I, Julie A Weast, hereby submit this original work as part of the requirements for the degree of Doctor of Philosophy in Psychology.

It is entitled:
Informational constraints on perception of maximum reach-with-jump for others

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Informational constraints on perception of maximum reach-with-jump for others

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by
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Abstract

Humans can perceive affordances—-invariant combinations of surface/substance properties of the environment taken with reference to an animal’s action capabilities that describe possibilities for action—for themselves and others. For example, we can perceive the affordance of reach-with-jump (RWJ)—the maximum height one can reach overhead while jumping—for another person without ever seeing the person jump. Accurate perception of affordances for others requires perceptual information about the other’s capacity to produce force; after observing another’s walking patterns, observers improve in their perception of the other’s RWJ height, suggesting there is structure in a person’s walking kinematics which is informative about his/her ability to jump to reach an object.

Athletes demonstrate a superior ability to perceive the action capabilities of others; after basketball players observe an actor’s walking patterns, they improve in their perception of RWJ for the actor more so than controls. This implicates movement kinematics as the fundamental information provided by walking motion, and suggests basketball players are more sensitive to the structure available in the kinematics that allows accurate affordance perception; however, the nature of this structure remains unclear.

A technique for identifying the structure in movement that is relevant to action is the use of principal components analysis (PCA), which extracts relevant information from high-dimensional data sets by identifying hidden structure that best explains the variance of the data set. This analysis may be a useful tool for identifying information in walking kinematics that specifies characteristics of the walker.

The current research used PCA to identify information in human walking kinematics that specifies the RWJ affordance, and to determine whether athletes are more sensitive than controls to the structure in question. In Experiment 1, kinematic data during treadmill walking was collected from 14 models using an Optotrak motion-capture system. PCA was performed on the motion data of all models to obtain the loading values for all input variables (i.e. the time series of each marker movement in the x and y directions) of the first principal component of each model. In Experiment 2, recorded kinematics of point-
light walkers were manipulated using the PCA loading values obtained in Experiment 1 to determine how changes in body-segment movements impact perception of RWJ, as well as the impact of sports experience on sensitivity to these changes. The results suggest that perceivers rely on the global movements of the body (or some relation among all major segments) rather than the movements of individual body segments when anticipating the action capabilities of others, and athletes may be more sensitive than non-athletes to the dynamic spatiotemporal organization of the moving body. Thus, global kinematic structure of walking as captured by the loading values determined by PCA was found to carry information that specifies maximum RWJ for an actor. Athletes were found to be more sensitive than controls to manipulations to this global kinematic structure of walking movements, indicating they are better attuned to useful kinematic information as a result of their sports experience.
Acknowledgements

I would like to sincerely thank my dissertation committee, Drs. Kevin Shockley, Michael Riley, Michael Richardson, and Sarah Cummins-Sebree, for their guidance, patience, and support. I would also like to thank all of the graduate and undergraduate students of the UC Center for Cognition, Action, and Perception, for their help, support, and good company.
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Chapter I

Introduction

One of the goals of perceptual-motor research is to identify the information that supports our perception of the world around us. James Gibson (1979/1986) proposed that humans perceive by detecting information that specifies possibilities for performing an action. That is, humans can successfully perform actions because they can perceive affordances: invariant combinations of surface/substance properties of the environment taken with reference to an animal’s action capabilities that describe possibilities for action. Humans perceive affordances via the detection of informational variables, available in structured energy patterns such as the optic array—the pattern of light defined with respect to the observer. Accurate perception of affordances, then, requires the pickup of information that is relevant to the action in question (Gibson, 1979/1986).

