Artificial Neural Networks for Analyzing Inter-limb Coordination: The Golf Chip Shot

Peter F. Lamb\textsuperscript{a,b}, Roger M. Bartlett\textsuperscript{a}, Anthony Robins\textsuperscript{c}

\textsuperscript{a}School of Physical Education, University of Otago, Dunedin, New Zealand
\textsuperscript{b}Faculty of Sports and Health Science, Technische Universität München, Munich, Germany
\textsuperscript{c}Department of Computer Science, University of Otago, Dunedin, New Zealand

Abstract

Motor control research relies on theories, such as coordination dynamics, adapted from physical sciences to explain the emergence of coordinated movement in biological systems. Historically, many studies of coordination have involved inter-limb coordination of relatively few degrees of freedom. Moreover, the majority of experimental studies of coordination also involve continuous cyclic movements. This study had two aims: a) to explain the changes in inter-limb coordination used to perform the golf chip shot at varying distances and b) to ascertain the validity of Self-Organizing Maps (SOMs) as an analysis technique for high-dimensional discrete movement coordination. The experimental setup was specifically chosen to target a gap in the motor control literature in which discrete movements involving coordination of many degrees of freedom are underrepresented. The golf chip shot was chosen as a movement model. Four golfers performed ten chip shots to each of six target distances. 24 kinematic variables were used as input for a SOM in order to compress the data to a low-dimensional mapping. In this study, the trajectory of consecutive best-matching nodes on the output map was used as a collective variable and subsequently fed into a second SOM which was used to create a visualization of coordination stability. The SOM trajectories showed changes in coordination between movement patterns used for short chip shots and movement patterns used for long chip shots. The stability of coordination for Player MW showed a non-linear phase transition from 4 m to 20 m. For Players HI and PB the instability between stable states of coordination was not as clear as it was for Player MW, therefore, the existence of a phase transition for these two players is speculative. Player AW
did not show phase transitions or even uni-modal coordination at any of the six distances. The concept of degeneracy was used to explain both the high variability between players and the variability within chipping distances for Player AW. The methods used this study may offer a solution for researchers from a coordination dynamics perspective who intend to use data obtained from discrete high-dimensional movements.

**Keywords:** Coordination, Neural Networks, Self-Organizing Maps, Golf

### 1. Introduction

Understanding how individuals coordinate the movements of many different body parts to produce a functional outcome is important for researchers, clinicians, movement analysts and educators. For any whole body movement, cellular units of the order of $10^{14}$, in hundreds of varieties, must organize to operate nearly 800 muscles (Turvey, 1990). Such complexity makes the process of coordination a challenging program of study. Nicolai Bernstein recognized the challenge as that of overcoming the complexity by mastering the redundant biomechanical degrees of freedom to produce controlled movement (Bernstein, 1967). Turvey expressed the redundancy problem that expands on what Bernstein may have meant by mastering redundant degrees of freedom. As put by Turvey, “...every movement comprises a state space of many dimensions; the problem of coordination, therefore, is that of compressing such high-dimensional state spaces into state spaces of very few dimensions” (Turvey, 1990, p. 938–939). The task of compressing redundant information into useful low-dimensional information represents a significant challenge to studies of coordination.

Intuitively, researchers have looked for answers to how coherent macroscopic behavior in human movement is achieved from apparent disorder at the microscopic level, in theories of complex physical systems (for example, chaos theory and dynamical systems theory). From physical systems the concept of self-organization states that a system’s components can coalesce to produce organized behavior without the intervention of an outside agent. Under the framework of coordination dynamics, concepts have been developed to relate physical systems to neurobiological systems. According to coordination dynamics, the collective variable specifies the relationships among the interacting components of the system (Bressler and Kelso, 2001). Often the collective variable represents the relative phase between two oscil-
lating components of the system. The control parameter is a variable that leads the system through a range of coordinative states, which are measured using the collective variable. Haken et al. (1985) conducted an experiment involving coordinated index finger movements of both hands. In the experiment, participants oscillated their fingers either in-phase or anti-phase. If the participant began in an anti-phase state of coordination and the oscillation frequency (the control variable) was increased, a sudden switch to in-phase coordination occurred at a critical frequency. The sudden switch in coordination was marked by instability, measured by an increase in variability in the relative phase of the oscillating fingers (the collective variable). If, however, the participant began oscillating in in-phase coordination, no change in coordination was seen when oscillation frequency increased. The lack of change in coordination from in-phase to anti-phase implied that the in-phase patterning of movements was stable for all tested values of the control parameter, while anti-phase coordination was only suitable at lower frequencies. Moreover, since in-phase coordination was stable for low and high frequencies, when the frequency decreased, no spontaneous shift back to anti-phase coordination from in-phase coordination occurred.

