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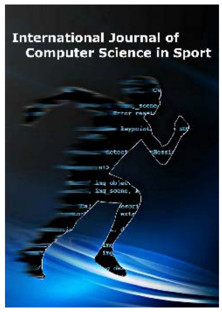

Intra-seasonal Variability of Ball Speed and Coordination of Two Team-Handball Throwing Techniques in Elite Male Adolescent Players.

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ABSTRACT

In sports biomechanics and motor control, a thorough study of coordination variability is important to understanding how the human movement system is organized. From a more applied sport science perspective, knowledge about performance variability is essential regarding the evaluation of true sport specific effects of any intervention. While there are many reports of intervention studies in team-handball, no description of the amount of normal variability is available. This study investigated variability of two important throwing techniques in team-handball within elite junior players over a 4-month period during a competitive season. To evaluate ball speed variability, the intra-individual coefficient of variation was calculated. The 95th percentile of ball speed variability over all players was 7%, which can be used as an effect size estimate in future research. For coordination variability, a qualitative description based on the output of neural networks was used. All participants presented multiple coordination patterns, representing multi-stability on a month-to-month timescale and switched between stable states without the manipulation of any control variable. Some limitations in the methodology and applications of neural networks in the present study and in biomechanics and motor control in general are highlighted. When more researchers adopt these methodologies, a more coherent framework for their application can emerge.

KEYWORDS: TEAM-HANDBALL, BIOMECHANICS, COORDINATION DYNAMICS, ATTRACTOR DIAGRAM, SELF-ORGANIZING MAPS

INTRODUCTION

Team handball is a complex sport on both the team- and individual level. Many throwing techniques are involved in team handball (jump shot, standing throw with run-up, pivot throw, side throw, desaxé and penalty throw). Previous biomechanical analyses assessed the relationship of ball speed and accuracy with throwing kinematics under various task constraints or between groups (van den Tillaar & Ettema, 2003, 2011; Wagner, Buchecker, von Duvillard, & Müller, 2010a, 2010b; Wagner, Pfusterschmied, von Duvillard, & Müller, 2012). In a recent review, Wagner, Finkenzeller, Würth, & von Duvillard (2014) reported a lack of studies in team-handball aimed at training performance and general coordination. To further training interventions, a better understanding and a quantification of normal amounts of variability is necessary (i.e. intra-seasonal variability without application of specific interventions). Team-handball players are involved in a constant learning process during regular training and competitions that already have an effect on coordination and performance. Isolating these from effects due to interventions can be hard and researchers should be aware of this when evaluating interventions. Longitudinal studies of Gorostiaga, Granados, Ibáñez, González-Badillo, & Izquierdo (2006) and Granados, Izquierdo, Ibàñez, Ruesta, & Gorostiaga (2008) in which elite male and female team-handball players were followed throughout an entire season of regular training and competition showed significant increases in ball speed. However, this increase was not a continuous pattern and showed both up- and downward fluctuations throughout the season. Preatoni et al. (2012) reviewed the importance of coordination variability and stated that the effects of factors such as environmental changes, training procedures, learning phenomena, latent pathologies and incomplete recoveries could be masked by variability. It is therefore important to explore the intra-seasonal variability in performance before evaluating the efficacy of any intervention. To our knowledge, no such intervention study for elite youth players or exploration of intra-seasonal performance variability has been done. In more experienced team-handball players, different kinds of training interventions have demonstrated significant changes in ball speed ranging between 1.4% and 24.2% increases (Chelly, Hermassi, Aouadi & Shephard, 2014; Ettema, Glosen & van den Tillaar, 2008; Hermassi, van den Tillaar, Khlifa, Chelly & Chamari, 2015; Saeterbakken, van den Tillaar & Seiler, 2011; van den Tillaar & Marques, 2011; Wagner & Müller, 2008). Only the latter two of these studies also analyzed the changes in biomechanical parameters in response to the training and found several changes in kinematic variables.

To our knowledge, no studies have been performed evaluating intra-seasonal variability in coordination in team-handball players. Wagner, Pfusterschmied, Klous, von Duvillard & Müller (2011) analyzed the variability of six kinematic variables in three handball throwing techniques at three different skill levels on ten consecutive trials in one day, which can be considered a snapshot as compared to a longer training period of different months. The two-timescale landscape model of Newell, Mayer-Kress, Hong & Liu (2009) which decomposes the performance dynamics into a slow (learning) and fast (adaptation) timescale illustrates that products of human motor behavior can change on more than one timescale. Coordination variability might also exist on more than one timescale and knowledge of variability on a timescale larger than trial-to-trial is still lacking. In gait analysis, it is already shown that within a single day and on consecutive days, it is possible to discriminate between patterns without an application of any intervention (Horst et al., 2015; Horst, Eekhoff & Schöllhorn, 2014). Seifert, Button & Davids (2013) pointed out that the variability of human movement not only reflects motor command error, but also the ability of the motor system to adapt to external perturbations or changing task constraints. Motor learning needs exploration of the degrees of freedom during task performance (Kelso, 1995; Schorer, Baker, Fath & Jaitner, 2007).

Consequently, forcing an athlete into a rigid motion pattern (role-model imitation) does not stimulate the self-organizing nature to search an individual task-specific optimal solution (Ohnjec, Antekolovic & Gruic, 2010; Pori, Bon & Sibila, 2005). Lamb, Bartlett & Robins (2011) described a method to visualize the coordination stability as an arbitrary potential function which allows an interpretation analogous to potentials in classical physics (~ coordination potential) and the original studies in bimanual coordination dynamics (HKB-model: Haken, Kelso & Bunz, 1985). Local minima in the coordination potentials correspond to stable motion patterns (critical points in the language of dynamical systems theory), while local maxima or inflection points reflect instabilities. Basically, their method first reduces the dimensions of the original dataset to a two-dimensional map and then clusters the overall pattern in a one-dimensional string. Using this method in a longitudinal setting could be an interesting way to study coordination variability on a longer timescale. Seeing how the clustering (position of the critical points) changes over time can give us information on coordination stability over longer periods of time.

The aim of this study is to use this method to describe the stability of throwing coordination of elite adolescent team-handball players on a month-to-month timescale. Also the variability in their throwing speed will be measured to use as a reference for future training studies. As this is an exploratory study, no hypotheses about the outcome were formulated.

METHODOLOGY

Subjects

For this study, thirteen handball players were selected from the national selection under nineteen year from the Belgian National Handball Federation. Four of these subjects were enrolled at the Topsportschool Hasselt (talent program of the Flemish government for youth top-level sport) and most of the others had been at the school until the previous year, but were now in their first year at college/university. All thirteen subjects were also playing in a first or second team in the first league of the Belgian Handball competition. Individual data on anthropometric and team-handball characteristics are provided for all players in Table 1. We selected players from all different playing positions to account for any possible differences between throwing techniques.

All of our subjects were free of any injury which would limit the performance of maximal velocity throws. They were informed about the study protocol and informed consents were signed by the participants and by their parents if they were under eighteen years old. This study was approved by the Ethics Committee of the University Hospital Brussels. The subjects performed the protocol on three occasions during the handball season over a four-month period (February, April, May 2014) where the time between measurements was typical for intervention studies. Of our thirteen subjects, five were unable to attend the third measurement due to illness (S2, S6, S10) and personal circumstances (S8, S12). Two subjects (S9, S13) also participated in another project two months before the start of the longitudinal follow-up (December 2013). At that time they were asked to perform the same tasks under the same conditions as during the longitudinal follow-up, so these measurements are also included here and these players have thus four sessions.