Two categories of affordances have been identified—body-scaled and action-scaled (Fajen, Riley, & Turvey, 2009). Body-scaled affordances capture the relation between properties of the environment and some dimension of the body of the perceiver; for example, the relation between the height of an object and a person’s arm length determines if the object is reachable for that person while standing (Ramenzoni, Riley, Davis, Shockley, & Armstrong, 2008). Action-scaled affordances capture the relation between properties of the environment and the action capabilities of the perceiver; for example, the relation between the height of an object and a person’s vertical force production capability determines if the object is reachable by jumping (Ramenzoni et al., 2008; Ramenzoni, Riley, Shockley, & Davis, 2008a, 2008b; Weast, Shockley, & Riley, 2011).
There is extensive evidence of our ability to perceive body-scaled affordances, and recent studies have demonstrated the ability to perceive several action-scaled affordances as well; humans can perceive affordances both for themselves as well as for others, and are surprisingly accurate at doing so (Carello, Grosofsky, Reichel, Solomon, & Turvey, 1989; Fajen, 2007; Fajen et al., 2009; Gibson, 1979/1986; Mark, 1987; Mark, Balliett, Craver, Douglas, & Fox, 1990; Stoffregen, Gorday, Sheng, & Flynn, 1999; Warren, 1984). For example, humans can perceive the affordance of reaching-with-jump (RWJ)—the maximum height one can reach overhead while performing a vertical jump from a standing position—and their perception changes appropriately when their maximum RWJ height is changed by wearing ankle weights (Ramenzoni et al., 2008b). Moreover, they can perceive this affordance for other actors as well, based only upon observation of the walking kinematics of the actor (i.e., without ever seeing the person jump; Ramenzoni et al., 2008; Weast et al., 2011).

Accurate perception of action-scaled affordances of another person requires perceptual information about forces (or the other person’s capacity to produce them). Because motion is lawfully related to the forces that generated that motion, information about those forces is available for perceivers in movement kinematics (the kinematic specification of dynamics [KSD] principle; Runeson 1977/1983). Accordingly, after observing another’s walking patterns, observers improve in their ability to accurately perceive the other’s maximum RWJ height, even when the actor’s maximum RWJ height is changed by wearing ankle weights (Ramenzoni et al., 2008; Weast et al., 2011). This indicates that observers are capable of distinguishing their own affordances from those of others, and is evidence that walking patterns contain information about the walker’s capacity to produce a different but related action, jumping to reach an object.
Perception of Biological Motion

The evolution of the human visual system has resulted in perceptual sensitivity to human motion (Johansson, 1973), which may facilitate action prediction. Observers are able to identify many characteristics of a moving actor even when perception is constrained by limited available information, such as when the biological motion of the human body is displayed as point-light videos: ambiguous displays of isolated points of light corresponding to joint centers on the body that disambiguate once movement occurs (Abernethy, Gill, Parks, & Packer, 2001; Johansson, 1973; Troje, Westhoff, & Lavrov, 2005; Troje, 2012). An advantage of showing point-light walkers instead of live or filmed walkers is that while these displays lack the detail available in live or filmed movements (e.g. texture, color, form), the information available is sufficient for observers to accurately perform a number of tasks. These include the identification of the walker’s sex (Kozlowski & Cutting, 1977), age (Montepare & Zebrowitz-McArthur, 1988), and emotional state (Dittrich, Trosclair, Lea, & Morgan, 1996); differentiation of walkers as team-mates or strangers (Steel, Adams, & Canning, 2007); self-recognition of walking patterns from those of others (Jokisch, Daum, & Troje, 2006); and estimation of the perceived velocity of a walker (Groner & Schollerer, 2005). Thus, despite the reduction in detail, these displays preserve the kinematic information essential for ‘unambiguous perception’ (Abernethy et al., 2001, p. 248).

Perception of RWJ for another actor improves after seeing live walking or squatting movements of the actor, but does not improve after seeing live twisting movements (Ramenzoni, Davis, Riley, & Shockley, 2010; Ramenzoni et al., 2008). This increase in accuracy also occurs when an actor’s movements are displayed as point-light videos (Weast, Walton, Chandler, Shockley, & Riley, submitted). Perception of the action-scaled affordances of a point-light
walker, then, becomes more accurate after observing movements related to the affordance in question, suggesting even the limited information provided by point-light walking movements contains information about the actor’s capacity to jump to reach an object.