A visualization of a ball rolling on a landscape composed of one or many valleys – usually called basins – has been used to illustrate coordination stability (Haken et al., 1985). A deep basin represents stable coordination and a shallow basin represents relatively unstable coordination. There can be many basins of attraction for a system, representing many possible coordination states. For the ball to move from one basin to another, the system must be perturbed. Accordingly, a stronger perturbation is required to unsettle a stable state of coordination compared to a less stable state. Once perturbed sufficiently the ball may settle in a different basin, representative of a different stable state of coordination.

The attractor basins have typically been used to depict the stability of coordination for cyclic bimanual movement tasks. However, the principles of discrete and cyclic movement generation may not be as closely related as once thought (Hogan and Sternad, 2007; Sternad and Schaal, 1999). Further, Rein et al. (2010) have identified that there may be a task bias in experiments involving continuous cyclic movements of relatively few degrees of freedom. Although the task goal and the movement pattern maybe coupled tightly in experiments of bimanual coordination, this may not necessarily be true for everyday tasks. Indeed, constraints imposed on laboratory bimanual movement tasks may limit the way in which new movements are patterned.
Without the experimental constraints common in the bimanual coordination paradigm there may exist a larger set of possible movement solutions involving greater degrees of freedom (Hong and Newell, 2006; Obhi, 2004). To test whether current motor control theories can be applied to more complex tasks, involving high-dimensional coordination, such movement tasks need to be studied.

In studies of multi-limb coordination the analyses are complicated by the high-dimensional input space of multiple time-series data that represent the movements. Furthermore, the large amount of data collected using modern biomechanical equipment compounds the problem of identifying the important information that underlies coordination (Barton et al., 2006). Therefore, the goals of this study were: a) to explain the changes in inter-limb coordination used to perform the golf chip shot at varying distances and b) to ascertain the validity of SOMs as an analysis technique for high-dimensional discrete movement coordination. We selected the golf chip shot as the movement model for this study.

2. Methods

2.1. Participants

Four low-handicap (handicap = 2.2 ± 2.7, experience = 13.5 years ± 10.3, age = 25.7 years ± 11.0) male golfers volunteered to participate in this study. All players were healthy and had not experienced any injuries in the six months preceding the study. Each participant signed a consent form and ethical approval was granted by the University of Otago Ethics Committee.

2.2. Task

Each player performed 60 golf chip shots which were used for analysis. The players aimed for targets at distances from 4 m to 24 m and all distances between at 4 m intervals. The trials were split evenly across two data collection sessions for each player. The participants used the same club – an 8-iron – for all trials and the reflective markers were not removed from the club at any time during the study. The players were only instructed to try to get the ball as close to the target as possible.

2.3. Data Collection

Participants were prepared with passive reflective markers on the following anatomical landmarks: left and right (l/r) acromion process, lateral
humerus (l/r), posterior humerus (l/r), medial epicondyle of humerus (l/r),
lateral epicondyle of humerus (l/r), radial forearm (l/r), posterior forearm
(l/r), radial styloid (l/r), ulnar styloid (l/r), posterior hand (l/r), sternal
notch, xiphoid process, C7, T5, T12, L3, PSIS (l/r), ASIS (l/r), greater
trochanter (l/r), lateral thigh (l/r), anterior thigh (l/r), lateral epicondyle
of femur (l/r), medial epicondyle of femur (l/r), lateral shank (l/r), anterior
shank (l/r), lateral malleolus (l/r), medial malleolus (l/r), fourth metatarso-
phalangeal joint (l/r), distal second toe (l/r), first metatarsal-phalangeal joint
(l/r) and heel (l/r). In addition, four markers were placed on the floor and the
edges of the hitting mat to identify the target line and a line perpendicular to
the target line. Five markers were placed on the golf club (three on the shaft,
one just below the grip, one midway down and one just above the hosel) and
two markers were fixed to the heel and toe of the club, respectively.

A three-dimensional motion capture system (Motion Analysis Corporation
Inc., Santa Rosa, CA, USA) with 12 digital cameras was used. The
sampling rate was set at 100 Hz. The order of the target distances was
randomized with each distance being used ten times and repeated for each
participant. Target distance ordering was randomized to improve the ecolog-
ical validity of the study.

2.4. Post-processing

A three-dimensional 16-segment model was created using the Visual3D
software package (C-Motion, Inc.). Functional joint centres for the ankle,
knee, hip, shoulder, elbow and wrist were estimated using calculations from
Schwartz and Rozumalski (2005). Each participant performed a movement
trial used solely for computing the functional joint centres according to the
procedures of Begon et al. (2007). After a visual inspection of the frequency
spectra, raw displacement data were filtered using a second order Butter-
worth filter set at a cut-off frequency of 10 Hz. A dual direction low pass
filter was then applied to remove the effects of phase shifting.

