand also maintained the spatial properties despite instructed speed. The return supplemental trajectories from the Uppercut changed in space with the speed. Notice that fast U2 occupies a different region of space (different curvatures, orientations and lengths) than slow U2 despite the fact that the preceding U1 segments were statistically invariant to speed changes. *Arrows* indicate the flow of the motion

separable movements also had different purposes. The strike segments corresponded to staged segments performed toward a goal (e.g., hit the face area of an imaginary opponent). The transitional retracting movements supplemented the main goals. We then posed a main hypothesis in this work: speed changes will have a different effect on the movement trajectories of the goal-directed segments than on those from the supplemental segments, incidental to each staged technique, with marked differences in their statistical patterns of variability.

We found evidence in support of the hypothesis. There are two fundamentally different classes of movements to be simultaneously controlled, serving different functions. The instructed changes in speed affected their trajectories differently. These effects were quantified in the maximum bending and in the maximum speed of the trajectories from both movement types. The class of movement explicitly sub-serving a set of goals (goal-directed) tended to conserve the physical curves of the trajectories and had different latencies and different temporal profiles. The supplemental class of movements manifested different trajectories—each corresponding to a speed level (i.e., to a given latency and temporal profile family).

These findings held independent of the level of training or skill of the participant. The different instructed speeds in the expert and novices alike had a fundamentally different effect on the movement segments that were staged and deliberately aimed toward a goal than the effects they had on the supplemental transitions of each technique. Specifically, when moving the hand between the same two locations in space, the system made different uses of the sensory input provided by the movement (i.e., from the kinesthetic sense of body position and body movement) when the motion was goal-directed than when it was supplemental. When instructed to move faster, the system scaled the tempo of the movement along a statistically similar physical path if the motion was staged to punch the opponent. When retracting the hand as the other hand simultaneously deployed the next punch, the retracting path to the same initial spatial location spanned a significantly different physical trajectory for different instructed speeds. Each speed level spanned curves with a distinct geometry:

