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Robustness to temporal constraint explains expertise in ball-over-net sports

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A B S T R A C T

The present study investigated motor expertise in interpersonal competitive ball-over-net sports in terms of a dynamical system with temporal input. In a theoretical framework, the behavior of the system is characterized by a fractal-like structure according to switching input, which changes uniquely according to the duration of input and internal parameter of the system. We investigated periodic movements, in which the player executed a forehand or backhand stroke repeatedly, and continuous switching movements, in which the player continuously switched between two movement patterns corresponding to hitting the ball under two ball directions and with six temporal constraint conditions during a table tennis rally. In the periodic movement, we observed two limit-cycle attractors corresponding to each direction in the phase space independent of temporal constraint or skill level. Conversely, in the continuous switching movement, a transition in trajectories between the two limit-cycle attractors was observed in the phase space, and this transition was characterized by a fractal-like structure. The fractal-like structure moved closer to the random structure as temporal constraint increased independent of skill level. However, the temporal constraint condition closest to the random structure was higher for the advanced players than for the novices, indicating that robustness to the temporal constraint was higher for the advanced players than for the novices. Our results suggest that motor expertise in interpersonal competitive ball-over-net sports is more robust to temporal constraints with various inputs.

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1. Introduction

Research on expertise in interpersonal competitive ball-over-net sports, such as table tennis and regular tennis, has shown that it is difficult for an individual player to produce the same level of skilled motor behavior in a match as is produced in a practice session. Novice players often find that they are able to successfully perform stable periodic movements in response to constant ball trajectories during long, repetitive practice sessions, but are unable to do so during competition. This is because during a match, the player is required to switch between different movement patterns within a finite period of time to hit every ball returned by the opponent.

Several recent studies have investigated hitting behavior during a match to clarify the skilled motor behavior involved in interpersonal competitive ball-over-net sports. Although several studies have investigated the discrete movements involved in serving and returning the serve (Abernethy, Farrow, Gorman, & Mann, 2004; Elliott, 2006; Hodges, Starkes, & MacMahon, 2006), little is known about the skills involved in continuous switching movements in which execution of the movement pattern corresponds to the current position of ball even as the direction of the ball changes constantly.

Rhythmic movements, as observed in repetitive practice, have been extensively investigated from the viewpoint of dynamical systems theory (Kelso, 1984; Haken, Kelso, & Bunz, 1985; Buchanan & Kelso, 1993). Extending this theoretical discourse, Yamamoto and Gohara (2000) developed a novel method for assessing continuous switching movement in tennis by incorporating a theoretical framework that took into account the behavior of continuous dynamical systems with external input (Gohara & Okuyama, 1999; Gohara & Okuyama, 1999).

Within this theoretical framework, external input is defined as a set of input patterns that represent spatio-temporal information with a finite time length. When the same input pattern is repeatedly fed into the system, the state of the system is a limit-cycle attractor. However, when the input patterns are switched stochastically, the state of the system is characterized by a fractal-like structure according to transitions between attractors, each of which corresponds to the current input pattern.

Yamamoto and Gohara (2000) defined a single input pattern as the tennis ball projecting to either the forehand or backhand side at a given time. One complete striking action was represented as a trajectory in the cylindrical phase space matching one cycle as the time length of one input pattern. Repeating the same input pattern was represented as two stable trajectory sets in the phase space, namely the two limit-cycle attractors, corresponding to each input of periodic movement. Moreover, the switch between the two patterns in the continuous switching movement was characterized by the transition of trajectories between subsequent attractors in the phase space. Thus, when inputs are switched stochastically, the dynamics are characterized by trajectories with fractal-like structures.

Gohara and Okuyama (1999) theoretically demonstrated how the characteristics of the fractal-like structure depend on internal and external parameters (Wada & Gohara, 2001; Nishikawa & Gohara, 2008). The internal parameter affects how the trajectory converges on an attractor, and the external parameter corresponds to the duration of the input pattern. Moreover, the authors identified a correlation between the period to converge on an attractor and the duration of the input pattern. When the time length of the input pattern is sufficient to converge on an attractor, the trajectory will converge on an attractor corresponding to the current input pattern before the next input is fed into the system. Following this, the trajectory will begin to converge on an attractor corresponding to the next input and will do so within a finite period of time. When these transitions are repeated, the behavior of the system reveals a limit-cycle attractor similar to the periodic input condition, even under the switching input condition.

Conversely, when the time length of the input pattern is shorter than the period to converge on an attractor, the trajectory cannot converge on the current attractor before the next input is fed into the system, and the trajectory therefore diverges from the attractor. The trajectory then starts from the divergent state and moves on to the next attractor corresponding to the next input. When these transitions are repeated, the behavior of the entire system is characterized by a fractal-like structure because the trajectories are distributed around each attractor in an orderly manner. If, however, the period to converge on an attractor is lengthened or the duration of the input pattern is shortened, the behavior of the system resembles a random structure revealing that the order of the system has been compromised.

The time length of the input pattern functions as a temporal constraint for the system, and the temporal constraint may be associated with the random structure and the internal parameter. A system with a longer period to converge on an attractor would be a random structure under low temporal constraint compared with a system with a shorter period. The duration of an input pattern exhibiting a random structure should be considered as robustness corresponding to temporal constraint up until the moment when the fractal-like structure can maintain an ordered state (Kitano, 2004).

We incorporated these theoretical perspectives and research methods into our study of interpersonal competitive ball-over-net sports by postulating that a hitting interval can be construed as a spatio-temporal constraint. We hypothesized that the internal parameter corresponds to the skill level of the observed player. Conversely, despite skill level or hitting interval, the behavior of the dynamical system within the periodic movement would exhibit a limit-cycle attractor as a result of the player's ability to execute stable movement patterns repeatedly, and the hitting behavior of the continuous switching movement would be characterized by a fractal-like structure based on the requirement to switch to different movement patterns.