Table 1: Anthropometric and team-handball characteristics.

Subjects	Weight (kg)	Height (m)	Age (years)	Team-handball experience (years)	Position
S1	77.0	1.86	18	10	BC
S2	67.5	1.73	18	5	P
S3	71.5	1.73	17	7	W
S4	79.5	1.79	18	8	BC
S5	80.0	1.89	17	8	BC
S6	67.5	1.73	18	13	BC
S7	65.1	1.74	17	9	P
S8	75.5	1.70	17	10	W
S9	62.5	1.68	17	6	BC
S10	98.0	1.93	17	13	BC
S11	78.0	1.75	18	10	W
S12	67.0	1.75	17	10	W
S13	68.0	1.80	17	8	W
Mean	**73.6**	**1.78**	**18.4**	**9.0**	
SD	**9.4**	**0.08**	**0.5**	**2.4**	

BC = Backcourt, P = Pivot, W = Wing

Protocol and measurements

After a warm-up period of at least fifteen minutes (including general warm-up and throwing exercises), the players were instructed to perform four throws with maximal speed of two throwing techniques (penalty throw and jump shot). The throw was valid if it hit the target (the target was a cross with arms of 0.4 m, 1.60 m high) and when they did not cross the line from which they had to throw. For the penalty throw, their front foot had to stay on the 7 m line and they had to land before or on this line with the jump shot. Players did require only four or maximum five throws to perform four valid ones, which is in agreement with the low speed-accuracy tradeoff seen in elite team-handball players (van den Tillaar & Ettema, 2006). A regular handball (IHF-3: circumference 58-60 cm, weight: 425-475 g) was used for throwing. The sequence of the throwing techniques were random for each subject and on every occasion. At least 30 s of rest between throws was assured to eliminate possible effects of fatigue. Players were equipped with thirty-five retro-reflective markers placed on anatomical landmarks (left & right spina iliaca anterior superior, sacrum, left & right acromion, two markers on the sternum, seventh cervical and twelfth thoracic vertebrae, left & right trochanter major, left & right epicondylus lateralis and medialis femoris, left & right lateral and medial malleolus, left & right epicondylus lateralis and medialis humeri, left & right olecranon, left & right processus styloideus ulnae and radius, left & right metacarpal II and IV), four markers were placed on the ball. Three-dimensional kinematic data were captured with a six-camera VICON MX F-20 system at 250 Hz (VICON® Peak, Oxford UK) operated with VICON Nexus 1.8.2 software. The origin of the global reference frame was placed on the 7 m line from where the players had to throw, with the positive Y-axis towards the target, the positive X-axis to the right and the positive Z-axis upward. Three-dimensional marker trajectories were reconstructed, labeled and gaps were filled in the VICON Nexus 1.8.2 software and smoothed with a low-pass fourth order Butterworth filter (zero lag) at a cut-off frequency of 13 Hz.

Data processing

Coordinates (xyz) of the marker trajectories were exported from VICON Nexus to a .csv file and imported into a custom-made algorithm in Mathcad 14.0 (Parametric Technology Corporation, MA, USA). Ball speed data were calculated in Mathcad with the central difference method based on the centroid of the 4 ball markers. Ball speed at release was extracted to an Excel 2013 file to calculate means and standard deviations (SD) for all players in every month. Ball release was defined as the moment where a sudden increase in ball-to-hand distance was observed (van den Tillaar & Ettema, 2004). To estimate the intra-seasonal variability in ball speed, the coefficient of variation [CV = (SD/mean)*100%] was calculated over all twelve trials for subjects that attended all three measurements (only eight trials for S2, S6, S8, S10 and S12 and sixteen trials for S9 and S13).

Local orthonormal reference frames for the pelvis, trunk, upper arm and lower arm were constructed based on the ISB guidelines for joint coordinate systems (Wu et al., 2005). Segment angles for the pelvis and trunk in the global reference frame were calculated with the Cardan rotation sequence of forward/backward tilting, left/right lateral tilting and rotation. Shoulder angles were calculated with the Euler rotation sequence of horizontal ab/adduction, ab/adduction and endo/exorotation. The elbow was modeled as a 1-degree of freedom joint and the longitudinal vectors of upper- and lower arm were used to calculate this angle. All segment- and joint-angle time series were calculated within a time-span of 400 ms before ball release (100 data-frames) until 80 ms after ball release (20 data-frames). The Euler/Cardan rotation sequences yielded no gimbal-locks during this time-period. The segment- and joint-angle time series were differentiated with respect to time with the central difference method. Afterwards, these were transformed to express them in the original coordinate frame to calculate the angular velocity vector (Zatsiorsky, 1998). All kinematic variables for the three left-handed players were transformed so the kinematic time series showed the same pattern as for all right-handed players, this way positive and negative values had the same anatomical meaning for right- and left-handed players. This gave us twenty time series (ten segment/joint angles and ten segment/joint angle velocities) that were used to evaluate the coordination dynamics. Coordination is not only the relative position of body segments, but also their velocity and underlying kinetics and muscular activity. We chose to use angles and angular velocities to represent coordination as they are the final product and are most directly linked to ball speed.

Data analysis with Self-Organizing Maps

To study the coordination dynamics of the throwing motions, a class of neural networks (Self-Organizing Maps, SOM) was used. These SOMs have been proposed as an effective tool for visualization and analysis of high-dimensional data (Kohonen, 2001; Lamb et al., 2011; Schöllhorn, 2004). Due to non-linear properties and an unsupervised competitive learning algorithm, SOMs have the ability to compress high dimensional input data onto low dimensional output maps, while preserving its topologic structure (Kohonen, 2001; Vesanto, Himberg, Alhoniemi, & Parhankangas, 2000). Many visualization techniques exist for these SOMs and therefore, they are an attractive tool for explorative analysis of high-dimensional coordination. The fact that they can reduce high-dimensional data to useful information on a two-dimensional output map, allows us to use them to extract an order parameter (i.e. the collective coordination variable) that can be used to identify attractor states in a coordination potential. Because of the high inter-individual differences in throwing techniques and because coordination dynamics is per definition a very subject-specific process with a delicate interplay between anthropometrics, muscle mass, muscle innervation, handball experience, position on the field, etc., we constructed SOMs for all subjects separately. This makes comparison between subjects difficult, but because the aim of this paper was to study changes in coordination within subjects, this was not an issue. The same intra-individual SOM analysis was followed in Lamb et al. (2011). Because it was not the objective of this research to analyze differences in coordination dynamics between throwing types (they are inherent to the sport and therefore of less interest here), separate SOMs were constructed per throwing type. The aim of this research was to describe what happens with the motion pattern over time and see if the SOM can recognize possible changes. Therefore all throws from all sessions were used for the SOM training. Other options for different research settings might use only the throws from the first session as a reference and see how it changes with respect to these first measurements or update the map after every new measurement.