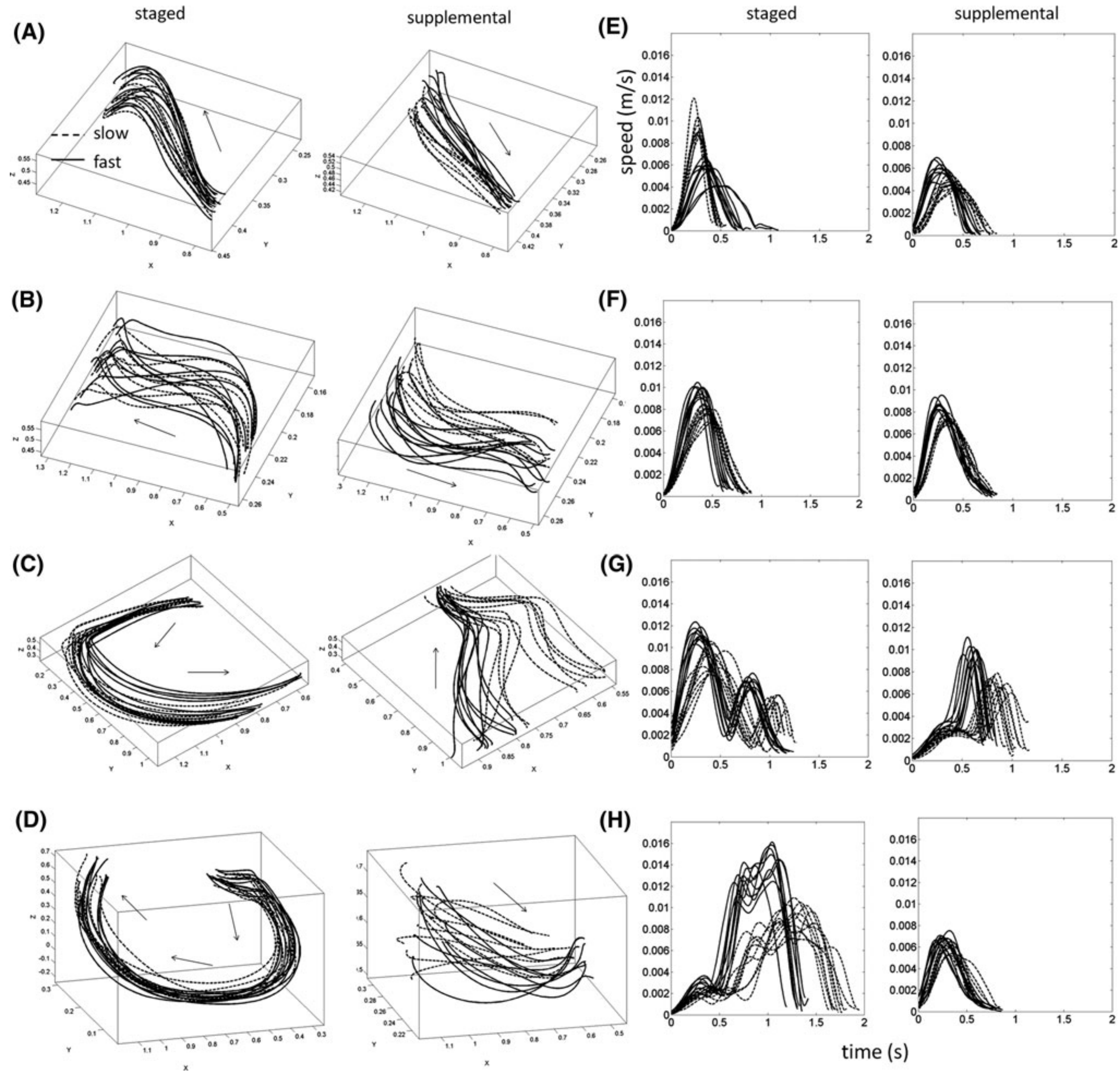

Fig. 5 Different effects of speed changes on the striking (goal-directed) and retracting (supplemental) movement trajectories remained in novice during the learning of these routines for the first time. **a**–**d** Intended movements from the staged segments of the technique were not significantly different with speed changes (see text). *Arrows* indicate the flow of the movement. However, supplemental segments changed the trajectories with changes in speed. **e**–**h** Speed profiles from each technique segment and speed type

different path length, different curvature, different orientation, etc. Likewise, there was a gradient of variability in the speed parameters that differed between the two blindly separated groups of movements. Specifically, the values of the maximum speed along the hand trajectories manifested two distinct signatures of variability according to the Gamma-distribution family's m.l.e. These signatures were different for each subject and had different values for the strike than for the retracting segments. The two movement types were at a larger distance in the Gamma-distribution parameter space in the expert's case compared to novices. This suggests that the more the system practices, the farther apart the statistical signatures of variability from these two movement types may become. We are currently testing this hypothesis in other experts.

We also found skewed distributions of the peak velocity not previously reported in complex sequences (although we had reported them in rhesus monkeys performing the center-out reaching planar task Torres et al. SFN 2010, San Diego, CA). These new findings in complex sequential motions