**Affordance Perception in Sport**

Accurate affordance perception is crucial in fast-paced environments such as those found in team sports, as athletes must be able to perceive the action capabilities of both their opponents and teammates within fractions of a second (Araújo & Davids, 2009; Fajen et al., 2009). Athletes demonstrate a superior ability to perceive the action capabilities of others as a result of long-term perceptual-motor experience in playing a sport, suggesting athletes have become attuned to different perceptual information than novices throughout the course of their sports training (Abernethy, 1990; Abernethy et al., 2001; Aglioti, Cesari, Romani, & Urgesi, 2008; Hohmann, Troje, Olmos, & Munzert, 2011). After basketball players observe another’s walking patterns, they improve in their ability to accurately perceive the maximum RWJ height for the other person more so than controls; however, they do not improve in their ability to accurately perceive the maximum standing-reach height for the other person (Weast et al., 2011). Basketball players, then, are not more sensitive to perceptual information generally. Rather, there is structure in a person’s walking kinematics (e.g., in the motion of the joint centers on the person’s body: Abernethy et al., 2001) which is informative about his/her ability to jump to reach an object (Ramenzoni et al., 2008), and basketball players are better able to capitalize on that structure than novices in perceiving the person’s action-scaled affordance of RWJ (Weast et al., 2011).

Weast et al. (submitted) found that basketball players remain superior in their perception of RWJ after exposure to biological motion of the human body displayed as point-light videos.
After basketball players observed point-light walkers, they were more accurate in perceiving RWJ for the walker than controls. Essential kinematic information provided in point-light walking movements, then, is sufficiently rich for perceiving RWJ, and basketball players appear to be more sensitive to the structure available in the kinematics that allows accurate perception of an affordance related to their sport (Abernethy et al., 2001; Weast et al., 2011; Weast et al., submitted).

Accurate affordance perception involves the detection of informational variables that specify the affordance in question (Gibson, 1979/1986; Jacobs, Runeson, & Michaels, 2001; Jacobs & Michaels, 2007; Michaels & Carello, 1981). Athletes may be attuned to these specifying variables, whereas non-athletes may instead rely on non-specifying variables: information available to perceivers that is not specific to (or useful for) perception of the affordance in question. The perceptual improvement in athletes may indicate an education of attention: Because of their sports experience, they have ‘learned’ to rely on informational variables that are useful for affordance perception (Beek, Jacobs, Daffertshofer, & Huys, 2003; Jacobs & Michaels, 2007). For example, skilled tennis players are more accurate in predicting the direction of a filmed shot when compared to controls, possibly because they fixate on more useful portions of the visual display (e.g. the trunk-hip and head-shoulder areas) when compared to controls (e.g. the racket and racket-ball contact region; Ward, Williams, & Bennett, 2002). Perhaps athletes improve in their perception of affordances because their extensive perceptual-motor experience allow the detection of more useful informational variables; however, the biomechanical invariants that provide this information for athletes but not controls have not been identified (Abernethy et al., 2001).
Methods for Identifying Perceptual Information

Previous research has identified information in biological motion patterns that is both useful and not useful to observers for perceiving certain characteristics of another actor. For example, both structural and dynamic cues have been identified as useful for gender classification of point-light walkers (e.g. the ratio of shoulder width to the hips and the body’s center of moment, respectively), whereas others have been identified as not useful (e.g. walking speed and stride length: Cutting, Proffitt, & Kozlowski, 1978; Mather & Murdoch, 1994). The specific structural and/or dynamic cues in an actor’s movement patterns that facilitate action anticipation, however, remain unclear.

One method that has recently emerged for the identification of gait patterns in motion data is principal components analysis (PCA: Daffertshofer, Lamoth, Meijer, & Beek, 2004; Diaz, Fajen, & Phillips, 2012; Huys, Canal-Bruland, Hagemann, Beek, Smeeton, & Williams, 2009; Huys, Smeeton, Hodges, Beek, & Williams, 2008; Troje, 2002a, 2002b, 2008). PCA extracts information from high-dimensional data sets by identifying hidden structure that best explains the variance of the entire data set. This dimensionality reduction reveals information embodied in movement kinematics by measuring the continuously changing state of $n$ variables, each a potential source of perceptual information. This analysis, when applied to the kinematic data sets, allows for the detection of patterns in human locomotion (Daffertshofer et al., 2004; Davis, Ounpuu, Tyburski, & Gage, 1991; Troje, 2002a, 2002b). Additionally, PCA can be used to generate new data sets (and thus new point-light stimuli), thus allowing the manipulation of movement kinematics displayed during video playback (Troje, 2002a, 2002b, 2008).