We will briefly introduce the SOM algorithm here, more technical information can be found in Kohonen (2001) and Vesanto et al., (2000). A SOM consists basically of a number of output nodes or units that are all connected to each other and to a number of input nodes. Every unit has a weight vector with the same dimension as the input vectors (i.e. number of variables). The input vectors in our study are the twenty joint angles and – angular velocities at the 121 data frames for all throws. So every unit represents a specific coordination state at a specific time point: a set of the twenty discrete values for joint angles and angular velocities. The metric used by the SOM algorithm is Euclidean and therefore, input vectors need to be normalized so that all components of this vector are on a comparable scale. Otherwise, components of this vector with the highest values (e.g. shoulder internal rotation velocity around ball release) will dominate the SOM algorithm. The normalized input vectors are then fed to the input nodes in the SOM in an iterative fashion. At every step, the best-matching unit in the output layer is searched by the algorithm by calculating the Euclidean distance between weight- and normalized input vector. The unit with the smallest distance to an input vector is that vector's best-matching unit. During this iterative process, the weight vectors are updated by decreasing the Euclidean distance with the input vector in a competitive learning process, for better representing the original data. The best-matching unit's weight vector is updated by the largest amount and surrounding units are updated by decreasingly smaller amounts. The neighborhood of units that are updated is defined by the neighborhood radius and neighborhood function. The further away from the best-matching unit, the less a unit's weight vector gets updated. This mechanism is responsible for the topological preservation of the original data-set and because this is done for all vector-components independently, variables which operate on different timescales, may be included in the input vectors (Lamb, Bartlett, Lindinger, & Kennedy, 2014).

A first visualization for coordination patterns may be done with a unified distance matrix (U-matrix: see Figure 1). It is possible to draw trajectories of consecutive best-matching units on this matrix (white lines in Figure 1) that represent the collective coordination state throughout the throwing motion. The different phases of the motion can be recognized in this matrix. The U-matrix shows the SOM-units in a grid of cells (little hexagons in Figure 1) where the distance between neighboring units (similarity of weight vectors) is represented with a color scale. The cells that represent the units themselves are colored according to the mean distance to the surrounding units. Blue represents SOM units that lie close together, while red indicates a large distance to neighboring units. So in the example of Figure 1, we see that the units on the left and middle part of the map (high on the color scale) form a ridge in weight space, separating the units that represent the different phases of the throwing motion. For this reason, the U-matrix is sometimes referred to as a hybrid representation of grid space and weight space (Lamb et al., 2011) and can be interpreted as a coordination landscape. These best-matching unit trajectories were used as the collective variable (order parameter) for the further analysis with a second SOM.

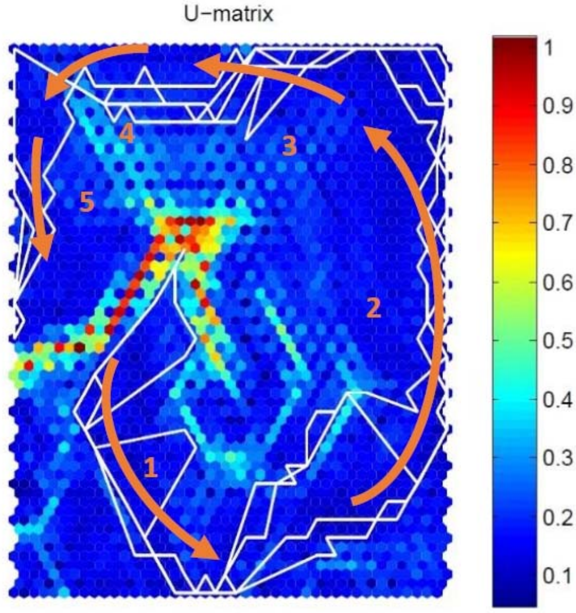

Figure 1: U-matrix visualization of the SOM with best-matching unit trajectories of 4 throws of one session. The color map indicates the Euclidean distance between neighboring units. The orange arrows indicate a general reference to the throwing phases: (1) preparation phase, (2) cocking phase, (3) acceleration phase, (4) ball release and (5) follow-through phase. If defined, these phases could be visualized exactly, but this was not the aim of this study. Notice that two trials follow the outer part of the map in the lower right corner while two trials follow the path between the two low ridges (light blue cells). This indicates two different patterns during the cocking phase.

The second SOM (1-dimensional SOM this time) was then trained with the weight-space coordinates of the best-matching unit trajectories of all trials. This part of the data-analysis was done with the same algorithm as in (Lamb et al., 2014, 2011) and more detailed information can be found in those papers. Basically, the second SOM is used to cluster coordination patterns into attractor diagrams that can be visualized as arbitrary coordination potentials. Firstly, the weight vectors of the best-matching unit trajectories are projected into a two-dimensional weight space by Sammon's mapping technique (Sammon, 1969). These coordinates are used to train a one-dimensional SOM where every SOM-unit represents an entire throwing pattern (whereas the SOM-units in the first SOM represented coordination states at a specific data frame). Basins in these potentials (global or local minima of the coordination potential) indicate SOM units with a stable coordination pattern for that specific month. The depth of the basin is set according to the hit frequency of best matching units and proximity of neighboring units. The algorithm visualizes the one-dimensional SOM as a theoretical line that is bent downward every time a unit is hit by an input vector. The deeper and the steeper the basin, the more trials are mapped into the same pattern and this indicates a stable motion pattern. Coordination stability is decreased when shallower and broader basins are observed, meaning that different adjacent units were activated. If the basin is shifted along the unit-index between months, this indicates that a shift in the high-dimensional coordination space is observed between the months. The stability on the intra-seasonal timescale of the coordination pattern can then be qualitatively analyzed as a shift/stationary of the basin of attraction along the unit-index.

The analysis of the coordination with the SOMs was done in Matlab R2015a with the open-source SOM-toolbox (Vesanto et al., 2000). The construction of the attractor diagrams of the coordination stability was done with the same algorithm as in the study of Lamb et al. (2011, 2014). All SOM-parameters are shown in Table 2. Also provided in Table 2 are the quality parameters of the SOMs (quantization and topographical errors). The quantization error is the mean Euclidean distance between the best-matching units and the input vectors and the topographical error is the percentage of data vectors for which the best-matching and second best-matching units are not neighbors (Vesanto et al., 2000).

Table 2: SOM training– and quality parameters

Parameter	**1st SOM**	**2nd SOM**
Normalization	Range scaling to [-1 1]	Range scaling to [0 1]
Lattice / Shape	Hexagonal / Sheet	Hexagonal / Sheet
Neighborhood function	Gaussian	Gaussian
Training type	Batch	Batch
Map size	based on ratio of first two eigenvalues	1 x 16
Initialization	Linear	Linear
Steps (rough training)	7	5
Radius (rough training)	4 → 1	2 → 1
Learning function (rough training)	Reciprocally decreasing	Reciprocally decreasing
Steps (fine tuning)	26	20
Radius (fine tuning)	1 → 1	1 → 1
Learning function (fine tuning)	Reciprocally decreasing	Reciprocally decreasing
Quantization error (range over all players)	0.091 – 0.189	0.073 – 0.284
Topographical error (range over all players)	0.000 – 0.073	0.000 – 0.088

For the radius parameter, the arrow indicates what the initial and final neighborhood radius was

RESULTS

Table 3 summarizes the data on ball speed for all thirteen subjects for every month that they participated in the study (mean and SD on the four trials). There is no clear pattern in the ball speed data, showing any systematic increase or decrease throughout the season across subjects, indicating no structural trend due to fatigue or other reasons. In ball speed of the penalty throws, the highest values were observed for players S5, S10 and S13. The ball speed data of jump throw reveal the same three athletes who achieved the top speeds over all trials. Lowest mean ball speeds over all penalty throws were observed for players S2, S4 and S11 and for the jump shots by players S7, S9 and S11. The last column in Table 3 gives the coefficient of variation (CV) of the ball speed over all sessions. This is the variation in ball speed that is to be expected due to normal intra-seasonal variations. For the penalty throw, an intra-seasonal variation between 2.57% and 11.05% in ball speed was observed in between months. For the jump shot, the observed variations were between 1.57% and 8.02%. These data can be used as normative data for the evaluation of experiments targeting improvements in ball speed in elite youth team-handball players.