Furthermore, we hypothesized that changes in the hitting interval would be shorter for skilled players and thus would correspond to random structural changes in the fractal-like structure. By identifying the threshold of the hitting intervals during continuous switching movements, differences between skill levels would reveal differences in robustness to the temporal constraint.

We examined periodic and continuous switching movements under six temporal constraints during a table tennis rally. We assessed the hitting behavior of players with different skill levels and distinguished between temporal constraints as random and fractal-like structures during the continuous switching movement to determine whether skill differences could be explained by robustness in response to the temporal constraint in the continuous switching movement, but not in the periodic movement. Furthermore, we investigated the limit-cycle attractor during each periodic movement and the fractal-like structure during each continuous switching movement.

2. Method

2.1. Participants

The study was conducted using 14 participants divided into two equal groups of seven. The "advanced players" group comprised skilled college-age players with at least 5 years of high level of proficiency in table tennis, and the "novice" group consisted of college-age individuals with no or limited experience in table tennis. The advanced players were instructed to use the shake-hand grip, but no restrictions were placed on how the beginners should handle their racket. All participants were right-handed.

Our study was approved by the Ethics Committee of the Research Center of Health, Physical Fitness and Sports, Nagoya University, and all participants provided informed consent.

2.2. Experimental setting

The experimental setup (Fig. 1) consisted of a ball projection machine (Umehara A1, Umehara, Japan) positioned 500 mm from the table and opposite the participant, and a 950-mm-high turntable was located at the center of the service line.

The ball projection machine was set up to deliver a ball to the participants forehand or backhand in an area 100 mm wide and 200 mm long, located 100 mm to the right or 200 mm to the left of the center line and 300 mm from the edge of the table. Furthermore, we adjusted the position on the forehand side to be different from that of backhand side to project symmetrically from the participant's right arm. The accuracy of the ball projection machine was tested by projecting 100 balls in a pilot study before the experiment.

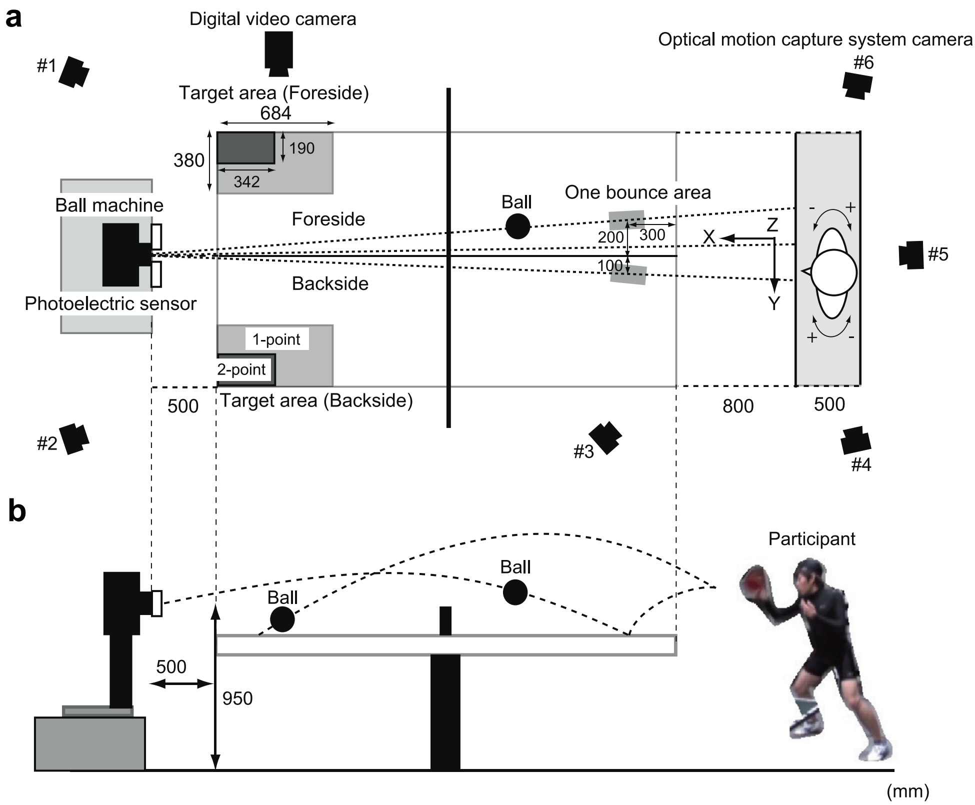

Fig. 1. Schematic of the top (a) and side (b) views of the experimental setup. A ball-projection machine was positioned 500 mm from the table and opposite the participant, who stood 800 mm from the table. The ball-projection machine was directed to project the ball to the forehand or backhand side 100 mm to the right or 200 mm to the left of the center line. Wide target areas were marked at both corners of the table, and narrow areas were marked within the wide target areas.

The mean interval between ball projection and bounce on the table was 415 ± 7 ms, and the duration for ball movement from projection to the participant in the standing position was 1000 ± 9 ms. A photoelectric sensor (Omron S3D2-CK, Omron, Japan) was installed on the ball projection machine to record when a ball left the machine. The standard deviation (SD) of the time period for ball projection was 5.5 ms, and those of the ball projection by position were 57 mm in the sagittal plane and 13 mm in the frontal plane.

All participants stood an average of 800 mm behind the table and were required to return the balls to the target areas as accurately as possible using a forehand or a backhand stroke according to the ball's direction.

Wide target areas (684 mm length × 380 mm width) were set at both corners of the table on the side opposite the participant. Narrow areas (342 mm length × 192 mm width) were marked within the wide target areas to encourage the advanced players to perform at their best under the experimental condition.