The broad aim of this project was to explore the informational constraints on perception of maximum RWJ for others. Addressing this aim first required identifying the particular
structure in human walking kinematics that specifies the RWJ affordance (Experiment 1). In Experiment 2, I evaluated whether athletes are more sensitive than controls to the identified structure in the kinematics by manipulating the structure in question and evaluating the influence on perceptual reports.
Chapter II

Experiment 1

In order to evaluate the impact of manipulations to kinematic information on perception of RWJ, the information specifying the jumping abilities of a point-light walker must first be identified. PCA is one potential technique for identifying structure in movement coordination patterns. This analysis transforms a high-dimensional data set into a smaller set of new variables expressed as principal components; linear combinations of the original variables that describe their weighted linear relationships, of which the first component accounts for the most variance of the entire data set, and each succeeding component is ordered in descending component variance. Each principal component, also referred to as modes, includes a set of correlation coefficients, one for each of the original $n$ variables, called loadings. Each loading value (when squared) represents the proportion of the overall variance of the data set accounted for by each original variable (Daffertshofer et al., 2004, p. 426; Troje, 2002a, 2002b).

PCA may be particularly useful for identifying patterns in the high-dimensional kinematic data sets used to create point-light displays (e.g. time series data of $n$ markers in both the x [anterior-posterior] and y [vertical]-directions). PCA can be used to reduce each marker trajectory to a loading value that (when squared) indicates the degree to which the marker’s movements contribute to the overall variance of the data set being accounted within each component (Daffertshofer et al., 2004; Davis et al., 1991). The greater the loading value, the greater that variable contributes to the variance of the data set; thus, within each component, loading values indicate the degree to which each marker (e.g. each body segment) contributes to the overall variability in the movements of a point-light walker. For example, Huys et al. (2008) used PCA to identify coordination patterns in kinematic data sets of expert tennis players.
performing shots. PCA results revealed that almost 90% of the variability in movement kinematics while performing a shot is accounted for by the first three principal components, with all body segments contributing to the movement variability but to a varying degree across components.

Similarly, Diaz et al. (2012) used PCA to identify patterns in kinematic data sets of expert soccer players performing a penalty kick. They examined the reliability of several sources of movement information in indicating the direction of a kick. They identified both local and distributed sources of kinematic information (such as the yaw and pitch angles of body segments, and the interrelations between movements of the joints) that serve as reliable indicators of kick direction. Importantly, they found that these identified sources also served as the information used by perceivers for anticipating kick direction. Thus, there is information in movement kinematics that specifies kick direction, and this information resides within the structure identified by PCA. PCA, then, may also be used to identify distributed sources of information in walking kinematics that facilitate the prediction of other types of actions.

In order to identify sources of information in walking kinematics that facilitate the prediction of RWJ, kinematic data for normal treadmill walking was collected. PCA was then applied to the kinematic data sets to determine the contribution of different body segments to the overall variability in a person’s walking movements. This experiment focused only on the application of PCA to the kinematic data sets used for the animation of point-light stimuli; models participated only in the collection of walking data and provided no perceptual reports.
Method

Participants

Fourteen students (seven males and seven females) at the University of Cincinnati participated for course credit (mean age = 22.0 years ± 3.3). Table 1 includes anthropometric information for each model, as well as each model’s maximum RWJ height and preferred treadmill walking speed.

Table 1.