Table 3: Ball speed data (m/s) as means ± SD per month for all subjects and CV (%)

Subjects	December	February	April	May	CV
Penalty throw					
S1	--	19.69 ± 0.80	18.49 ± 1.47	19.74 ± 0.63	5.87
S2	--	19.33 ± 0.27	16.46 ± 1.70	--	11.05 (**)
S3	--	17.95 ± 0.42	18.59 ± 0.24	17.96 ± 0.56	2.75
S4	--	17.18 ± 1.48	17.78 ± 0.16	16.74 ± 0.27	4.94
S5	--	22.64 ± 0.35	23.38 ± 0.53	22.81 ± 0.44	2.23
S6	--	18.74 ± 0.01	19.58 ± 0.45	--	2.86
S7	--	18.83 ± 0.87	18.29 ± 0.75	19.07 ± 0.53	3.78
S8	--	20.06 ± 1.06	19.18± 0.43	--	4.45
S9	18.87 ± 0.32	19.04 ± 0.01	18.75 ± 0.54	19.28 ± 0.71	2.57
S10	--	23.12 ± 1.27	23.83 ± 0.17	--	3.53
S11	--	17.86 ± 0.27	16.63 ± 0.38	15.44 ± 0.38	6.38
S12	--	19.25 ± 0.89	18.55 ± 0.87	--	4.64
S13	22.82 ± 0.97	23.26 ± 0.53	21.84 ± 1.51	22.12 ± 1.35	5.10
Jump shot					
S1	--	19.19 ± 1.72	19.57 ± 0.08	20.06 ± 0.21	3.68
S2	--	19.90 ± 0.26	20.24 ± 0.30	--	1.57
S3	--	20.00 ± 0.44	19.93 ± 0.41	19.61 ± 0.16	1.80
S4	--	19.20 ± 0.27	19.16 ± 0.49	18.58 ± 0.88	3.57
S5	--	23.95 ± 1.47	23.10 ± 0.41	-- (*)	4.28
S6	--	19.55 ± 0.58	20.32 ± 0.71	--	3.60
S7	--	17.98 ± 1.11	18.97 ± 0.24	19.32 ± 0.35	4.86
S8	--	20.21 ± 0.61	20.48 ± 0.18	--	2.10
S9	18.87 ± 0.28	18.47 ± 0.36	17.60 ± 0.88	18.06 ± 0.48	3.63
S10	--	22.78 ± 0.20	21.84 ± 0.90	--	3.52
S11	--	18.18 ± 2.61	17.57 ± 1.06	16.28 ± 0.71	8.02 (**)
S12	--	19.86 ± 0.57	19.40 ± 0.95	--	4.00
S13	22.24 ± 0.40	23.20 ± 0.11	21.95 ± 1.45	21.98 ± 0.41	3.24

(*) subject S5 was injured to the knee at the measurements in May, limiting him to perform the jump shot; (**) the CV for S2 on the penalty throw and S11 on the jump shot were statistical outliers, but we recalculated these ball speeds and they were correct, thus providing useful information. It is noteworthy that both outliers show a decreasing trend in ball speed between months.

The stability of the coordination pattern can be quantified as a trajectory through a coordination landscape. A complete example is given of the SOM analysis of player S13, thereafter we summarize the results of all players. The orientation in time of the best-matching unit trajectories is clockwise in all four panels in Figures 2 and 3, starting at the lower right or central region of the coordination landscape. For the jump shots (Figure 2), we clearly see a shift in the initial coordination states from the lower right on the SOM in December to the central region of the SOM in February and April. In May, the initial coordination states are situated in both regions (two trials start in each region). Also during the early cocking – (lower left region), late cocking – (upper left region) and acceleration phases (upper region), shifts toward other SOM regions are observed in between months, but these shifts appear smaller. To explore what these changes mean in terms of the original variables was not the aim of this study, but for illustrative purposes, we included the component planes for all variables in the Appendix. The fact that mostly differences in the early part of the motion occur, indicates that the coordination pattern converges to a similar state from different initial coordination states. The point of ball release is situated in the top-right region for all trials. Very low variability is observed in the coordination pattern during the acceleration and follow-through phase (vertical, downward best-matching unit trajectories after ball release). The lowest within-month variability in the best-matching unit pattern is observed in December and April, resulting in the deepest and steepest basins in the coordination potentials (Figure 4, left). The

SOM trajectories showed obvious differences in hit frequencies of best matching units between months. The coordination patterns of the trials in February and May were not mapped onto the same unit in the one-dimensional SOM, creating a very broad, unstable basin, characterized by three or four discernible patterns (three or four adjacent units in the one-dimensional SOM were activated).

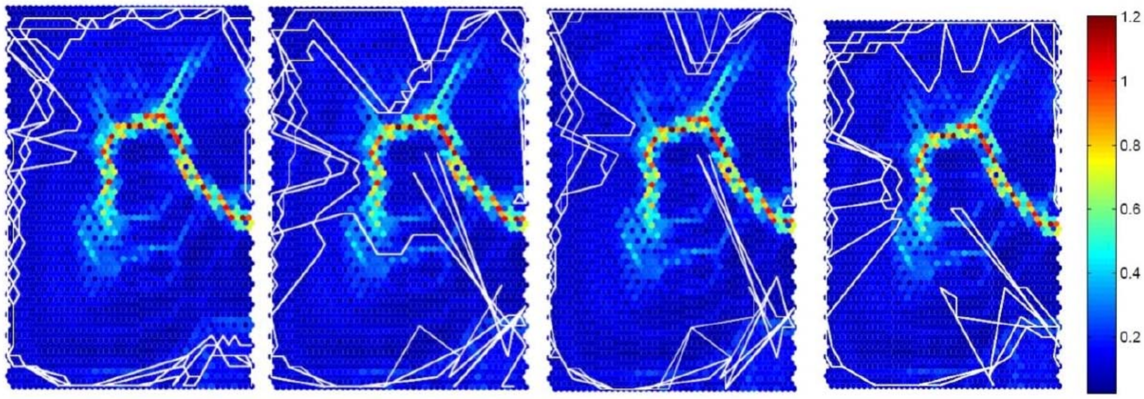

Figure 2: SOMs (visualized by U-matrices) and best-matching unit trajectories (white lines) for the jump shots of subject S13 on all 4 sessions (from left to right: December, February, April, May). The color map indicates the Euclidean distance between adjacent units.

For the penalty throws (Figure 3), we see that the initial conditions (begin of the best-matching unit trajectory in the SOM) are similar between December and February (lower mid region), but are shifted more to the right in April and May. Another easy discernible difference is the coordination variability. During the late cocking phase and begin of the acceleration phase, we observe very little variability in May and a lot more variability in the other months. The attractor diagrams for the penalty throw (Figure 4, right) show very broad basins for December, April and May with a high similarity between the December and May attractor. The only stable attractor is seen in February, mapping all four trials in unit six. The attractor of April shows a plateau region, indicating an instability around unit six, which was two months earlier an attractor.