Torso rotation about its longitudinal axis was represented by two angles:
shoulder rotation and hip rotation. Shoulder rotation angle was defined as
the rotation of an axis, which passed through both shoulder joint centres,
about the z-axis of the lab coordinate system. Hip rotation was defined,
similar to shoulder rotation, as the rotation an axis which passed through
both hip joint centres about the z-axis of the lab (Cole and Grimshaw, 2009).
The lab coordinate system was set so that the x-axis was parallel to the target
line, the y-axis was the horizontal perpendicular to the target line and the
z-axis the vertical perpendicular to the target line. A rigid spine segment
was created which joined the bisections of the axes joining the hip joint
centres and shoulder joint centres, respectively. Spine angular displacement
was defined as the rotation of the spine segment about the x-axis of the
lab coordinate system. Hip, shoulder and spine angular displacement were
measured relative to the starting position of the movement. Right and left
arm ab-adduction angles were calculated using the Euler angle in the frontal
plane. An angle representing radial and ulnar deviation was created as a
three-dimensional angle between the left forearm segment and the shaft of
the club segment. The displacement was calculated in a plane where the
smallest angle existed. This constitutes a four-point angle with a variable
axis of rotation as suggested by Pickering and Vickers (1999). Finally, the
linear displacement of the centre of the player’s head and the heel of the golf
club in three dimensions were used as linear variables. Derivatives of the
above variables were taken, using the raw data sampling rate and movement
time, to create a 24-dimensional dataset.

The start of the trial was defined as the first frame of the clubhead move-
ment away from the target during the backswing. The end of the movement
was defined as the tenth frame after ball contact. Angular displacement vari-
ables were normalized to a range of -1 and 1, to remove scaling of range of
motion. Angular velocities and linear displacements and velocities were nor-
malized to a maximum or minimum of 1 or -1 to preserve the zero value. This
was considered important both to represent the phase space to the network
and maintain the (0,0,0) starting position from which linear displacements
were measured.

3. Analysis

3.1. SOM overview

If we wish to study multi-limb coordination, a method for identifying the
important information that describes the dynamics of the system, which may
be more numerous than when dealing with bimanual coordination, is neces-
sary. Unique properties of Artificial Neural Networks (ANN) allow them to
learn underlying, and potentially complex and non-linear, patterns in data
and compress them to useful information. SOMs, a specific type of ANN,
seem to be an attractive analysis tool for biomechanical studies because they:
a) require large datasets, b) compress redundant high-dimensional informa-
tion to a low-dimensional mapping and c) preserve non-linear topological relationships in the data.

SOMs are a special class of ANN, created by Teuvo Kohonen, effective for visualizing and clustering data (Kohonen, 2001). The basic architecture of a SOM consists of a layer of output nodes, fed forward by a layer of input nodes (see Fig. 1).

Figure 1: The connections between input and output layers, where \( x_1 = (\xi_{1,1}, \xi_{1,2}, \ldots, \xi_{1,p}) \) and \( x_2 = (\xi_{2,1}, \xi_{2,2}, \ldots, \xi_{2,p}) \).

The input nodes are fed information from the environment. Nodes are fed a series of inputs represented by input vectors, for example, \( x_i = (\xi_{i,1}, \xi_{i,2}, \ldots, \xi_{i,p}) \), where \( i \) is the index of the input vector and \( p \) is the number of variables in the input, or its dimensionality. Each node in the output layer has an associated weight vector, \( y_j = (\eta_{j,1}, \eta_{j,2}, \ldots, \eta_{j,p}) \), here \( j \) is the index of the node on the map. Note that the dimensionality, \( p \), is the same for input and weight vectors.

Each input node is connected to all output nodes, while nodes in the output layer are connected to adjacent nodes by a neighborhood relation which thus determines the topology of the output map. The space spanned by the weights constitutes a Euclidean space, thus the distance calculated between a weight vector and an input vector must be a Euclidean distance. The Euclidean distance between the input vector \( x = (\xi_1, \ldots, \xi_p) \) and the weight vector \( y = (\eta_1, \ldots, \eta_p) \) is calculated by

\[
d_E(x, y) = \sqrt{(\xi_1 - \eta_1)^2 + (\xi_2 - \eta_2)^2 + \ldots + (\xi_p - \eta_p)^2}. \tag{1}
\]
Through an iterative training process the weights are adjusted to best match the input by minimizing the Euclidean distance between the input and the weights.