*Model Anthropometric Features, Preferred Treadmill Speed, and Maximum RWJ Height*

<table>
<thead>
<tr>
<th>Model</th>
<th>Gender</th>
<th>Age (yrs)</th>
<th>Height (cm)</th>
<th>Weight (lbs)</th>
<th>Maximum RWJ height (cm)</th>
<th>Walking speed (mph)</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>Female</td>
<td>26</td>
<td>167.0</td>
<td>117.0</td>
<td>221.0</td>
<td>1.30</td>
</tr>
<tr>
<td>2</td>
<td>Female</td>
<td>26</td>
<td>152.5</td>
<td>120.0</td>
<td>232.7</td>
<td>2.30</td>
</tr>
<tr>
<td>3</td>
<td>Male</td>
<td>18</td>
<td>190.5</td>
<td>160.0</td>
<td>286.0</td>
<td>1.50</td>
</tr>
<tr>
<td>4</td>
<td>Male</td>
<td>19</td>
<td>178.0</td>
<td>135.0</td>
<td>283.0</td>
<td>2.50</td>
</tr>
<tr>
<td>5</td>
<td>Male</td>
<td>20</td>
<td>193.0</td>
<td>225.0</td>
<td>299.0</td>
<td>2.20</td>
</tr>
<tr>
<td>6</td>
<td>Male</td>
<td>19</td>
<td>180.0</td>
<td>163.0</td>
<td>279.0</td>
<td>2.50</td>
</tr>
<tr>
<td>7</td>
<td>Male</td>
<td>20</td>
<td>180.0</td>
<td>150.0</td>
<td>260.0</td>
<td>2.50</td>
</tr>
<tr>
<td>8</td>
<td>Male</td>
<td>19</td>
<td>162.5</td>
<td>125.0</td>
<td>246.0</td>
<td>2.00</td>
</tr>
<tr>
<td>9</td>
<td>Female</td>
<td>22</td>
<td>167.0</td>
<td>120.0</td>
<td>234.0</td>
<td>2.30</td>
</tr>
<tr>
<td>10</td>
<td>Female</td>
<td>27</td>
<td>168.0</td>
<td>120.0</td>
<td>240.0</td>
<td>2.30</td>
</tr>
<tr>
<td>11</td>
<td>Female</td>
<td>23</td>
<td>158.0</td>
<td>150.0</td>
<td>215.0</td>
<td>2.20</td>
</tr>
<tr>
<td>12</td>
<td>Male</td>
<td>23</td>
<td>173.0</td>
<td>183.0</td>
<td>277.0</td>
<td>2.30</td>
</tr>
<tr>
<td>13</td>
<td>Female</td>
<td>27</td>
<td>167.0</td>
<td>125.0</td>
<td>244.0</td>
<td>1.80</td>
</tr>
<tr>
<td>14</td>
<td>Female</td>
<td>19</td>
<td>165.0</td>
<td>150.0</td>
<td>247.0</td>
<td>2.00</td>
</tr>
</tbody>
</table>

Materials

Data were recorded using an OptoTrak (Northern Digital Inc., Waterloo, Ontario) Certus motion capture system. This system tracks the three-dimensional trajectories of infrared markers with spatial accuracy in the range of 0.1 mm and a temporal resolution of 120 Hz. Locomotion
was recorded while participants walked on a motorized treadmill (Fitnex Fitness Equipment Inc., Model #4821).

**Procedure**

**Recording of walking data.** Participants wore tight-fitting clothing, however most markers were attached directly onto the skin. Markers were affixed to all major joints of the body (ankles, knees, hips, wrists, elbows, and shoulders) as well the temples (markers were attached to elastic bands worn around the head such that one marker was placed at each temple) for a total of 14 markers. Models were instructed to walk on a treadmill while their locomotion was recorded. Each model adjusted the speed of the treadmill to a comfortable pace (average speed = 2.1 mph ± 0.4), and were told they would be walking for no more than 15 minutes. To ensure that walking was natural, participants walked for approximately five minutes before one full minute of walking was recorded, and were not informed when recording started (cf. Troje, 2002a). Once recording was complete, anthropometric information was collected, as well as the maximum RWJ height for each model (maximum RWJ height was determined after the model attempted several reach-with-jumps (each followed by adjustments to the height of an object based on the preceding jump) and reported the object was at the maximum height it could be for the model to reach it while performing a vertical jump (cf. Weast et al., 2011)).