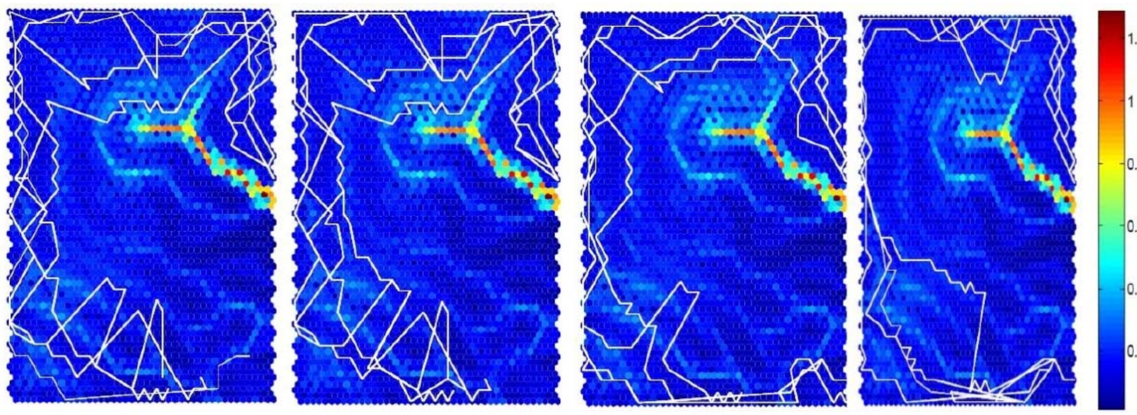

Figure 3: SOMs (visualized by U-matrices) and best-matching unit trajectories (white lines) for the penalty throws of subject S13 on all 4 sessions (from left to right: December, February, April, May). The color map indicates the Euclidean distance between adjacent units.

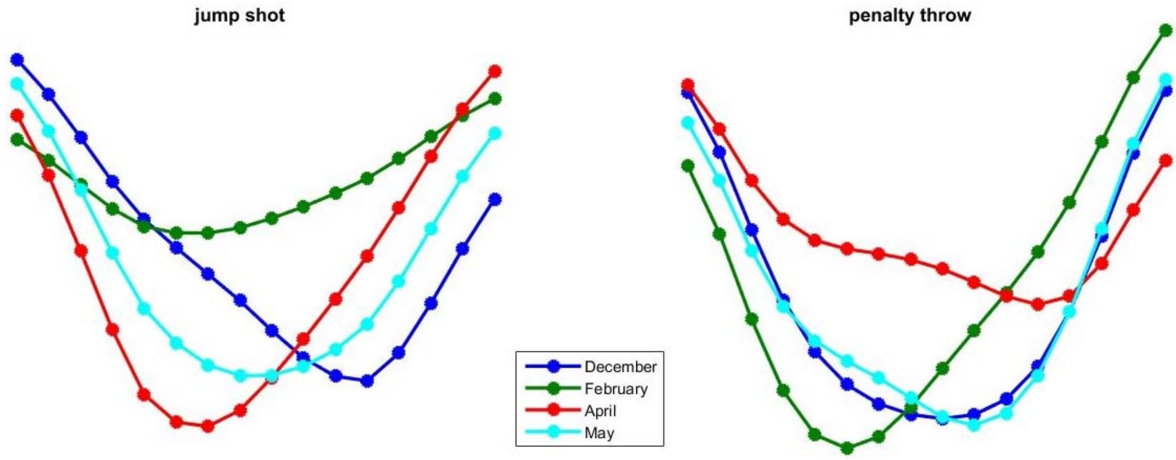

Figure 4: attractor diagrams for subject S13 during the 4 months for the jump shot (left) and penalty throw (right). On the horizontal axis is the unit-index (1 – 16) and on the vertical axis is the arbitrary potential value corresponding to every unit. These values have no real meaning, the only relevant aspect is the relative vertical and horizontal position of the basins in between months.

The analysis with SOMs gives us insight into the stability of the motion pattern as visualized by attractor diagrams and we can see the clustering of the trials per month on the attractor by mapping them on their best-matching units. The example of S13 indicates that stability of the coordination pattern is not constant in time and changes continuously. The one-dimensional SOM was able to cluster the trials of different months into different basins. This illustrates the necessity of establishing intra-individual baseline levels of coordination patterns and variability therein. If all the attractors were stable (steep and deep basins) and located at (approximately) the same SOM units, coordination variability would be similar on both the trial-to-trial and month-to-month timescale and the effect of an intervention would be easily spotted by a shift of the basin along the one-dimensional SOM. Figures 5 and 6 show the attractor visualizations for the penalty throw and the jump shot respectively for all players during all months. Most players back up the conclusion of the example of S13: coordination patterns change over time without the manipulation of control variables.

Penalty Throws

For the penalty throws (Figure 5), the coordination potentials of subjects S1, S2 and S12 are characterized by a shift of the basin of attraction along the unit index, indicating a change in the pattern. Subjects S3 and S8 show beside a small change along the unit index also a steepening/broadening of the basin. S7, S10 and S11 swap between stable and unstable coordination potentials. For S9, the basin stays around the same unit over M1, M3 and M4, but is shifted to the right at M2. The other subjects show more interesting phenomena. For instance S4 goes from a totally unstable basin in M1 to a stable basin on the left at M2 and then shifts to a new and even more stable basin at the other side of the SOM at M3. This might indicate that this subject shifts between these two patterns over time, and a combination of both was used when measuring him at M1. Subject S5 has a stable basin at M1, while at M2 and M3, his basin shifts to the left, while becoming increasingly more unstable shown by the broadening of the basin. Subject S6 has a mono-stable potential at M1 and a bi-stable potential at M2 with these two very small basins closely to the original.