The method of activation in SOMs is called competitive learning and gets its name from the so-called winner take all activation rule, where nodes in the output layer compete amongst themselves to best represent a given input vector. The winner node $c$ for each input $x_i$, which is a row in the matrix $X$, is that input’s best-matching node

$$\| x_i - y_c \| = \min_j \| x_i - y_j \|. \tag{2}$$

Although only one node is activated and termed the best-matching node, the influence of the input in learning is spread across the user-defined neighborhood radius. Accordingly, the weight vectors $j$ in this study were updated using the Kohonen batch training algorithm

$$y_j(t + 1) = \frac{\sum_{i=1}^{n} h_{cj}(t) x_i}{\sum_{i=1}^{n} h_{cj}(t)} \tag{3}$$

where $h_{cj}(t)$ is the Gaussian distribution

$$h_{cj} = e^{d_{cj}^2 / 2\sigma^2}, \tag{4}$$

$d_{cj}$ is the Euclidean distance between the best matching unit, at time $t$, and all other map units and $\sigma$ is the neighborhood radius. The neighborhood function, $h_{cj}$, is the feature of SOMs which preserves the topology of the input dataset.

3.2. Neural Network Architecture

Because of high inter-individual variability in the training data, separate SOMs were trained on each player’s respective kinematic data. This method emphasizes the differences in coordination within each individual and complements the concept of individual variation (Newell and Vaillancourt, 2001; Riley and Turvey, 2002). These SOMs were useful for clustering phases of the movement. Subsequently, a second SOM for clustering trials of the dataset
was trained using the best-matching nodes from the previous SOM for each respective player.

Training parameters for the first SOM are shown in Table 1 and for the second SOM in Table 2. The SOM Toolbox (Vesanto et al., 2000) was integrated into the software tool for the analysis. Nodes in the output layer were organized into a two-dimensional hexagonal lattice. The size of the output map was determined after calculating the eigenvalues and corresponding eigenvectors of the input. The ratio of the two largest eigenvalues, $\lambda_1$ and $\lambda_2$ respectively, was used to determine the dimensions of the map.

$$\frac{n}{m} = \sqrt{\frac{\lambda_1}{\lambda_2}},$$

where $n$ and $m$ are the respective map side-lengths. Map initialization and neighborhood sizes were based on the principal components of the input distribution which, in some cases, led to different parameter values between players.

Quantization and topographical errors were used to assess the representational power and interpretability of the SOM. The topographic error (Kiviluoto, 1996) is a measure of how well the SOM has been able to shape itself to represent the input. A topographic error of zero indicates that any best matching node would have one of its neighboring node be the second best matching node. Quantization error shows how closely an input vector is represented by its best matching node's weight vector.

3.3. U-matrix

Much research has been focused on visualization techniques for the low dimensional map outputs (Kohonen, 2001; Pampalk et al., 2002; Pölbauer et al., 2005). To show the coordination state at a given time frame, the map can be arranged into a fixed grid (grid space) with the best matching node highlighted. Similarly, a trajectory can be added on top of the grid to show several consecutive coordination states throughout the trial (Barton, 1999; Barton et al., 2006; Bauer and Schöllhorn, 1997; Lees and Barton, 2005; Schöllhorn and Bauer, 1998). The grid trajectory is an advantageous visualization technique because qualitative changes in coordination are easily seen.

This study used a unified distance matrix (U-matrix) (Iivarien et al., 1994; Kraaijveld et al., 1992) for visualizing the trained network and the
<table>
<thead>
<tr>
<th>Parameter</th>
<th>AW</th>
<th>HI</th>
<th>MW</th>
<th>PB</th>
</tr>
</thead>
<tbody>
<tr>
<td>initialization</td>
<td>‘linear’</td>
<td>‘linear’</td>
<td>‘linear’</td>
<td>‘linear’</td>
</tr>
<tr>
<td>lattice</td>
<td>‘hexagonal’</td>
<td>‘hexagonal’</td>
<td>‘hexagonal’</td>
<td>‘hexagonal’</td>
</tr>
<tr>
<td>shape</td>
<td>‘sheet’</td>
<td>‘sheet’</td>
<td>‘sheet’</td>
<td>‘sheet’</td>
</tr>
<tr>
<td>neighborhood</td>
<td>‘Gaussian’</td>
<td>‘Gaussian’</td>
<td>‘Gaussian’</td>
<td>‘Gaussian’</td>
</tr>
<tr>
<td>training algorithm</td>
<td>‘batch’</td>
<td>‘batch’</td>
<td>‘batch’</td>
<td>‘batch’</td>
</tr>
<tr>
<td>map size ((i))</td>
<td>24 × 16</td>
<td>25 × 15</td>
<td>25 × 15</td>
<td>24 × 16</td>
</tr>
<tr>
<td>rough training</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>steps ((t))</td>
<td>12</td>
<td>12</td>
<td>12</td>
<td>12</td>
</tr>
<tr>
<td>radius ((\sigma))</td>
<td>3 → 1</td>
<td>4 → 1</td>
<td>4 → 1</td>
<td>3 → 1</td>
</tr>
<tr>
<td>fine-tuning</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>steps ((t))</td>
<td>200</td>
<td>200</td>
<td>200</td>
<td>200</td>
</tr>
<tr>
<td>radius ((\sigma))</td>
<td>1.5 → 1</td>
<td>1.5 → 1</td>
<td>1.5 → 1</td>
<td>1.5 → 1</td>
</tr>
<tr>
<td>quantization error</td>
<td>0.491</td>
<td>0.461</td>
<td>0.650</td>
<td>0.461</td>
</tr>
<tr>
<td>topographical error</td>
<td>0.011</td>
<td>0.012</td>
<td>0.023</td>
<td>0.023</td>
</tr>
</tbody>
</table>