**Preparation of walking data for analysis.** Several steps were taken to prepare data for analysis. Data files for each model included the three-dimensional movement trajectories of 14 markers in the sagittal (x-direction), frontal (y-direction), and transverse (z-direction) planes during 60 s of treadmill walking. Because the goal of the experiment was to identify structure in the movement kinematics of point-light walkers (e.g. in two-dimensional point-light displays), marker trajectories in the transverse plane (z-direction) were removed from all data files.
Additionally, the movement trajectories for the markers placed at the temples were averaged, such that movement of the head was now represented by one ‘virtual’ marker. This resulted in a total of 13 markers: one marker on each major joint of both sides of the body (ankles, knees, hips, wrists, elbows, and shoulders) as well as one ‘virtual’ head marker, each represented by two movement trajectories (one in the sagittal (x) plane and one in the frontal (y) plane). Finally, to reduce any spatial differences between data sets due simply to height differences across models, each data set was height-normalized using the mean height (in cm) of all models (c.f. Diaz et al., 2012).

This resulted in 14 kinematic data sets, one for each model, each a $26 \times 7200$ matrix of the spatial location of 13 markers in two (x [anterior-posterior] and y [vertical]) directions during a 60 s walking trial recorded at 120 Hz. These data sets were used in both the PCA described below, as well as in the generation of all point-light stimuli used in Experiment 2.

**Results and Discussion**

PCA was applied separately to the motion data set of each model. Each analysis included 26 input variables (the two-dimensional movement trajectories of 13 markers), which produced 26 principal components for each data set. On average, the first principal component accounted for 72.3% ($\pm 8.7$) of the overall variability of each data set. Each principal component included 26 loading values (one for each input variable) indicating the contribution of each marker trajectory to the overall variability in movements of the walkers. The original (non-squared) loading values for the first principal component of each model are included in Table 2.
Table 2.

*Loading Values of First Principal Component for Marker Movements in X and Y Directions.*

<table>
<thead>
<tr>
<th>Marker</th>
<th>Head</th>
<th>Left Shoulder</th>
<th>Left Elbow</th>
<th>Left Wrist</th>
<th>Right Shoulder</th>
<th>Right Elbow</th>
<th>Right Wrist</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td>x</td>
<td>y</td>
<td>x</td>
<td>y</td>
<td>x</td>
<td>y</td>
</tr>
<tr>
<td>Model 1</td>
<td>0.07</td>
<td>0.01</td>
<td>0.06</td>
<td>0.04</td>
<td>0.12</td>
<td>0.14</td>
<td>0.27</td>
</tr>
<tr>
<td>Model 2</td>
<td>0.00</td>
<td>0.02</td>
<td>0.05</td>
<td>0.03</td>
<td>0.19</td>
<td>0.03</td>
<td>0.34</td>
</tr>
<tr>
<td>Model 3</td>
<td>0.12</td>
<td>0.01</td>
<td>0.03</td>
<td>0.03</td>
<td>0.06</td>
<td>0.14</td>
<td>0.16</td>
</tr>
<tr>
<td>Model 4</td>
<td>0.00</td>
<td>0.02</td>
<td>0.03</td>
<td>0.03</td>
<td>0.06</td>
<td>0.14</td>
<td>0.16</td>
</tr>
<tr>
<td>Model 5</td>
<td>0.02</td>
<td>0.00</td>
<td>0.07</td>
<td>0.02</td>
<td>0.12</td>
<td>0.03</td>
<td>0.23</td>
</tr>
<tr>
<td>Model 6</td>
<td>0.01</td>
<td>0.01</td>
<td>0.02</td>
<td>0.02</td>
<td>0.16</td>
<td>0.03</td>
<td>0.38</td>
</tr>
<tr>
<td>Model 7</td>
<td>0.04</td>
<td>0.02</td>
<td>0.02</td>
<td>0.02</td>
<td>0.19</td>
<td>0.03</td>
<td>0.19</td>
</tr>
<tr>
<td>Model 8</td>
<td>0.01</td>
<td>0.00</td>
<td>0.08</td>
<td>0.02</td>
<td>0.16</td>
<td>0.03</td>
<td>0.35</td>
</tr>
<tr>
<td>Model 9</td>
<td>0.02</td>
<td>0.01</td>
<td>0.01</td>
<td>0.02</td>
<td>0.14</td>
<td>0.03</td>
<td>0.32</td>
</tr>
<tr>
<td>Model 10</td>
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<td>0.00</td>
<td>0.07</td>
<td>0.03</td>
<td>0.18</td>
<td>0.03</td>
<td>0.37</td>
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<tr>
<td>Model 11*</td>
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<td>0.01</td>
<td>0.03</td>
<td>0.03</td>
<td>0.19</td>
<td>0.05</td>
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<tr>
<td>Model 12*</td>
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<td>0.01</td>
<td>0.03</td>
<td>0.03</td>
<td>0.19</td>
<td>0.05</td>
<td>0.19</td>
</tr>
<tr>
<td>Model 13</td>
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<tr>
<td>Model 14</td>
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<td>0.03</td>
<td>0.03</td>
<td>0.14</td>
<td>0.04</td>
<td>0.20</td>
</tr>
</tbody>
</table>