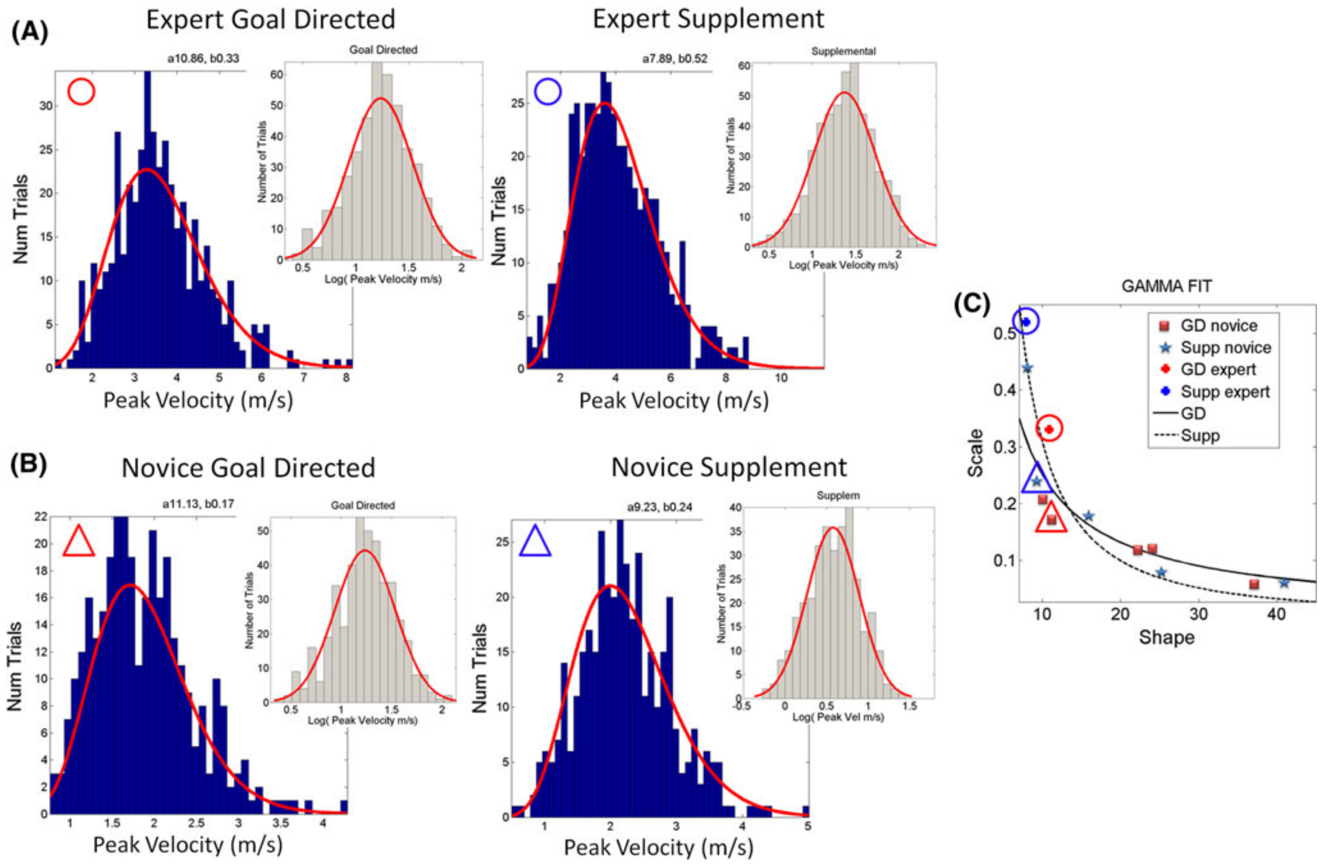

Fig. 6 Gamma fitting to skewed distributions of the individual's hand peak velocity across sessions. **a** Expert performance (439–480 trials across sessions). Skewed distribution of peak velocities for both Jab segments, staged and supplemental fitted by the Gamma family (see text for bib size determination). Insets are the distributions of the log of the peak velocity which distributes normally. Mean and variance for staged are 3.61 and 1.20 m s^{-1}, respectively. Gamma maximum likelihood best fitting parameters are 10.85 (shape) and 0.33 (scale) with 95% confidence intervals [9.28 12.69] and [0.28 0.39], respectively. Supplemental movements had mean and variance 4.12 and 2.15 m s^{-1}, respectively. Gamma maximum likelihood best fitting parameters are 7.89 (shape) and 0.52 (scale) with 95% confidence intervals [6.77 9.19] and [0.44 0.61], respectively. **b** Novice performance (329–386 trials across sessions). Same format as expert data. Mean and variance for staged movements are 1.87 and 0.31 m s^{-1}, respectively. Gamma maximum likelihood best fitting parameters are 11.13 (shape) and 0.16 (scale) with 95% confidence intervals [9.56 12.95] and [0.14 0.19], respectively. Supplemental movements had mean and variance 2.23 and 0.54 m s^{-1}, respectively. Gamma maximum likelihood best fitting parameters are 9.23 (shape) and 0.24 (scale) with 95% confidence intervals [7.94 10.73] and [0.20 0.28], respectively. **c** Gamma family fit across all 5 novices and 1 expert plotted in parameter space (*squares* are from goal-directed trials, *stars* are from supplemental trials). *Circles* enclose the expert in **a** and triangles the novice in **b**. Notice that each movement type has a different statistical signature for each subject. The power fit model $f(x) = ax^b$ (6 subjects) for the goal-directed yielded ($a = 2.15$, $b = -0.93$, R-square 0.67, rmse 0.06). In the spontaneous case the rate of decay was faster-larger absolute value of the exponent ($a = 13.57$, $b = -1.64$, R-square 0.89, rmse 0.01). Expert points for goal-directed and supplemental movements were farther apart in Gamma phase space

performed by humans paired with the finding that the log of the parameter distributes normally may be of interest to the computational community. There are fundamental statistical differences between symmetric and skewed distributions in terms of additive versus multiplicative effects (Limpert et al. 2001). Both the log-normal and the Gamma family provided good fits to the kinematics data. These results invite investigation of the statistical patterns of variability from other movement variables and their potential roles as possible task-dependent control parameters in stochastic models of optimization with constraints.

The present results have potential therapeutic value in clinical research. As in our recent reports from patient data involving sequential visually guided reaches (Torres et al. 2010, 2011), here in more complex sequential movements, we were also able to use this dichotomy between task-relevant and task-incidental aspects of the movements to identify in the patterns of movement variability the most adequate movement-based feedback to guide a system. This turned out to be from the supplemental movements. Using the present objective metrics, we will be able to track learning gains in patients.