best matching node trajectory. Each ‘unit’ in the U-matrix will be referred to as a cell for clarity, so that it is not confused with nodes in the output layer. Recall that each output node in the SOM has an associated weight vector. The U-matrix represents each output node (grid space) as a black cell. Between each pair of nodes (black cells) the surface of the U-matrix is colored, which represents the similarity of the weight vectors of that pair of nodes. Blue represents a pair of weight vectors which are close (in the input or weight space), red represents vectors which are far apart. Hence for each pair of adjacent nodes in the output layer there is also a color gradient representing how similar the weight vectors of those two nodes are. To further aid in visualizing similarity between neighboring weight vectors the Euclidean distance between them is shown as the height on the z-axis. Including information relating to similarity between weight vectors makes the U-matrix a hybrid representation of grid space and weight space.

The phases of the chip shot were represented by certain regions on the U-matrix (see Fig 3). The phases were: backswing, downswing and follow-through. These phases occurred between the events shown in Figure 2, re-
Table 2: Second SOM training parameters for all players (AW, HI, MW, PB)

<table>
<thead>
<tr>
<th>Parameter</th>
<th>AW</th>
<th>HI</th>
<th>MW</th>
<th>PB</th>
</tr>
</thead>
<tbody>
<tr>
<td>initialization</td>
<td>'linear'</td>
<td>'linear'</td>
<td>'linear'</td>
<td>'linear'</td>
</tr>
<tr>
<td>lattice</td>
<td>'hexagonal'</td>
<td>'hexagonal'</td>
<td>'hexagonal'</td>
<td>'hexagonal'</td>
</tr>
<tr>
<td>shape</td>
<td>'sheet'</td>
<td>'sheet'</td>
<td>'sheet'</td>
<td>'sheet'</td>
</tr>
<tr>
<td>neighborhood</td>
<td>'Gaussian'</td>
<td>'Gaussian'</td>
<td>'Gaussian'</td>
<td>'Gaussian'</td>
</tr>
<tr>
<td>training algorithm</td>
<td>'batch'</td>
<td>'batch'</td>
<td>'batch'</td>
<td>'batch'</td>
</tr>
<tr>
<td>map size (i)</td>
<td>$32 \times 1$</td>
<td>$32 \times 1$</td>
<td>$32 \times 1$</td>
<td>$32 \times 1$</td>
</tr>
<tr>
<td>rough training steps (t)</td>
<td>10</td>
<td>10</td>
<td>10</td>
<td>10</td>
</tr>
<tr>
<td>radius (σ)</td>
<td>$3 \rightarrow 1$</td>
<td>$3 \rightarrow 1$</td>
<td>$3 \rightarrow 1$</td>
<td>$3 \rightarrow 1$</td>
</tr>
<tr>
<td>fine-tuning steps (t)</td>
<td>75</td>
<td>75</td>
<td>75</td>
<td>75</td>
</tr>
<tr>
<td>radius (σ)</td>
<td>$1.5 \rightarrow 1$</td>
<td>$1.5 \rightarrow 1$</td>
<td>$1.5 \rightarrow 1$</td>
<td>$1.5 \rightarrow 1$</td>
</tr>
<tr>
<td>quantization error</td>
<td>0.405</td>
<td>0.349</td>
<td>0.486</td>
<td>0.340</td>
</tr>
<tr>
<td>topographical error</td>
<td>0.026</td>
<td>0.034</td>
<td>0.023</td>
<td>0.046</td>
</tr>
</tbody>
</table>

3.3.1. Attractor Layout Diagram

The SOM trajectory on the U-matrix can be thought of as a composite variable which represents high-dimensional coordination. Therefore, treating the SOM trajectory as a collective variable, as described in coordination dynamics (see Kelso (1995) for a review), seems appropriate. Attractor diagrams have been used to describe the stability of coordination at specified control parameter values (Burgess-Limerick et al., 2001; Haken et al., 1985) and theoretically for golf (Knight, 2004). Here, constructing an attractor diagram represents a second stage in the analysis.