*Model selected for creation of point-light stimuli in Experiment 2*
The loading values for each trajectory (e.g. the distribution of variance accounted for by each of the 26 input variables within the first principal component) were quite similar across models. The average standard deviation of the loading values associated with each trajectory was 0.04 across models, with the least variability in loading values for markers associated with movements of the shoulders and hips, and the greatest variability in loading values for markers associated with movements of the ankles and wrists. Additionally, much of the redundancy in walking kinematics is reflected in the loading value of each trajectory. For example, on average, those with the largest spatial displacement such as the trajectories of ankle and wrist movements in the horizontal axis account for 54% and 30% of the variance, respectively, whereas those with little displacement such as the trajectories of hip and shoulder movements account for 1% and 4% of the variance, respectively.

A number of physical, anthropometric, kinetic, and kinematic characteristics have been identified as being related to an actor’s maximum vertical jumping height. Some examples include age, percent body fat, the girth of the calves, lower extremity muscular strength, maximal isometric force of the knee extensors, and skeletal muscle fiber composition (Davis, Briscoe, Markowski, Saville, & Taylor, 2003; Jaric, Ristanovic, & Corcos, 1989). Kinematic characteristics related to perceiving maximum vertical jump height for an actor, however, have yet to be identified. The PCA results of this experiment were used for modifying the movements of point light walkers in Experiment 2 in an attempt to identify the perceptual information inherent in walking kinematics that facilitates prediction of maximum RWJ.
Chapter III

Experiment 2

The information to which perceivers are sensitive may be different for athletes than non-athletes given that athletes are more accurate than non-athletes at perceiving reach-with-jump. This perceptual sensitivity in athletes may indicate attunement to specifying variables: information available to perceivers that is specific to (and useful for) perception of the affordance in question. The specific structure in another person’s movement patterns to which basketball players are attuned, however, remains unclear. While several studies of biological motion perception have evaluated action prediction by unskilled controls versus skilled athletes, none have directly manipulated the movement kinematics in an attempt to identify the perceptual information relevant to perceiving affordances for another actor. Athletes may rely on local kinematic information available in the movements of specific body regions when anticipating the actions of others (Abernethy, 1990; Abernethy & Zawi, 2007; Ward et al., 2002), however it is also possible that global kinematic information in movements of the body in motion serve as the structure to which athletes are attuned (Williams, Ward, Knowles, & Smeeton, 2002).

One method for identifying perceptual information involves modifying the kinematic data sets being used to generate point-light displays in order to systematically manipulate any structural or dynamic information within the displays. In Experiment 2, the recorded kinematics of point-light walkers were manipulated to evaluate the impact of changes to both local and global sources of movement information on perception of RWJ, and to determine whether sports experience influenced sensitivity to these manipulations.

In addition to the PCA results already discussed, PCA produces a data set of principal component scores, equal in size to the original data set, which represents the original data
projected into principal component space. Simply speaking, this is accomplished by projecting
the original data set onto its corresponding principal components. In order to recover the original
data set after PCA has been applied, one can simply project the set of principal component scores
back onto their corresponding principal components (Abdi & Williams, 2010). During the last
step in recovering the original data set, the loading values within each principal component can
be modified, producing a new data set in which each variable’s contribution to the variance
within the data set is manipulated. Increasing the loading value attributed to movements of the
marker placed on the knee, for example, increases the contribution of movements of the knee to
the overall variability in movement. Modifying a loading value and projecting the principal
component scores through the modified loading, then, modifies the movement trajectory of its
corresponding marker in the original data set accordingly, allowing manipulation of the
movement kinematics displayed during video playback while still preserving the appearance of
natural walking movements.