The ability to track learning gains in patients to identify the most effective form of sensory-motor feedback for a given individual could facilitate the identification of relevant movement parameters to tailor personalized therapies that exploit the best learning predispositions and the best sensory capabilities of each given individual. In this sense, the present methodology may be useful in spectral developmental disorders—such as Autism—and in spectral neurodegenerative disorders as well—such as Parkinson's disease. Both disorders—whether present at the beginning or at the end of the human lifespan—produce a constellation of sensory-motor deficits with variable degrees of severity from individual to individual. Thus (all things being equal in a task), the personalized signature of motor variability (e.g., our Gamma parameterization of variability providing a continuum of signatures across subjects) can be informative of where the individual falls in relation to typical controls along a continuum gradient of variability for each movement type. In turn, this can inform us which form of sensory-motor feedback could potentially be more suitable for a given patient within a given spectrum [Jose et al. 2011, Torres et al. (2010, 2011)]. Additionally, since supplemental movements are a by-product of or support goal-directed behaviors, they require no explicit instructions. This is to our advantage since the majority of the patient populations from whom we assess naturalistic movements may have difficulties following precise instructions. Thus, we could target these spontaneous supplemental motions to track performance gains.

The conservation versus non-conservation of the movement trajectories with speed changes could have implications for theoretical work in movement control. Two qualitatively different solutions emerged to move between the same two regions of space: one which gave rise to a unique curve with multiple temporal profiles and latencies (goal-directed case) and another (supplemental case) which gave rise to different families of curves, each one of which had a unique temporal profile and latency. This new result extends the empirical results from our previous work on the reaching family (Torres 2010) to more complex choreographic routines that simultaneously engaged all limbs, trunk, and the head. There is to my knowledge no single computational principle that could explain and account at once for these two qualitatively different solutions to the problem of moving the hand between the same two spatial locations. These new empirical results pose a new theoretical question: given two points in space, how do we connect them by moving deliberately and how do we do so by moving spontaneously using a unique physical principle? Based on our data, we conjecture that two distinct sets of principles must govern these motions' dynamics, and therefore, we can consider goal-directed and supplemental movements as two distinct classes of motor behavior, possibly primarily controlled by different parts of the nervous system. Further research will be required to address this conjecture.