Each time a participant returned the ball to the target area, the experimenter rang a bell as a feedback signal. When the ball landed within the wide target area, a score of 1 point was awarded, and when the ball landed in the narrow target area, 2 points were awarded.

The most common table tennis grip styles are the shake-hand grip and the penholder grip. All participants in our study showed a preference for the more versatile shake-hand grip, as it eliminates the need to rotate the trunk during the backhand stroke, as observed with a penholder grip, and the grip remains the same for forehand and backhand strokes.

The kinematics of the hitting behavior was recorded using six optical motion-capture system cameras (Qualysys oqus 300, Qualisys AB, Sweden). The sampling frequency of the cameras was 500 Hz. Then, 20-mm markers were attached to participants' right and left acromion, and the positions of both were digitized. A right-handed orthogonal reference frame was used, and the vectors X, Y, and Z defined its axes. Z was vertical, X was horizontal and was directed along one sideline toward the opposite court, and Y was perpendicular to the other two axes and pointed toward the outside of the table. The mean errors of calibration were different for each participant because the calibration was carried out before each participant's session. The root mean square errors for the static and dynamic calibrations were less than 1.5 mm and 1.0 mm, respectively. The landing position of the ball on the table was recorded using a digital video camera (SONY HDR-HC3, SONY, Japan) to identify balls returned to the target areas.

2.3. Experimental conditions

Six temporal constraint conditions were set at 620, 660, 710, 770, 840, and 920 ms, and these independent variables were manipulated throughout the duration of the input pattern (T).

The temporal constraint conditions were mapped at ±150 ms from 770 ms, following the clarification proposed by Yuza et al. (1992), which stated that the interval between hitting the current ball and hitting the next ball is 766 ms on average during matches involving Japanese elite players.

In our experimental setting, the conditions were not equally spread out over the interval because we set high temporal constraint conditions to illustrate differences in skill levels.

2.4. Task

Participants were required to perform a periodic- and a switching-input task under each temporal constraint condition. During the periodic-input task, the same input pattern (forehand or backhand) was repeated for 30 trials, whereas during the switching-input task, two input patterns (forehand and backhand) were executed for 203 trials.

To accommodate the sheer number of trials in the second task and to avoid unreliable data due to participant fatigue, the 203 trials were broken down into seven sub-sets of 29 trials, each executed without stopping; a rest period was provided between sets.

Furthermore, similar to the methods described by Yamamoto and Gohara (2000) to generate regularity in the fractal-like structure in the switching input task, the 203 trials included a third-order sequence effect denoting the following eight input pattern sequences: forehand–forehand–forehand side (FFF), forehand–forehand–backhand side (FFB), forehand–backhand–forehand side (FBF), forehand–backhand–backhand side (FBB), backhand–forehand–forehand side (BFF), backhand–forehand–backhand side (BFB), backhand–backhand–forehand side (BBF), and backhand–backhand–backhand side (BBB).

To ensure accurate and appropriate data collection, the first two trials in each set were not analyzed. Special precautions were taken to ensure that of the sequence of 189 trials (27 trials × 7 sets) under each temporal constraint condition, at least 23 trials for each of the eight sequences, as well as the remaining trials were divided randomly. In sum, all participants completed 263 trials for each temporal constraint condition, amounting to a total of 1,578 trials (263 trials × 6 conditions) under all temporal constraint conditions.

2.5. Procedure

Prior to data collection and following a sufficient warm-up period, the experimental procedure was explained once more before the participants were required to perform a 10-minute practice session to become familiar with the experimental setup. Each participant was instructed to execute a single periodic input task on the forehand side first, then on the backhand side under same temporal constraints. Seven sets of switching input tasks were performed and recorded in rapid succession under the same conditions. The order of the temporal constraint conditions was randomized within each new set, and each recorded dataset was followed by at least a 3-min rest between sets before the next set began. The experiment took 2–3 days per participant.

2.6. Data analysis

2.6.1. The hyper cylindrical phase space $\mathcal{M}$ and the Poincaré section Σ

Following the widely accepted technique of Winter (1990), high-frequency noise was reduced using a second-order Butterworth digital filter for the digitized data at 6–11 Hz cutoff frequency. The cutoff frequency was determined using residual analysis.

The midpoint velocity of the left and right acromions at the Z-axis and the angular velocity of the shoulder segment on the X–Y plane were used to analyze the kinematics of hitting behavior. Midpoint velocity was selected as a dependent variable following the observation of Meinel (1960) that the dexterity of human movement is characterized by rhythmicity in a cyclic movement. We observed rhythmicity in all of our participants as they raised or lowered their body in a rhythmic motion. Wickstrom (1975) reported three stages of motion development: the arm domination, unitary action, and an opening pattern, all closely associated with hitting behavior in terms of the forward swing, the timing of the arm motion, and the rotation of the trunk.

In this respect, the rotation of the trunk was more important for hitting behavior, and therefore, the angular velocity of the shoulder segment in the X–Y plane was used as the other dependent variable. The segment angle at the shoulder was defined as the angle between the reverse of vector Y and the vector from the left to the right shoulder projected onto the X–Y plane.

The midpoint velocity was designated x_1, and the angular velocity of the shoulder segment was x_2. These time-series data were normalized by calculating the maximum value in all trials as 1, and the minimum value as 0 for each kinematic parameter. The data were depicted in a hyper-cylindrical phase space $\mathcal{M}$ as trajectories beginning the moment the ball left the ball projection machine; the Poincaré section $\Sigma(\theta = 0)$, until the next ball was shot, and $\Sigma(\theta = 2\pi)$ as a continuous dynamical system (see Fig. 3).