The attractor diagram was created according to the hits on the second SOM. Inputs for the second SOM were created from projecting the weight vectors into weight space using the Sammon’s mapping technique (Sammon Jr, 1969). The two-dimensional coordinates of each consecutive best-matching node, in weight space from the original SOM, were used to create an input vector representative of an individual trial. For this, 101 x-
Figure 2: Events of the golf chip shot. The frontal plane view is shown in the top row and the sagittal plane view shown in the bottom row. From left to right: address position, top of the backswing, contact and follow-through.

Figure 3: Phases of the golf chip shot shown on the U-matrix.

coordinates followed by 101 y-coordinates made up the input vector for one trial. Other methods (Perl, 2004; Perl and Dauscher, 2006) suggest reducing dimensionality for input into a second SOM to avoid the high-dimensionality
Figure 4: The sequence of consecutive best matching nodes from the first SOM is used as input for the second SOM. The frequency of activated locations on the second (one-dimensional) SOM is depicted by the depth of the basin. Frequently visited areas are analogous to stable patterns in the coordination dynamics paradigm.

of the input merely adding statistical noise. This recommendation was not followed because of the low variability in the dataset within each individual. The extra dimensionality – representing phases of the movement – was needed to make a detailed grouping based on the time-series coordination exhibited by the players.

Each input’s best-matching node bends a theoretical line down on the y-axis while dragging its neighbors with it (see Fig 4). The amount one node drags its neighbor was weighted according to the Euclidean distance between the interacting nodes. A node with a neighbor separated by a short Euclidean distance to it is dragged more than a neighbor with a larger Euclidean distance. This process was performed after training the second SOM, so constructing the visualization did not affect the training process. The neighborhood influence allows the visualization to represent basins in which similarly patterned trials would collect. Deeper basins represent attractors, as those nodes have been hit more frequently for the specified shooting condition.
4. Results

4.1. Player AW

Figure 5: Player AW, trajectories for shot distances: (a) 4 m, (b) 8 m, (c) 12 m, (d) 16 m, (e) 20 m and (f) 24 m.

The trajectories for Player AW show shifts in coordination at different shooting distances (see Fig 5). At 4 m (see Fig 5(a)), the trajectories hit nodes close to the brightly colored, central region for all phases of the movement. The trial trajectories for the 8 m distance (see Fig 5(b)) activate some of the nodes representing the 4 m shots but mostly hit nodes slightly further from the central region. The trend toward edge nodes continues as shooting distance increases, with the 20 m and 24 m shots hitting nodes along the edge of the map (see Figs 5(e) and (f)).

4.2. Player MW

The trajectories for the 4 m shots (see Fig 6(a)) start along the edge of the three-dimensional distance matrix, then jump to nodes near the central region where the trajectories stay until the end of the movement. For the 8 m shots (see Fig 6(b)), the trajectories start out similarly to the 4 m shots then jump to the nodes near the central region – but not as close to the central
Figure 6: Player MW, trajectories for shot distances: (a) 4 m, (b) 8 m, (c) 12 m, (d) 16 m, (e) 20 m and (f) 24 m.

region as the 4 m shots. At 12 m (see Fig 6(c)), some of the trial trajectories start close to the central region, with a few remaining trials still starting out toward the edge. Instead of jumping to inside nodes, near the central region like the short shots, the trajectories tend toward the edge of the map after the backswing phase. This trend continues as distance increases, with the 20 m and 24 m shots (see Fig 6(e) and (f)) consistently starting near the central region then hitting nodes along the edge after the backswing.

4.3. Player HI

The trajectories for Player HI are similar to Player MW. The 4 m trajectories (see Fig 7(a)) start out along the edge then jump to the central region after the backswing phase. The 8 m trajectories (see Fig 7(b)) are similar to the 4 m trajectories; however, during the downswing phase the activated nodes are generally further from the central region. As distance increases, the trend of downswing and follow-through nodes being further from the central region continues to what is shown in the bottom row in Figures 7(d)–(f). At 16 m (see Fig 7(d)) the trajectories start near the central region during the backswing phase. After the backswing phase they move to edge nodes for
4.4. Player PB

The pattern of the trajectories on the three-dimensional distance matrix for Player PB, as distances increases, is similar to Players MW and HI. The 4 m and 8 m shots (see Fig 8(a) and (b)) clearly start along the edge and jump to more central nodes after the backswing. The transition from the short shot pattern to the long shot pattern starts at 12 m (see Fig 8(c)) for Player PB. For the 12 m shots and longer (Figures 8(c)–(f)), the backswing is represented by nodes close to the central region. Following the backswing, nodes closer to the edge are activated, compared to the 4 m and 8 m shots.