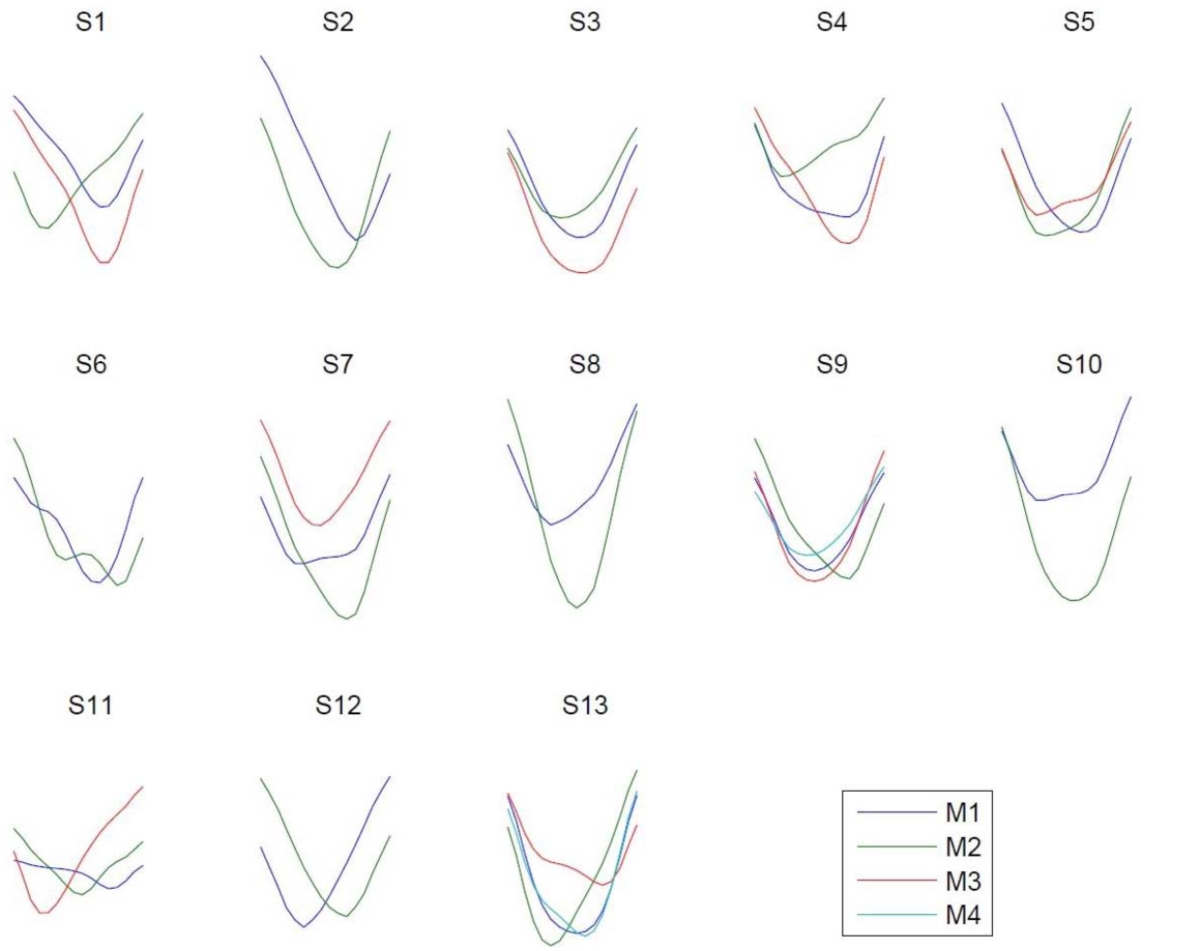

Figure 5: attractor visualizations (coordination potentials) for the penalty throw. For all players except S9 and S13: M1 = February, M2 = April, M3 = May. For S9 and S13: M1 = December, M2 = February, M3 = April, M4 = May.

Jump Shots

A different image can be observed in the coordination potentials of the jump shot analyses (Figure 6). Whereas S1 had three stable patterns in the penalty throw, he shows a very shallow basin at M1 for the jump shot (the same for S2 at M2). Subject S3 had three stable basins on the penalty throw, showing longitudinal stability, but for the jump shot, he shows a different longitudinal pattern. At M1, he has a basin on the left and a plateau region on the right (instability). Later at M2 and M3, the basin is located around the unit where the original plateau region was located. Comparable to the penalty throw, S4 shows an unstable pattern at M1 and stable patterns at M2 and M3. The history of S5 is also interesting from a clinical perspective. At M3, he was unable to perform the jump shot trials because he was recovering from a jumper’s knee, but the trainers and physiotherapist allowed him to perform the penalty throws. We observed two stable coordination potentials for the jump shot at M1 and M2, but the penalty throws showed increasing instability at M2 and M3. Whether this was due to the injury or not, was not part of this investigation and therefore we gave no special attention to it, but this could certainly be a study on its own. The other subjects all show differences between penalty throws and jump shots, but no overall discernible differences or similarities across the group are visible. It is not the case that more coordination stability is observed in any throwing type or in any month.

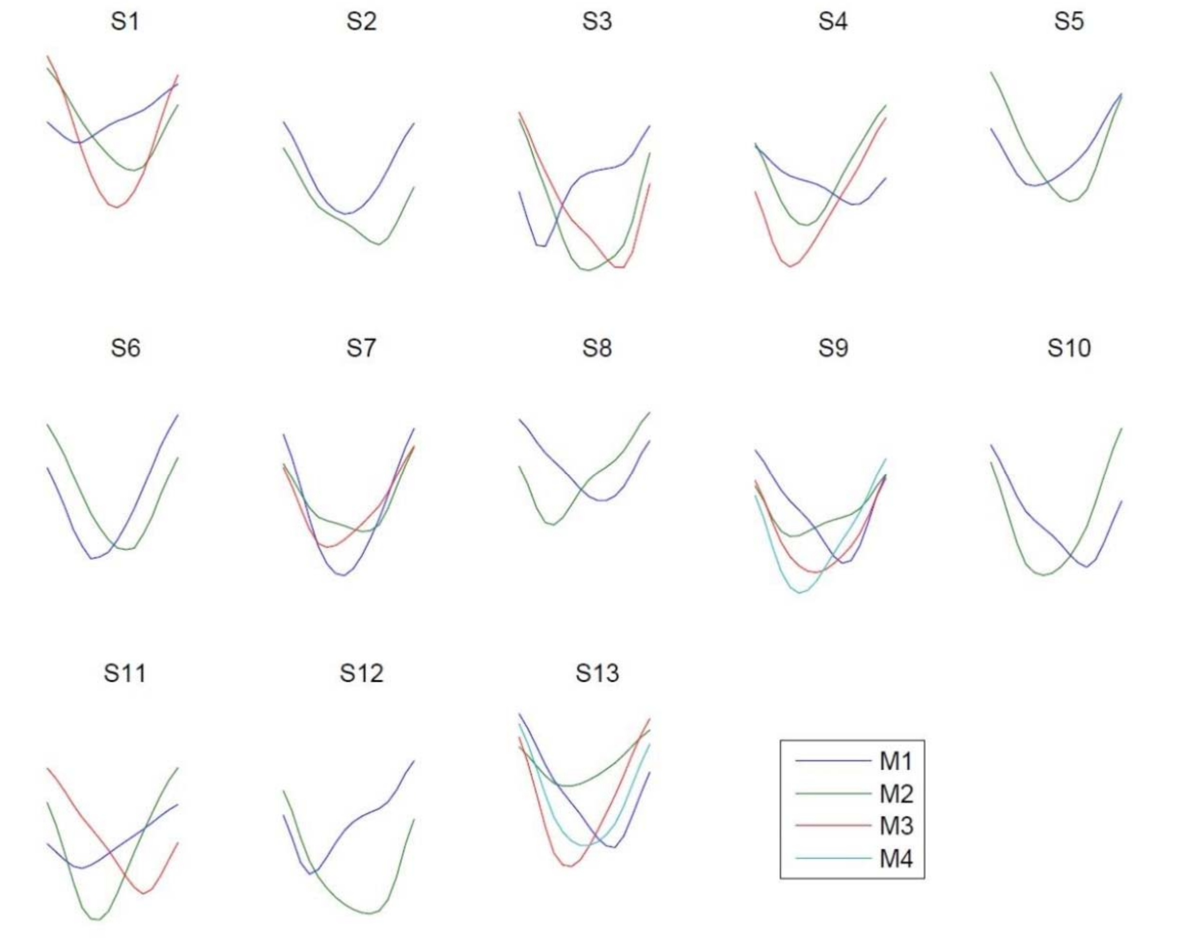

Figure 6: attractor visualizations (coordination potentials) for the jump shots. For all players except S9 and S13: M1 = February, M2 = April, M3 = May. For S9 and S13: M1 = December, M2 = February, M3 = April, M4 = May.

DISCUSSION

This study aimed to analyze the intra-seasonal variability in throwing speed (performance parameter) and in coordination dynamics. Given the high individual differences, a single-subject approach (Glazier, 2010) was used to analyze the data on a qualitative level. On the subject-level, many phenomena were observed, but these were mostly individual-specific and no patterns across the group were observable. The results of the analysis of ball speed variability are practically relevant for the evaluation of training interventions, while the coordination dynamics analysis offers insight into the motor control processes involved on a month-to-month timescale.