Periodic trajectories executed in the periodic-input task were considered the limit-cycle attractor, and the stable movement pattern as corresponding to each input pattern. Switching between two movement patterns during the switching-input task was considered to be the transition of a trajectory between two attractors with continuous temporal inputs (Yamamoto & Gohara, 2000).

Furthermore, the Poincaré maps, which consisted of trajectories, are shown in the Poincaré section to examine the discrete dynamical system geometrically. Finally, the characteristics of the Poincaré maps of the Poincaré section were estimated using the fractal dimension.

2.6.2. Fractal dimension

The fractal-based stochastic analysis is a suitable and powerful means of assessing the fractal characteristics of large, complex datasets, and hence was our preferred method of analysis.

Mandelbrot (1977) proposed that the fractal dimension refers to an index for quantifying the complexity of geometry with a fractal-like structure. If the fractal dimension is an integer value, for example, and if the dimension is equal to the value 2, the geometry does not have a fractal-like structure because the map spreads out randomly in one plane.

In contrast, if the fractal dimension is a non-integer value, the geometry has a fractal-like appearance. For instance, the fractal dimension of the Hénon map (Hénon, 1976) represents typical fractal geometry equal to 1.21 (Grassberger, 1983). However, if the value is greater than 1.5, it considered a Hénon map with noise (Argyris, Andreadis, Pavlos, & Athanasiou, 1998). Given a fractal geometry generated by a certain rule, an increase in the fractal dimension would represent some degree of noise.

Taking it a step further, if trajectories in the space $\mathcal{M}$ during the switching-input task have a fractal-like structure, the fractal dimension would have a non-integer value. The dimension would then move closer to the value 2 when the fractal-like structure changes to a more random appearance. In other words, if a completely random structure appears, the fractal dimension value equals 2. By analyzing the increase or decrease in the fractal dimension according to variable temporal constraints or varying skill levels of each individual player, we were able to identify robustness to each temporal constraint.

It should be noted that we did not calculate the fractal dimensions for the Poincaré maps during the periodic-input task. If the trajectories in the phase space for the task had a fractal-like structure, the structure would be generated by intrinsic fluctuation, such as the nervous system or the musculoskeletal system, similar to postural control and walking without perturbation (Davids, Glazier, Araújo, & Bartlett, 2003).

Thus, we considered the fractal-like structure during the periodic-input task to represent intrinsic fluctuation, whereas the structure during the switching-input task represents fluctuation of the hitting behavior in response to the external input. In this study, we focused on the external input fluctuation; thus, we calculated the fractal dimensions for the Poincaré maps during the switching-input task.

We estimated fractal dimension using a correlation dimension method, the most widely used approach for estimating the fractal dimension of small datasets such as ours. The correlation dimension was used as an estimate for the calculation of the correlation integral using the Grassberger-Procaccia method (Grassberger & Procaccia, 1983; Shelhamer, 2007).

2.7. Statistical analysis

The means and SDs of the performance scores and the correlation dimensions across all participants were calculated and assessed using a two-way analysis of variance (ANOVA) with skill level and temporal constraint conditions as variables. A one-way multivariate analysis of variance (MANOVA; Wilks' λ) was used to test the equality of the Poincaré maps for the two input patterns during the periodic-input task. A one-way MANOVA was used to test the third-order sequence effect of the Poincaré section during the switching-input task. p-values <.05 was deemed to indicate statistical significance and the effect size (η^2) was calculated using G* Power 3 in the ANOVA (Faul, Erdfelder, Lang, & Buchner, 2007).

3. Results

3.1. Performance

Fig. 2 shows the means and SDs of the performance variables under all temporal constraint conditions during the periodic and switching-input tasks. A two-way ANOVA for the periodic-input task revealed a main effect of skill level, $F(1,12) = 53.89$, $p = 8.96 \times 10^{-6}$, $\eta^2 = 0.82$, and the temporal constraint condition, $F(5,60) = 4.14$, $p = 2.70 \times 10^{-3}$, $\eta^2 = 0.26$; however, the interaction was not

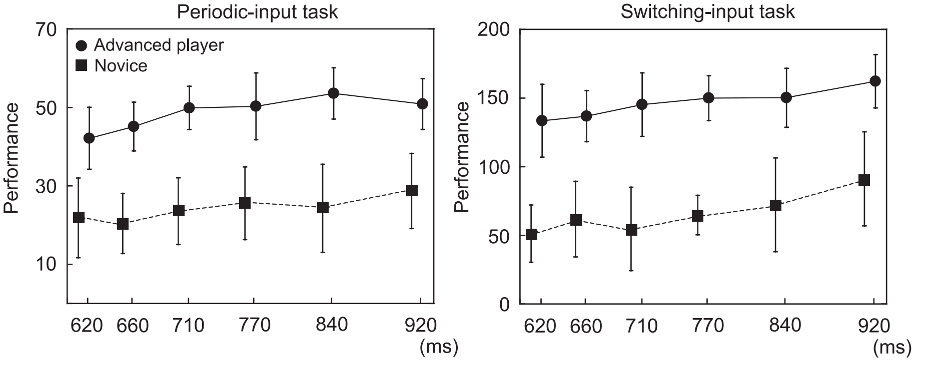

Fig. 2. Performance during the periodic-input and switching-input tasks. Participants were awarded 1 point when they returned the ball to the wide target area and 2 points when the ball landed within the narrow target area (see Fig. 1a). Performance was rated according to the sum of the points.