4.5. Attractor Diagrams

The SOM trajectories showed obvious differences in node hit trajectories between shooting distances, for all participants. The attractor diagrams were used to analyze the stability of the changes in coordination. Starting with Player AW, the 4 m and 8 m shots (see Fig 9(a)) show bi-modal coordination – often referred to as multistability in coordination dynamics (Kelso, 1995,
Figure 8: Player PB, trajectories for shot distances: (a) 4 m, (b) 8 m, (c) 12 m, (d) 16 m, (e) 20 m and (f) 24 m.

A deep basin is located near the middle nodes of the SOM. A slightly shallower basin is found to the left of the deep basin. At 12 m, the deep, central basin splits, forming two basins to either side of the deep basin shown in the diagrams for the 4 m and 8 m shots. The shallower basin on the left remains for the 12 m shots. At 16 m, from the deep basin that was split at 12 m, the basin on the right becomes the attractor basin. A wide shallow basin remains on the left but more central compared to the location of the left-most basin for the 4 m, 8 m and 12 m shots. For the 20 m and 24 m shots there are two attractor basins which represent the same nodes as the basin for the 16 m shots. However, the deep basin for the 20 m shots, the one on the right, becomes shallower for the 24 m shots where the attractor becomes the basin on the left. Player AW is the only player out of four to show strong bi-modal coordination, or multistability, but no distances where attractors representing uni-modal coordination exist. The distribution of node hits for Player AW is spread more evenly across SOM nodes within each distance compared to the other three players.

Player MW shows a more continuous shift from left to right compared to Player AW (see Fig 9(b)). The 4 m shots activate nodes on the left side of the
Figure 9: Attractor layout diagrams for a) Player AW and b) Player MW.
Figure 9: Attractor layout diagrams for c) Player HI and d) Player PB.
SOM, creating a deep attractor basin. There is also a plateau located more centrally. At 8 m, the plateau shown in the 4 m diagram becomes a basin, with two equally deep minima sharing the basin. Also in the 8 m diagram: a shallow basin emerges on the far right of the SOM, and the basin on the left from the 4 m diagram vanishes. In the 12 m diagram, the right side basin deepens, with multistability shown by three basins for the shooting distance. The basin on the right deepens for the 20 m and 24 m shots, showing strong attraction for the long shots.

For Player HI, there is a deep basin of attraction for the 4 m shots (see Fig 9(c)). The basin shifts to the right and becomes more shallow for the 8 m shots compared to the 4 m shots. A second basin on the far right also emerges for the 8 m shots for Player HI. At 12 m the deep basin shifts further to the right, now in the centre of the diagram. The shallow basin on the right, which emerged at 8 m, also becomes deeper at 12 m – the two basins show bi-modal coordination. At 16 m the deep basin at 12 m vanishes. Most trials at 16 m are represented on the right side basin. Uni-modal coordination is shown for 16 m, 20 m and 24 m shots by the deep basin represented by right side nodes in the diagrams.

The attractor layout diagrams for Player PB (see Fig 9(d)) are similar to the diagrams for Player HI. Similarities between the two players include: deep basins of attraction on the left side for short shots, bi-modal coordination at 12 m, and deep basins of attraction on the right side of the diagrams for the long shots. In contrast to Player HI, Player PB shows a slightly deeper basin on the right side for the 4 m shots, instead of at 8 m, where it exists for Player HI. Instability may be shown at 16 m by the wide and shallow basin that represents a wider range of coordination between trials. The instability at 16 m is greatly reduced at 20 m and even more at 24 m where the basin on the right side is very deep and narrow.

5. Discussion

5.1. Variability Between Individuals

Preliminary analyses identified high inter-individual variability between the four golfers of this study. The high inter-individual variability relative to the inter-condition (shot distance) variability for each player prompted SOMs specific to each player. Hong and Newell (2006) attributed their finding of individual differences to the concept of degeneracy. The concept of degeneracy may be appropriate here to explain the diversity of coordination.
among the players in the current study. Degeneracy is the motor system’s strategy of accomplishing similar tasks by coordinating structurally different components (Edelman and Gally, 2001). Hong and Newell (2006) attributed individual differences in a ski-simulator task to degeneracy. The authors explained that whole body movements, compared to low-dimensional coordination tasks, afford more potential for degeneracy. The results of four players in the current study lend support to the concept of degeneracy as all, highly skilled, performers recruited different coordination patterns to accomplish the same task. Data normalization procedures excluded range of motion and body size so that the differences shown between individuals in Figures 5–8 represent differences in coordination. Player AW also showed evidence of degeneracy between trials of the same distance.