One possible interpretation of these results is that during the staged segments of the techniques the "mind" dominates over the physics of the body to keep the body on a deliberately staged spatiotemporal course of the action as brain structures involved in the voluntary control of movements primarily guide the action. By contrast, in the supplemental movements, the "physics" runs the show as different systems involved in automated control may primarily guide the action without much conscious awareness. Smoothly transitioning between these two modes would allow flexibility in recruiting, releasing, balancing, and coordinating the degrees of freedom in our body while complying with concomitant environmental constraints (Torres and Zipser 2002). In this sense, the dichotomy unveiled here provides a unifying framework to study the physical movements of a biological entity in its natural environment. As others have previously pointed out in the context of rhythmic behaviors (Kugler and Turvey 1987), it is important to look at movement in a broad sense, inspired by the works of Nikolai Bernstein (Bernstein 1967) and motivated by the ideas of James Gibson (Gibson 1966). The present framework seeks to study natural movements in that broad context and take full advantage of the body of knowledge created by both the motor control community [e.g., (Shadmehr and Wise 2005; Lacquaniti et al. 1982; Terzuolo et al. 1982; Soechting and Terzuolo 1988; Flanders 2011)] and by the field of ecological psychology that highlights the complementary nature of sensory-motor processes [e.g., (Kelso 1995; Kelso and Engstrøm 2006)].

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Appendix

The first isolated technique is called a Jab. The Jab starts with the front hand extending toward the imaginary opponent's nose (J1), keeping the hand in a tight fist, making sure that the elbow does not hyperextend; the hand should be retracted while it is still slightly bent (Fig. 2a). At the same time that the Jab is being retracted (J2), the