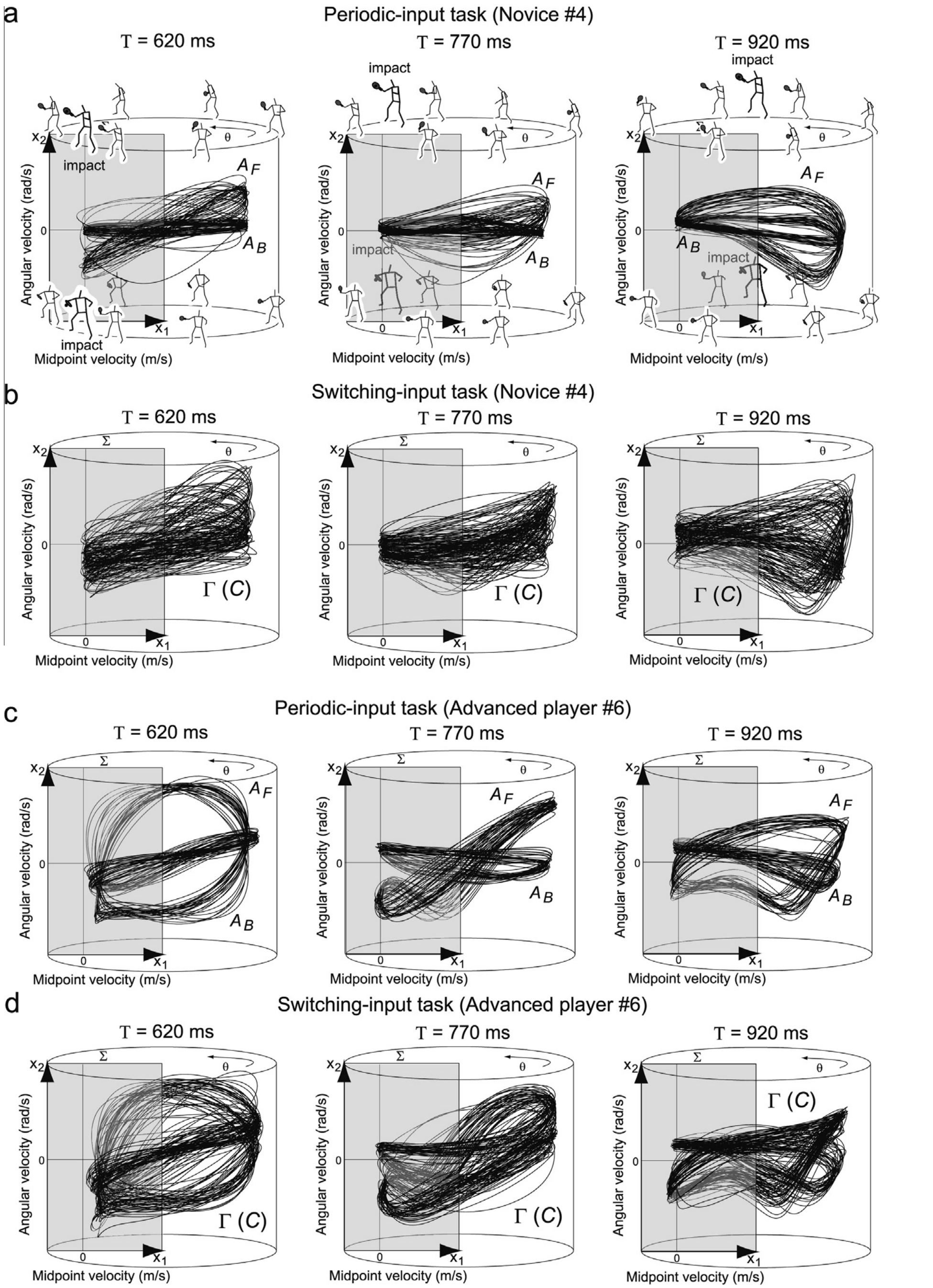

Fig. 3. Dynamics of the periodic- and switching-input tasks. Trajectories in the hyper-cylindrical phase space $\mathcal{M}$ during the periodic-input and switching-input tasks for novice #4 (a and b) and advance player #6 (c and d) under three temporal constraint conditions (620, 770, and 920 ms) as representative examples. The stick figures show the posture of the participants at each point in time divided by the period from $\theta = 0$ to $\theta = 2\pi$ into six and at the point of the ball impact in (a).

significant, $F(5,60) = 0.97$, $p = .44$. A two-way ANOVA for the switching-input task revealed main effects of skill level, $F(1,12) = 54.26$, $p = 8.66 \times 10^{-6}$, $\eta^2 = 0.82$, and the temporal constraint condition, $F(5,60) = 8.62$, $p = 3.36 \times 10^{-6}$, $\eta^2 = 0.42$; however, the interaction was not significant, $F(5,60) = 0.75$, $p = .59$.

3.2. The hyper cylindrical phase space $\mathcal{M}$ and the Poincaré section Σ

3.2.1. The periodic-input task

Fig. 3 shows the trajectories in the hyper-cylindrical phase space $\mathcal{M}$ during the periodic-input task for novice #4 (a) and advanced player #6 (c) under selected temporal constraint conditions (620, 770,