Ball speed variability

The first objective of this research was to analyze longitudinal performance variability of two team-handball throwing techniques. The intra-seasonal variability in throwing performance (CV in ball speed) showed variations between 2.5 and 11% on the penalty throws and between 1.6 and 8% for the jump shots. The variations observed are comparable to the results of the study of Gorostiaga et al. (2006) with elite adult players. These data can be taken as normative data for the evaluation of training or other kinds of interventions for adolescent male team-handball players. Taking these observed CV as minimum effect sizes, one can compare the effect of the interventions to these intra-seasonal variations. Interventions should be able to reach an effect of at least this CV to be able to speak of a real practical significant effect, surmounting intra-seasonal variation. For example, lower effects could be due to other factors as measurement error or the subjects having a good or bad day. Ideally, the individual variability of all players in a study should be established over a period similar in length to the intervention period and an individual analysis of effectivity should be done. However in most research settings, this would be impossible due to time and logistic constraints. The 95th percentile of all CV was 7.2%. Thus we can safely state, with a 5% error margin, that taking 7% as a minimum effect for interventions is a safe choice to exclude potential intra-seasonal variations in ball speed. With this guideline, a 10% increase would correspond to a 3% structural increase. Besides statistical significance, practical sport-specific significance can be evaluated. Due to the complexity of the motion and other factors that are difficult to control with in-season interventions (competition, tournaments, training), a high variability is seen in the performance. The data also showed great inter-individual differences in ball speed data, both in absolute values as in the direction of changes between months. These findings illustrate that researchers should perform a more thorough base-line measure of performance variability and take at least three measurements for evaluating intervention studies. Three longitudinal measurements (during or after the intervention) can distinguish between structural increases and intra-seasonal up/downward fluctuations. With these guidelines, only some of the studies mentioned in the introduction showed a real sport specific effect (Chelly et al., 2014; Hermassi et al., 2015; Wagner & Müller, 2008).

Coordination Dynamics

The second part of this study was to analyze the accompanying changes in coordination stability over the same four-month period. This was visualized with coordination potentials, and shifts of the basins along this potential indicating a change in motion pattern. No patterns, relating differences in the coordination stability to changes in ball speed, were visible across the group. This supports the highly individual and non-linear nature of coordination dynamics of the human movement system and warrants the use of single-subject analyses at the qualitative level. Using a group analysis might delete important information because the SOMs would have to map very different throwing techniques on the same set of units causing the within-subject intra-seasonal variability to get lost. Also no systematic differences or similarities between penalty throws and jump shots were observed across the group. This observation is similar to the study of Wagner et al. (2011), which showed significant main effects of throwing type and interaction effects between throwing type and skill level on movement variability, indicating a complex interaction between several factors specific to throwing types. As the jump shot is the most frequently used throwing technique in team-handball (Wagner, Kainrath & Müller, 2008), and occurs usually under much higher variable and dynamic conditions (opponents, run-up speed, point of take-off, …), this difference was to be expected.

We visualized the stability for all players individually (Figure 5 and 6) and found some very typical coordination-dynamics phenomena. The most important phenomenon is shown in almost all subjects in both throwing types: most subjects show a shift and/or a reshaping of their coordination potential between consecutive measurements. This means that the one-dimensional SOM clustered trials from different months on different units and thus demonstrating that the variability was different on both time-scales (a mono-stable motion pattern at a certain month does not mean that there was no variability, but that the overall coordination pattern was similar). Lees & Rahnama (2013), studying week-to-week variability in soccer instep kick kinematics, showed that in selected extrema of kinematic time series, a quantitative amount of variability of around 5% is to be expected. In our study, we showed that the variability is not only quantitative, but also that a qualitative change of the overall coordination pattern was present. This is quite remarkable, because qualitative changes of the coordination state are usually associated with phase transitions due to the manipulation of some control variable, while this study was a longitudinal observational study without intervention. Other phenomena like the switching between mono- and bi-stable potentials (S6, penalty throw) and stabilities becoming instabilities and vice versa (S4, penalty throw; S7, S9 and S12, jump shot) were also observed. Subject S6 showed a mono-stable potential in M1 and then changed to a bi-stable with both basins on opposite sides of the first one. This could mean that, starting from the original basin, the subject explored the surrounding coordination landscape and settled simultaneous in two neighboring basins (coexistent stabilities). Subjects that transformed their potentials in such a way that an instable unit became a stable one or vice versa, form a strong argument for a longitudinal multi-stability. The coordination landscape of these subjects has probably a highly variable shape without very stable task-solutions. A unit that was a stable attractor before but shows an instability the next month can be seen as remnants of a former stable pattern. The other way around, a unit formerly representing an instability but is about to change towards a stable one, represents a region in the coordination landscape that the subject is exploring.

These observations can be interpreted as a longitudinal multi-stability, where multiple coordination patterns coexist. Just like in gait (Horst et al., 2015, 2014), more complex motion patterns seem to fluctuate in a natural way without intervention. Kelso (2012) stated that multi-stability confers the ability of the motor system to switch between patterns to meet environmental or internal demands. A motion pattern can be stable at a certain timescale, but due to the highly redundant and degenerate nature of the human neuro-musculoskeletal system (Edelman & Gally, 2001) and due to self-organization and dynamic instabilities of synergies (Kelso, 2012), other stabilities are possible as well. The neural system may switch between these stabilities on a larger timescale depending on a complex interplay between several parameters (organismic-task-environment parameters (Newell, 1986)). The study of Morais, Silva, Marinho, Seifert & Barbosa (2015) illustrates the same principle, but for young swimmers. They used k-means and hierarchical cluster analysis to study the stability of performance and its determining factors (kinematics and anthropometrics) over a competitive season. They showed only moderate longitudinal cluster stability (range: 46.1% - 75%) and that the contribution of each performance determining factor changed over the season. More research in (young elite) athletes is necessary to get a better understanding of this phenomenon for both theoretical and practical reasons. Besides the fact that athletes are actually in a continuous learning process and the reshaping of the potential is natural, this multi-stability may also be used to prevent overuse injuries. Staying too long in the same coordination state, may put too much stress on the tissues in the same direction (Hamill, Palmer & Van Emmerik, 2012) and thus an optimal amount of variability could contribute to a non-pathological state (Bartlett, Wheat, & Robins, 2007; Stergiou & Decker, 2011). On a smaller timescale such as a team-handball game, the athlete can also benefit from this multi-stability. As opponents hinder the normal motion or fatigue limits normal performance, and a certain pattern is hard to maintain, the athletes can switch to other coordination states by addressing or forming other functional synergies able to perform the same task.

There were several limitations in the current study, that have to be kept in mind when interpreting the results. We had only a very small sample size (thirteen players), whereof five players were unable to attend the third measurement session in May. These players with only two potentials, can only be seen to switch between two basins of stability and are thus less informative than the others with three or four potentials. One player was unable to perform the jump shot in the last session due to a knee injury. It was not the objective of this research to analyze the effect of his injury on the stability, so the fact that his coordination potential in the penalty throw after his injury showed more instability, can be a coincidence. The relationship between coordination variability and injuries deserves more attention and could provide very insightful information for prevention strategies. A second limitation of this study was the number of trials that was performed during every measurement session. During every measurement session, the participants had to achieve only four valid trials. A higher number of trials could have revealed more multi-stability at the trial-to-trial timescale. We did not control for changes in strength or power of the subjects, which could also be an additional explanation for the variability in ball speed and coordination patterns. Nor could we control for differences in training because they belonged to different teams. We had three players from the same team (S2, S3 and S9) and two players from another team (S5 and S12). These players had the same training, but also within those groups, we could not see any structural patterns on ball speed and coordination between months. A final limitation is the reliability of the marker placement. Small differences in placement when measuring on different occasions are possible and could influence the calculated joint angles. However, we believe that this should not present problems because the raw joint angle and -velocity time series were spatiotemporally normalized within each subject and the vector quantization procedure of the SOM would map them in the same units if only the marker placement caused a difference.