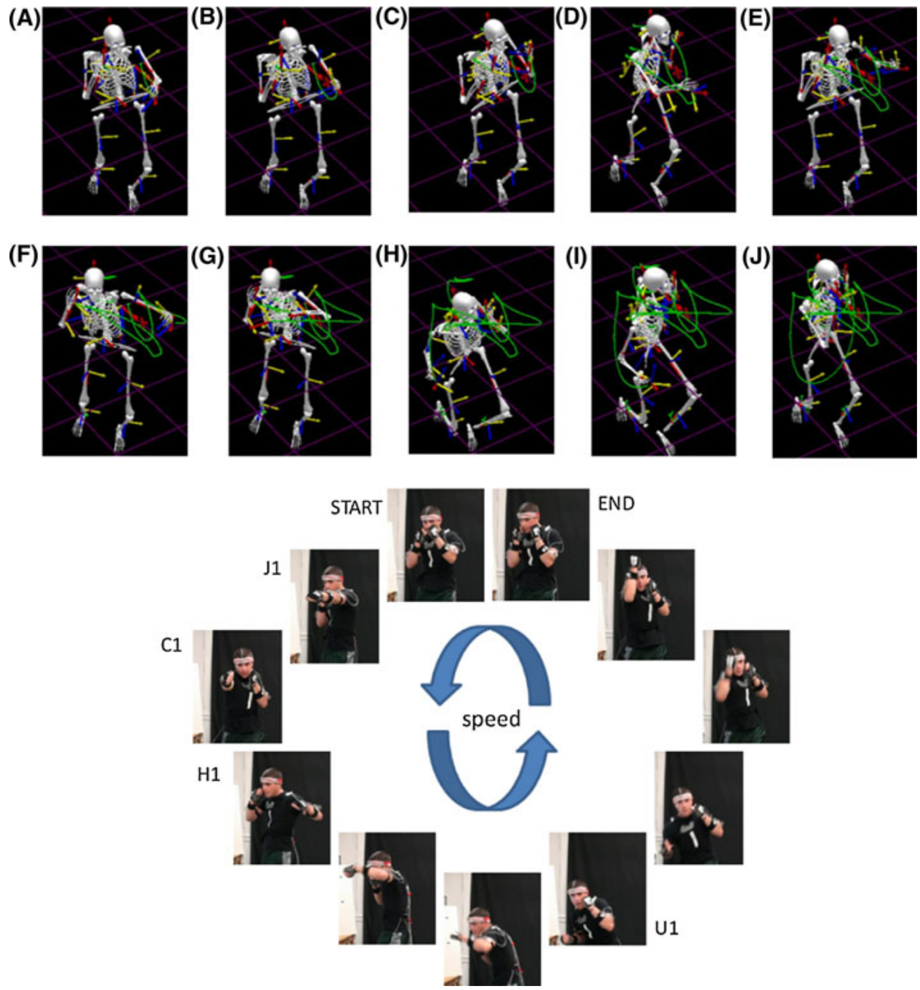

Fig. 7 Methods–Martial arts routine—Jab–Cross–Hook–Uppercut

Cross is being extended forward (C1). Again the imaginary target is used and the Cross is directed toward the nose. Simultaneously, the body is twisting, beginning with the back foot, then the torso and ending with the back of the hand extending forward. Because the body is already twisted, this motion naturally sets up the staged portion of the Hook (H1) aimed at the opponent. As the Cross (right hand) reverts back to its original position (C2), the left forearm is made into a C-shape with the hand in a fist and the palm facing down, and the body untwists itself, using the momentum of the body rather than the force of the hand to achieve the intended goal (to reach the opponent's face). As the body untwists itself in a supplemental H2, the knees bend slightly in preparation for the intended Uppercut (U1). After the knees are bent and the left hand is returning to its original positioning to protect the face, the right hand fist shoots up in a motion that resembles throwing a bowling ball, but the hand is kept tighter aligned to the body and the palm facing the body. The supplemental portion U2 brings the hand back, and the body adopts the defense position again (Fig. 7 bottom panel-end of the cycle). It is important to note that all routines where done in the presence of an expert instructor in order to minimize risk of injury. For further information and descriptions see our website for a detailed video tutorial on these techniques.

Three dimensional digital rendering frames from the expert's performance of one trial of J–C–H–U beginner's white belt technique using the real-time sensor outputs. Arrows mark the locations of 15 electromagnetic sensors recording at 240 Hz. The motion capture system provides the choice of outputting the raw accelerations and velocities (linear and angular) or various filtering and smoothing options. The system deals directly with potential spurious or noisy data due to estimation of higher order derivatives of position. Because of its reliability, this software-system is routinely used as a standard interface in sports training of the kind studied here. The update rate of 240 Hz per sensor and the latency of 3.5 ms permit real-time monitoring of the body motions. Each sensor has 6° of freedom (DOF) with static positional accuracy of 0.03in, static orientation accuracy of 0.15 deg RMS, a positional resolution of 4×10^{-5} cm at 30 cm range and a resolution of 1.2×10^{-3} deg of orientation. The range from the standard source is up to 1.52 m and the extended range is up to 4.6 m. Our experiments took place well within the standard source range. Several standard filtering algorithms are used by the professional software that comes with the Motion Monitor Sports Inn. We used a Butterworth filter (Butterworth 1930) with a cut-off frequency of 6 Hz. Further details about the electromagnetic system that our Motion Monitor uses can be obtained at the Polhemus company website.