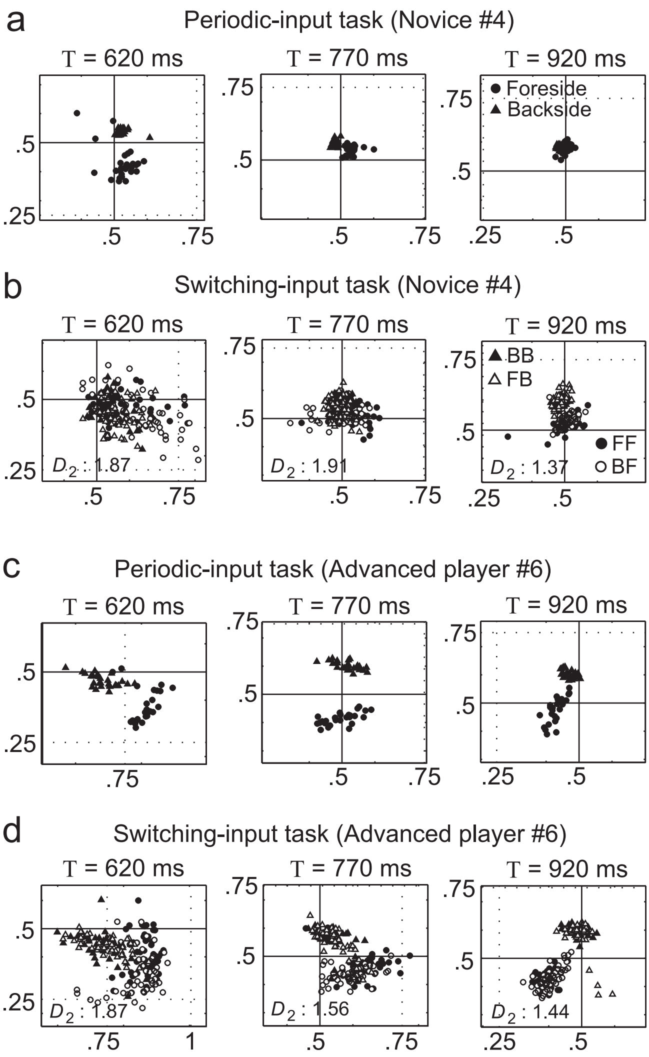

Fig. 4. Poincaré sections Σ at $\theta = 2\pi$ for the periodic- and switching-input tasks for novice #4 (a and c) and advanced player #6 (b and d) under three temporal constraint conditions (620, 770 and 920 ms) as representative examples. Panels (a) and (c) represent 60 trials, and (b) and (d) represent 189 trials.

and 920 ms). The stick figures show the posture of the participants at each time point divided by the period from $\theta = 0$ to $\theta = 2\pi$ into six, and at a time roughly equal to the impact of the ball (Fig. 3a).

Fig. 4(a and c) shows the Poincaré maps for the Poincaré section of novice #4 and advanced player #6 under the 620, 770, and 920-ms temporal constraint conditions corresponding to Fig. 3a and 3c, respectively. A one-way MANOVA was used to assess the equality of the multivariate means for each participant under all temporal constraint conditions (Table 1).

The results revealed a significant difference between two clusters on the forehand (•) and backhand (▲) sides on the Poincaré section Σ for all participants under all temporal constraint conditions. These results indicate that the external input pattern represented the forehand and backhand strokes as different stable movement patterns, and that these trajectories may be regarded as limit-cycle attractors.

3.2.2. The switching-input task

Fig. 3 shows the trajectories in the hyper-cylindrical phase space $\mathcal{M}$ during the switching-input task of novice #4 (b) and advanced player #6 (d) under the 620, 770, and 920 ms temporal constraint conditions as representative examples. Fig. 4 shows the Poincaré maps for the Poincaré section of novice #4 (b) and advanced player #6 (d) under the 620, 770, and 920 ms temporal constraint conditions corresponding to Fig. 3b and 3d, respectively.

By investigating the third-order sequence effect of the Poincaré section, Yamamoto and Gohara (2000) interpreted their results as indicating that hitting behavior during the switching-input task is characterized by a fractal-like structure. Similarly, we investigated the sequence effect. The filled symbols (•, ▲) in Fig. 4b and 4d indicate that the preceding and current input were identical, whereas the open symbols (○, △) indicate that the preceding and current input were different. A one-way MANOVA was performed to assess the quality of the multivariate means between the FF (•), in which the preceding and current input were on the forehand side, and the BF (○), in which the preceding input was on the backhand side and the current input was on the forehand side.

The same analysis was used for the BB (▲; backhand side for both preceding and current input), and the FB (△; forehand and backhand side for preceding and current input), respectively (Table 2).

These results reveal significant differences between the maps for FF (•) and BF (○) in 53 of 84 cases, between the maps of BB (▲) and FB (△) in 52 of 84 cases, and between the maps of the forehand side (FF and BF), and the backhand side (BB and FB) in 36 of 84 cases on the Poincaré section Σ for all the participants under all temporal constraint conditions.

In this scenario, significant differences were found between the maps of forehand side and those of the backhand side; thus, four clusters (FF, BF, BB, and FB) were generated on the Poincaré section by a combination of preceding and current inputs according to the third-order sequence effect. Yamamoto and Gohara (2000) confirmed that hitting behavior was characterized by a fractal-like structure as a result of the distribution of four clusters on the Poincaré section, which correspond to the hierarchical structure of the Cantor set with rotation.

As illustrated in this study, however, the four clusters were found in 36 of 84 cases, yet the distributions in these cases did not necessarily correspond to the Cantor set with rotation. Thus, the

Table 1
Differences between the mean forehand- and backhand-side input patterns on the Poincaré sections ($\theta = 2\pi$) during the periodic-input task (Wilks' λ).

Advanced player	T (ms)						Novice	T (ms)					
	620	660	710	770	840	920		620	660	710	770	840	920
#1	0.73*	0.36*	0.02*	0.01*	0.04*	0.04*	#1	0.08*	0.02*	0.02*	0.03*	0.15*	0.54*
#2	0.08*	0.06*	0.04*	0.03*	0.05*	0.06*	#2	0.31*	0.85*	0.24*	0.06*	0.05*	0.07*
#3	0.27*	0.03*	0.01*	0.02*	0.05*	0.02*	#3	0.15*	0.18*	0.21*	0.13*	0.45*	0.72*
#4	0.06*	0.06*	0.10*	0.08*	0.18*	0.10*	#4	0.30*	0.05*	0.21*	0.17*	0.19*	0.46*
#5	0.33*	0.04*	0.02*	0.01*	0.01*	0.17*	#5	0.14*	0.11*	0.34*	0.33*	0.69*	0.46*
#6	0.24*	0.18*	0.22*	0.04*	0.02*	0.21*	#6	0.20*	0.08*	0.14*	0.23*	0.68*	0.33*
#7	0.08*	0.01*	0.01*	0.01*	0.02*	0.04*	#7	0.06*	0.10*	0.08*	0.09*	0.20*	0.15*

* $p < .05$.