Self-Organizing Maps

A discussion of the use of SOMs in motor control studies deserves some attention because this methodology is relatively new. Although sport and human movement scientists have recognized their potential quite some time ago (Bartlett, 2006; Bauer & Schöllhorn, 1997), there is still no standardized use. As mentioned in the methodology, many alternatives exist on how to train and to use them. Also many options are available on which parameters to use in their construction (the options we used were displayed in Table 2, mostly these are the default parameters of the SOM Toolbox). While for some parameters, there can be a rationale, for others none yet exists. Normalization for instance has a natural choice: range scaling kinematic variables to a [-1 1] interval does not alter the trajectories, it only rescales them and this is also used in phase plane analyses. But training type (sequential vs. batch) or weight vector initialization (linear vs. random) do not seem to have natural choices. The quantization- and topographical error are the only check points for the quality of the map we have so far. Since there is no agreed-upon range for their values, these numbers are not very informative. Button, Wheat & Lamb (2014) have argued to use data-driven options for the construction parameters and these do seem to be the natural choice. An important question arises with regard to map size. In this study and in the one from Lamb et al. (2011), different map sizes for different players were created because this was data-driven based on the principal components of the original data-sets. These map sizes showed little difference between subjects and in the case of the second SOM, these maps yielded always between fifteen and seventeen units. Therefore we forced them all to have sixteen units. So when stating that a subject's stability shifted along the coordination potential, this means something completely different for every other subject and would need careful interpretations of the component planes to analyze what happened. The size of the 'difference' in coordination pattern in between months for different subjects needs not be of the same size in the original coordination space to show a similar effect on the SOMs. This makes it hard to generalize or to perform a quantitative study on longitudinal multi-stability. On a qualitative level however, regardless of the size of the difference, the fact that the SOMs cluster in different units for different months indicates that the patterns change.

Besides map quality and map size, other issues deserve attention too. This will need a study on its own and now that SOMs and other neural network applications seem to find their way into biomechanics and motor control, some guidelines become necessary.

Within the limits of this study and the limits of self-organizing maps, we have demonstrated that coordination stability differs between the trial-to-trial and month-to-month timescale and that both should be quantified before evaluating the effect of certain interventions (Preatoni et al., 2012).

CONCLUSIONS

This study evaluated both the intra-seasonal ball speed- and coordination variability over a 4-month period in two team handball throwing techniques in elite youth players. The observed variability in ball speed proved higher for many players than in some intervention studies (studies that showed statistical significance) targeting improvements in throwing speed. This highlights the importance for a better evaluation of intra-seasonal variability for testing sport-specific results of training programs. If an evaluation of natural variability is impossible in practical settings, a safe choice to exclude effects not due to the intervention is minimum a 7% difference. The analysis of the coordination dynamics showed that subjects changed between coordination patterns in between months and could be classified as longitudinal multi-stable. This appears to be a requirement for exploring the coordination landscape in order to find an optimal solution under the changing constraints associated with elite youth training. Many of the phenomena observed in coordination dynamics in low-dimensional continuous/rhythmic tasks were also observed in this complex discrete motion.

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APPENDIX

Figure A shows the 20 component planes for the SOM of S13 for the jump shot. These component planes correspond to the U-matrix and best-matching unit trajectories in Figure 2 from the main manuscript. The coordination states during the motion can be interpreted according to these planes. In Figure 2, we saw a shift in the initial conditions from the lower right corner of the map to higher and more centrally located parts of the map. In Figure A, we can see that this corresponds mainly to changes in pelvis lateral tilt angle (latPG), pelvis for/backward tilt angle and velocity (fwbwPG, VfwbwPG), trunk lateral tilt angle (latTG) and shoulder ab/adduction (Abad). Other variables show smaller differences between these two map regions.

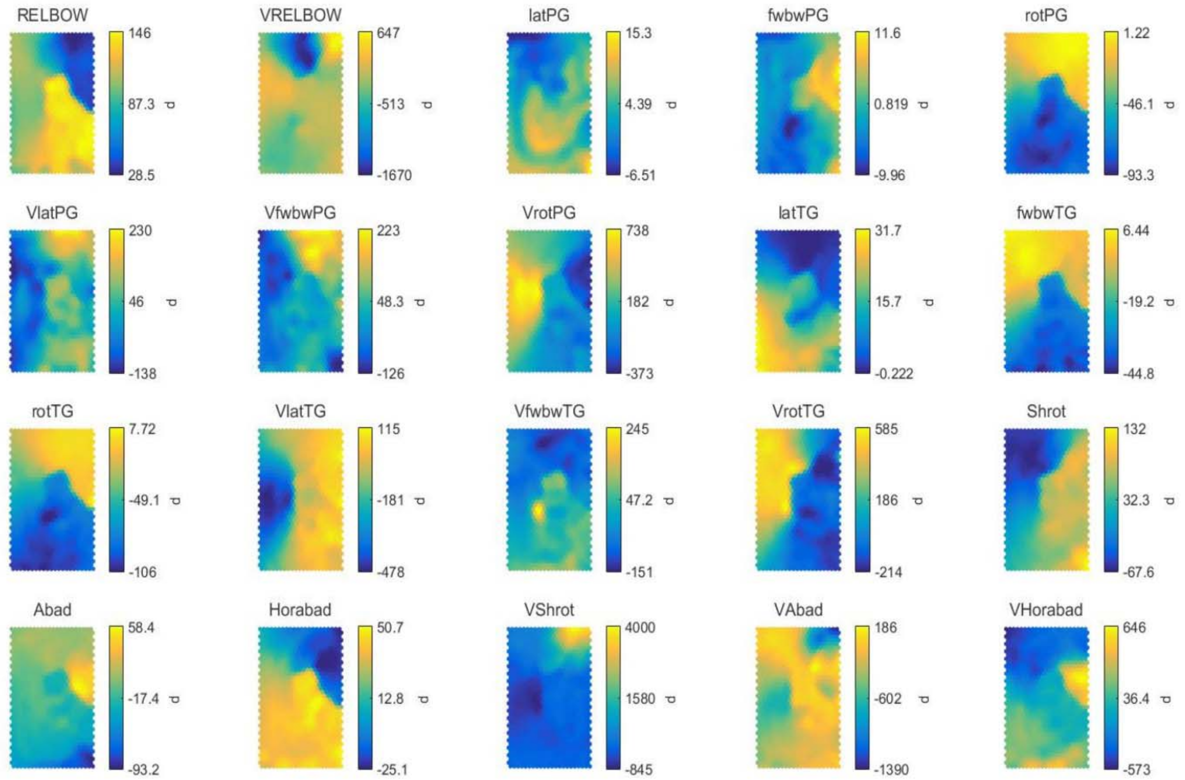

Figure A: Twenty component planes of the SOM from Figure 2 in the main manuscript. RELBOW = elbow angle (°, 0=full extension), VRELBOW = elbow angular velocity (°/s, + values are extension). PG and TG indicate the pelvis and trunk angles (°) in the global reference frame and V indicates their velocity (°/s): lat = lateral tilt (+ values are right tilt), fwbw = for/backward tilt (+ values are forward), rot = rotation (+ values are rotation toward the goal). Shrot, Abad, Horabad are shoulder endo/exorotation (+ values are endorotation), shoulder ab/adduction (+ values are abduction) and horizontal ab/adduction (+ values are horizontal abduction) respectively.