Green traces in the rendered figure mark the hand motions. Forward segments were away from the body and staged against an imaginary opponent. They coexisted with the supplemental transitions of the other limb simultaneously moving away from the opponent. (A) Jab1 in the forward direction, away from the body. (B-D) Jab 2 back toward the body simultaneously with Cross 1 forward. (E–F) Cross 2 back simultaneously with Hook 1 forward. (G-J) Hook 2 back simultaneously with U1, ending the routine with both hands back to protect the face. Bottom panel focuses on the expert's hands (Google my lab's website for more details and videos).

References

Abend W, Bizzi E, Morasso P (1982) Human arm trajectory formation. Brain 105(Pt 2):331–348

Atkeson CG, Hollerbach JM (1985) Kinematic features of unrestrained vertical arm movements. J Neurosci 5(9):2318–2330

Bernstein NA (1967) The co-ordination and regulation of movements, 1st English edn. Pergamon Press, Oxford

Berthier NE, Keen R (2006) Development of reaching in infancy. Exp Brain Res 169(4):507–518. doi:10.1007/s00221-005-0169-9

Butterworth S (1930) On the theory of filter amplifiers. Exp Wirel Wirel Eng 7:536–541

Conditt MA, Mussa-Ivaldi FA (1999) Central representation of time during motor learning. Proc Natl Acad Sci USA 96(20):11625–11630

Duda O, Hart P, Stork D (2001) Pattern classification, 2nd edn. Wiley, New York

Flanders M (2011) What is the biological basis of sensorimotor integration? Biol Cybern 104(1–2):1–8. doi:10.1007/s00422-011-0419-9

Gargner JM, Karmel BZ, Magnano CL, Norton KI, Brown EG (1990) Neurobehavioral indicators of early brain insult in high-risk neonates. Dev Psychol 26(4):563–575

Gibson JJ (1966) The senses considered as perceptual systems. Houghton Mifflin, Boston

Guigon E, Baraduc P, Desmurget M (2007) Computational motor control: redundancy and invariance. J Neurophysiol 97(1):331–347. doi:10.1152/jn.00290.2006

Isenhower RW, Metaxas DN, Jose JV, Torres EB (2011a) Movement variability as an objective classification tool for autism spectrum disorders. J Neurosci (submitted)

Isenhower RW, Metaxas DN, Torres EB (2011b) Physical metrics of fluency training and task complexity in the natural movements of children with ASD gauge learning in the classroom environment. Paper presented at the Society for Neuroscience (SFN), Washington

Izenman AJ (1991) Recent developments in nonparametric density estimation. J Am Stat Assoc 86(413):205–224

Jose JV, Isenhower RW, Torres EB (2011) Statistics of motor variability used as a classification tool for spectral disorders: application to Autism and Parkinson's disease. Paper presented at the Society for Neuroscience (SFN), Washington

Karmel BZ, Gardner JM (2005) Neurobehavioral assessment in the neonatal period—the impact of Ferenc Katona. Ideggyogy Sz 58(9–10):315–323

Karmel BZ, Gardner JM, Meade LS, Cohen IL, London E, Flory MJ, Lennon EM, Miroshnichenko I, Rabinowitz S, Parab S, Barone A, Harin A (2010) Early medical and behavioral characteristics of NICU infants later classified with ASD. Pediatrics 126(3):457–467. doi:10.1542/peds.2009-2680

Kelso JAS (1995) Dynamic patterns: the self-organization of brain and behavior. MIT Press, Cambridge

Kelso JAS, Engstrøm DA (2006) The complementary nature. MIT Press, Cambridge

Konczak J, Dichgans J (1997) The development toward stereotypic arm kinematics during reaching in the first 3 years of life. Exp Brain Res 117(2):346–354

Konczak J, Thelen E (1994) The dynamics of goal-directed reaching: a comparison of adult and infant movement patterns. In: Van Rossum JH, Laszlo JL (eds) Motor development: aspects of normal and delayed development. VU University Press, Amsterdam, pp 25–40

Kugler PN, Turvey MT (1987) Information, natural laws, and self-assembly of rhythmic movement. L. Erlbaum Associates, Hillsdale