Table 2
Differences between the forehand side–forehand side (FF) and backhand side–forehand side (BF), backhand side–backhand side (BB) and forehand side–backhand side (FB) input patterns on the Poincaré sections ($\theta = 2\pi$) during the switching-input task (Wilks' λ).

Advanced player		*T* (ms)						Novice		*T* (ms)					
		620	660	710	770	840	920			620	660	710	770	840	920
#1	FF/BF	0.84*	0.74*	0.98	0.85*	0.97	0.99	#1	FF/BF	0.75*	0.99	0.86*	0.91*	0.92*	0.99
	BB/FB	0.96	0.78*	0.97	0.90*	0.88*	0.79*		BB/FB	0.64*	0.94*	0.73*	0.72*	0.97	0.99
#2	FF/BF	0.80*	0.81*	0.95	0.93*	0.77*	0.91*	#2	FF/BF	0.59*	0.67*	0.91*	0.88*	0.69*	0.60*
	BB/FB	0.91*	0.95	0.84*	0.80*	0.82*	0.87*		BB/FB	0.59*	0.60*	0.72*	0.92*	0.89*	0.67*
#3	FF/BF	0.98	0.98	0.98	0.97	0.98	0.89*	#3	FF/BF	0.96	0.84*	0.73*	0.77*	0.89*	0.80*
	BB/FB	0.90*	0.97	0.69*	0.94	0.94	0.85*		BB/FB	0.95	0.92*	0.80*	0.88*	0.89*	0.97
#4	FF/BF	0.90*	0.97	0.96	0.91*	0.99	0.92*	#4	FF/BF	0.96	0.97	0.87*	0.88*	0.88*	0.95
	BB/FB	0.97	0.99	0.99	0.99	0.93*	0.91*		BB/FB	0.91*	0.91*	0.93	0.87*	0.97	0.89*
#5	FF/BF	0.71*	0.86*	0.89*	0.95	0.91*	0.77*	#5	FF/BF	0.91*	0.77*	0.96*	0.99	0.99	0.94
	BB/FB	0.95	0.98	0.87*	0.86*	0.85*	0.95		BB/FB	0.76*	0.97	0.91*	0.95	0.98	0.99
#6	FF/BF	0.82*	0.85*	0.69*	0.77*	0.99	0.94*	#6	FF/BF	0.73*	0.88*	0.99	0.65*	0.87*	0.68*
	BB/FB	0.96	0.93*	0.96	0.99	0.96	0.95		BB/FB	0.77*	0.94	0.97	0.56*	0.86*	0.98
#7	FF/BF	0.84*	0.55*	0.88*	0.97	0.91*	0.99	#7	FF/BF	0.73*	0.97	0.98	0.87*	0.98	0.96
	BB/FB	0.37*	0.71*	0.51*	0.81*	0.87*	0.73*		BB/FB	0.72*	0.85*	0.91*	0.88*	0.91*	0.93

* $p < .05$.

Table 3
Correlation dimensions for all participants under each temporal constraint condition.

Advanced player	T (ms)						Novice	T (ms)					
	620	660	710	770	840	920		620	660	710	770	840	920
#1	1.71	1.82	1.36	1.37	1.38	1.48	#1	1.75	1.58	1.68	1.52	1.63	1.52
#2	1.64	1.58	1.53	1.39	1.54	1.52	#2	1.72	1.90	1.84	1.30	1.44	1.42
#3	1.92	1.68	1.32	1.18	1.52	1.38	#3	1.93	1.89	1.72	1.80	1.80	1.53
#4	1.98	1.91	1.66	1.59	1.52	1.81	#4	1.82	1.80	1.74	1.91	1.82	1.37
#5	1.87	1.61	1.35	1.27	1.42	1.53	#5	1.80	1.94	1.99	1.86	1.88	1.31
#6	1.87	1.72	1.82	1.56	1.36	1.44	#6	1.97	1.90	1.86	1.85	1.78	1.74
#7	1.83	1.48	1.38	1.25	1.34	1.58	#7	1.90	1.92	1.73	1.81	1.81	1.76
M	1.83	1.69	1.49	1.37	1.44	1.53	M	1.84	1.85	1.79	1.72	1.74	1.52
S.D.	0.12	0.15	0.19	0.16	0.09	0.14	S.D.	0.09	0.13	0.11	0.23	0.15	0.18

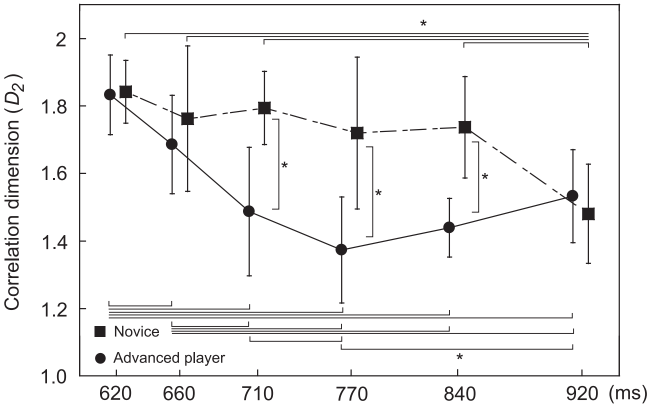

Fig. 5. Means and standard deviations of the correlation dimensions under the temporal constraint conditions for advanced players and novices. The asterisks and horizontal thin bars denote significant differences ($p < .05$) between means of the correlation dimension.

correct interpretation of these results is that the third-order sequence effect of the Poincaré section could only be partially verified.