5.2. Changes in Coordination Between Shooting Distances

All players showed gradual changes in coordination from short shots to long shots (or vice versa) and were consistent for all phases of the movement. Three of the players (MW, HI and PB) showed similar U-matrix trajectories for the backswing phase of the movement and all showed similar trajectories for the downswing and follow-through phases for the corresponding distances. A tempting mistake here, when comparing Figures 5, 6, 7 and 8, is to infer from the trajectories that the information represented by the activated nodes for the backswing of Player AW’s 4 m shots is similar to the information represented by the activated nodes for the backswing of the other three players’ 24 m shots, because of the nodes’ proximity to the central region. The similarity between distance matrices of the participants is intriguing but comparisons between players should be avoided because each player’s SOM is independent of each other player’s data. The next section in this discussion uses the attractor diagrams to evaluate the stability of coordination at the different chipping distances and to show whether the changes in coordination, that were shown on the U-matrices, were gradual or spontaneous.

5.3. Coordination Stability

Three of the players (MW, HI and PB), for the 4 m shots, showed deep attractor basins on the left side of the attractor diagrams (see Fig 9), where the activated nodes were associated with movement patterns used for short shots.

For Players MW, HI and PB, as distance increased to 8 m and then to 12 m, coordination gradually changed. Since the data have been normalized,
the gradual change does not represent scaling of range of motion. Instead, a gradual scaling of coordination toward kinematics associated with longer shots occurs. According to coordination dynamics, when two segments coordinate in-phase with each other, a non-linear phase transition is said to have occurred if the coordination of the segments changes spontaneously rather than gradually (linearly) as a result of instability. This study expands on the low-dimensional convention often used in coordination dynamics studies by adopting the U-matrix trajectory as a low-dimensional representation of high-dimensional coordination. The gradual changes in coordination for Players MW, HI and PB shown in the attractor diagrams, may represent high-dimensional phase transitions between certain distances.

Most notably, Player MW shows a stable coordination pattern at 4 m and a stable coordination pattern at 20 m and 24 m, separated by instability at 8 m, 12 m and 16 m. Instability at the middle distances by Player MW does not necessarily imply incoherent fluctuations around one coordination pattern but the selection of different coordination patterns ranging from movement patterns used for short shots to patterns used for long shots, shown by wide and shallow basins of attraction. Finally, as the distance increases to 20 m, or decreases to 4 m, one type of coordination pattern is consistently selected. Players HI and PB show stability at the extreme distances like Player MW but the instability at intermediate distances is not as clear.

Player AW showed different changes in stability in the attractor diagrams compared to the other three players. At 4 m there were two deep attractor basins and at 20 m there are also two deep attractor basins. Comparing the locations of the attractor basins for 4 m and 20 m, they are slightly offset, so for 4 m, one basin is on the extreme left of the diagram and one in the middle. For 20 m, one basin is situated left-centre on the attractor diagram and the other right-centre. An hysteresis effect would seem an appealing explanation for the bi-modal coordination. A study by Lames (1992) used target distance as a control parameter and the relative timing of the backswing and downswing as a collective variable. For successive trials, if the target distances were increasing changes in relative timing occurred at different distances compared to when the target decreasing in successive trials. However, unlike the Lames study, the distances in the current study were randomly ordered. Still, it is possible that the previous shot distances had an effect on coordination, but because of the randomized order of the trials much more data are needed to verify the possibility of an hysteresis effect. Alternatively, many complex factors could affect coordination, for example:
outcomes of previous shots, day-to-day variability, motivation or any combination of these factors. To expand on this slightly, for a long distance shot, if the player is confident he can produce a shot that travels the correct distance but is more concerned with the line of the shot, he may adjust the movement pattern so that he has more control of the line. To do this he may adopt certain characteristics of a movement pattern typically used for short shots. More data would be needed to determine if this kind of movement patterning occurs but it offers an example of how degeneracy could underlie the multiple stable solutions to a golf chip shot. This, of course, is a speculative explanation but similar findings of degenerate movement patterning in multi-segment movements have been reported (Chow et al., 2005).

6. Conclusion

This study looked at how movements were patterned when chipping to different target distances. The SOM best-matching node trajectories, visualized on the U-matrix, clearly identified changes in coordination between movement patterns used for short chip shots and movement patterns used for long chip shots. Changes in coordination were shown for all players and for all phases of the movement. The attractor diagrams seemed to accurately characterize coordination stability within each chipping distance. The SOM analysis showed the golf chip shot to be a degenerate movement pattern, evidenced by the variability between individuals and, for Player AW, within chipping distances.

The methods in this study may offer a solution for researchers who intend to apply modern motor control theories to discrete movements involving high-dimensional coordination. Studying movements which involve high-dimensional coordination helps bring current research based on simple laboratory experiments closer to broader applications either in everyday tasks or sports. Further research may be useful to evaluate the validity of the SOM best-matching node trajectory as a collective variable.


URL http://www.cis.hut.fi/projects/somtoolbox/