Lacquaniti F, Soechting JF, Terzuolo CA (1982) Some factors pertinent to the organization and control of arm movements. Brain Res 252(2):394–397

Limpert E, Stahel WA, Abbt M (2001) Log-normal distributions across the sciences: keys and clues. Bioscience 51(5):341–352

Mardia KV, Kent JT, Bibby JM (1979) Multivariate analysis. Probability and mathematical statistics. Academic Press, New York

Marey E-J (1874) Animal mechanism; a treatise on terrestrial and aerial locomotion. International scientific series (London, England), vol 11, 2nd edn. Henry S. King & Co., London

Marey ÉJ, Pritchard E (1895) Movement. D. Appleton and company, New York

Morasso P (1983) Three dimensional arm trajectories. Biol Cybern 48(3):187–194

Nishikawa KC, Murray ST, Flanders M (1999) Do arm postures vary with the speed of reaching? J Neurophysiol 81(5):2582–2586

Quian Quiroga R, Snyder LH, Batista AP, Cui H, Andersen RA (2006) Movement intention is better predicted than attention in the posterior parietal cortex. J Neurosci 26(13):3615–3620. doi:10.1523/JNEUROSCI.3468-05.2006

Redgrave P, Rodriguez M, Smith Y, Rodriguez-Oroz MC, Lehericy S, Bergman H, Agid Y, DeLong MR, Obeso JA (2010) Goal-directed and habitual control in the basal ganglia: implications for Parkinson's disease. Nat Rev Neurosci 11(11):760–772. doi:10.1038/nrn2915

Rencher AC (1995) Methods of multivariate analysis. Wiley, New York

Scott D (1979) On optimal and data-based histograms. Biometrika 66:605–610

Shadmehr R, Mussa-Ivaldi FA (1994) Adaptive representation of dynamics during learning of a motor task. J Neurosci 14(5 Pt 2):3208–3224

Shadmehr R, Wise SP (2005) The computational neurobiology of reaching and pointing: a foundation for motor learning. Computational neuroscience. MIT Press, Cambridge

Smith LB, Thelen E (1993) A dynamic systems approach to development: applications. MIT Press/Bradford Books series in cognitive psychology. MIT Press, Cambridge

Soechting JF, Terzuolo CA (1988) Sensorimotor transformations underlying the organization of arm movements in three-dimensional space. Can J Physiol Pharmacol 66(4):502–507

Terzuolo C, Fohlmeister JF, Maffei L, Poppele RE, Soechting JF, Young L (1982) On the application of systems analysis to neurophysiological problems. Arch Ital Biol 120(1–3):18–71

Torres EB (2010) New symmetry of intended curved reaches. Behav Brain Funct 6:21. doi:10.1186/1744-9081-6-21

Torres EB, Zipser D (2002) Reaching to grasp with a multi-jointed arm. I. Computational model. J Neurophysiol 88(5):2355–2367. doi:10.1152/jn.00030.2002

Torres EB, Zipser D (2004) Simultaneous control of hand displacements and rotations in orientation-matching experiments. J Appl Physiol 96(5):1978–1987. doi:10.1152/japplphysiol.00872.2003

Torres EB, Raymer A, Gonzalez Rothi LJ, Heilman KM, Poizner H (2010) Sensory-spatial transformations in the left posterior parietal cortex may contribute to reach timing. J Neurophysiol 104(5):2375–2388. doi:10.1152/jn.00089.2010

Torres EB, Heilman KM, Poizner H (2011) Impaired endogenously-evoked automated reaching in Parkinson's disease. J Neurosci (in press)

von Hofsten C (1991) Structuring of early reaching movements: a longitudinal study. J Mot Behav 23(4):280–292. doi:10.1080/00222895.1991.9942039

von Hofsten C, Lindhagen K (1979) Observations on the development of reaching for moving objects. J Exp Child Psychol 28(1):158–173

Zar J (1996) Biostatistical analysis. Prentice-Hall, Upper Saddle River