3.3. Correlation dimensions of the Poincaré maps

We calculated the correlation dimension on the Poincaré map during the switching-input task to determine whether the continuous switching movement could be characterized by the fractal-like structure.

Table 3 and Fig. 5 show the means and SDs of the correlation dimensions for each participant under all temporal constraint conditions. All correlation dimensions were non-integer values. These results indicate that the maps on the Poincaré section Σ in each condition have fractal-like structures (Strogatz, 2001).

We assessed the correlation dimensions using a two-way ANOVA with skill level and temporal constraint conditions to estimate the similarity of the fractal-like structure to a random structure.

The two-way ANOVA for correlation dimensions revealed a main effect of expertise, $F(1,12) = 12.78$, $p = 3.8 \times 10^{-3}$, $\eta^2 = 0.52$, and the temporal constraint condition, $F(5,60) = 14.49$, $p = 2.67 \times 10^{-9}$, $\eta^2 = 0.55$, and a significant interaction $F(5,60) = 5.80$, $p = 2.0 \times 10^{-4}$, $\eta^2 = 0.33$. Furthermore, Bonferroni post hoc multiple comparisons across the interaction revealed that the means of the novices under the 660-, 710-, 770-, and 840-ms temporal constraint conditions were higher than those of the advanced players.

Furthermore, the mean for the advanced player under the 620-ms condition was closest to the value 2, and it was higher than that under the other conditions. The mean under the 660-ms condition was higher than those under the 710-, 770-, 840-, and 920-ms conditions. Moreover, the mean under the 710-ms condition was higher than that under the 770-ms condition, whereas the mean under the 770-ms condition was, in turn, lower than that under the 920-ms condition. Furthermore, the mean under the 920-ms condition for the novices was lower than those under the 620-, 660-, 710-, and 840-ms conditions.

Our results clearly indicate that the fractal-like structure changes to a more random structure as the duration of the input pattern shortens, regardless of skill level. However, although the temporal constraint closest to the random structure was at 840 ms for the novices, it was 620 ms for the advanced players.

4. Discussion

We investigated motor expertise in the complex hitting movement found in interpersonal competitive ball-over-net sports, particularly table tennis. We used a theoretical framework for continuous dynamical systems with external input (Gohara & Okuyama, 1999) to identify the differences in motor expertise between advanced and novice players on two representative tasks with imposed temporal constraints.

Based on previous findings, we hypothesized that a limit-cycle attractor would occur in phase space during a periodic-input task regardless of skill level or changing temporal constraints. This assumption proved to be correct. Despite changing temporal constraints and skill levels, we found two stable trajectory sets in the phase space during the periodic-input task (Fig. 3a, c). Thus, the differences in skill level could not be explained in terms of players' ability to produce stable periodic movements corresponding to a constant ball trajectory.

Further analysis of the correlation dimension on the Poincaré map during the switching-input task revealed that all were non-integer values (Table 3), indicating that the hitting behavior under all temporal constraints for all participants had fractal-like characteristics. The estimated correlation dimension increased irrespective of skill level as the duration of the input pattern shortened, suggesting that the fractal-like structure of hitting behavior became more random, in keeping an increase in temporal constraints.

Moreover, the fractal-like structure was at its most random at a temporal constraint of 840 ms for novice and at 620 ms for advanced players. These results suggest that the skilled players' were more robust in adjusting to greater temporal constraints than the novices were.

The fact that the value of the correlation dimension was never 2 indicates that under extreme conditions in which temporal constraints are either too high or the skill level of the player is too low, human movements will never be totally random, as previously noted by Yamada (1995).

In summary, our findings clearly show that different skill levels under periodic-task movements do not explain whether a player will be able to execute a stable movement pattern corresponding to a constant ball trajectory. However, different skill levels during continuous switching movements can be explained as a difference in robust adjustment to temporal constraints. Thus, expertise in interpersonal competitive ball-over-net sports, as illustrated by table tennis players, should not be estimated according to stable periodic movements in repetitive practice but rather according to differences in robustness to temporal constraints when a large number of balls are being exchanged during a match.

Finally, we investigated the presence of a third-order sequence effect under each constraint condition during continuous switching movement similar to that reported by Yamamoto and Gohara (2000).

The results of the one-way MANOVA analysis of the Poincaré maps during the switching-input task revealed a third-order sequence effect in 36 of 84 cases, yet no consistent tendency was associated with a specific temporal constraint or skill level. One explanation may be differences in the kinematic factor between table tennis and regular tennis. In regular tennis, the rotation of the trunk for both the forehand and backhand stroke is almost symmetrical. In table tennis, however, the trunk rotation is more asymmetrical because the rotation of the backhand stroke is smaller than that of the forehand stroke. With this in mind, we were unable to fully establish the relationships between the indicators, and were only able to partially verify a third-order sequence effect of the Poincaré section.

5. Conclusion

We examined periodic and continuous switching movements in hitting behavior under six temporal constraint conditions during a table tennis rally to investigate motor expertise in interpersonal competitive ball-over-net sports. We found that different skill levels under periodic-task movements do not explain whether a player will be able to execute a stable movement pattern corresponding to a constant ball trajectory, whereas different skill levels during continuous switching movements can be explained as a difference in robustness to temporal constraints. Our findings showed that motor expertise in ball-over-net sports increases robustness to temporal constraints when various inputs are switched continuously.

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