Of the models recorded in Experiment 1, two were selected for the creation of new point-
light stimuli: the model with the lowest RWJ height (Model 11, henceforth referred to as Model A) and the model with the highest RWJ height (Model 12, henceforth referred to as Model B). Using the PCA results from Experiment 1, the loading values corresponding to the first principal component of each marker trajectory were modified to create new stimulus videos in which movement kinematics were manipulated.

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1 Note: RWJ heights (in cm) were rescaled for each model based on his/her relative height as determined during height normalization in Experiment 1.

2 Only the loading values of the first principal component were used for generating modified point-light stimuli to ensure any effects of the manipulation of movement kinematics could be attributed solely to the principal component that accounted for the most variance in each model’s movements.
Experiment 2A

Previous research suggests athletes rely on localized kinematic information available in the movements of certain body regions when anticipating the actions of others. For example, skilled athletes are more accurate in predicting the direction of a filmed shot when compared to controls in tennis (Ward et al., 2002), badminton (Abernethy & Zawi, 2007), and squash (Abernethy, 1990), but performance by experts in both sports deteriorates when movements of the arm and racket are occluded from the display, implicating the arm and racquet as local sources of kinematic information whose movements specify shot direction. It is possible that the movements of specific body segments (or more probably relations among specific body segments) serve as the informational variables to which athletes are attuned for perceiving RWJ for another. In Experiment 2A, point-light stimuli were manipulated by modifying the movements of selected markers to determine whether athletes are sensitive to changes in the local kinematic information available in the movements of particular body segments.

The loading value of each marker trajectory can be thought of as a single value that characterizes the contribution of that marker to the proportion of the variance in walking kinematics accounted for by the given principal component. Stepwise regression was performed using the PCA loading values of each marker as predictor variables, and maximum RWJ height as the dependent variable, in order to identify the body segments whose movements best predict RWJ height. Marker movements were then manipulated by modifying the PCA loading values determined in Experiment 1, after which the data set of principal component scores for each model was projected onto their corresponding principal components (with modified loading values within the first component), to create two new types of stimulus videos for each model.
The first type of video was generated after modifying the loading values of markers identified as significant predictors of RWJ height in the regression analysis (henceforth referred to as relevant markers). The movements of relevant markers were modified such that the kinematics in the low-jumper video specified a high RWJ height (i.e. the principal component scores of the low RWJ model were projected through the loading values of the high RWJ model), and the kinematics in the high-jumper video specified a low RWJ height (i.e., the principal component scores of the high RWJ model were projected through the loading values of the low RWJ model). A second type of video was generated in the same fashion after modifying the loading values of markers not identified as significant predictors of RWJ height (henceforth referred to as non-relevant markers), i.e. those with the least predictive power as determined by the regression analysis.

If the movement patterns of relevant markers capture the information that specifies RWJ height, basketball players may be more sensitive to these movements, thus their perception of RWJ may be effected by modifications to the movements of relevant markers. I hypothesized that modifications to relevant markers would significantly influence perception of RWJ for both models, more so for basketball players than non-players, whereas I did not expect modifications to non-relevant markers to influence reports for either group.

Method

Participants

Thirty-eight male undergraduate students at the University of Cincinnati participated in the study for course credit (mean age = 20.15 years ± 2.11). Participants included 20 basketball
players (all had played on an organized basketball team within two years prior to the study) and 18 non-player controls (none had ever played on a basketball team).

Materials and Procedure

Several steps were taken to prepare each data set for the generation of new point-light stimuli. Kinematic data underwent a transformation after which PCA was applied (for a second time) to the new, transformed data sets. These PCA loadings were then submitted to a regression analysis to determine which marker’s kinematics served as significant predictors of RWJ, after which new point-light videos were generated using the original kinematic data.

Selection of relevant and non-relevant markers. Each original kinematic data set underwent a Euclidean transformation to prepare movement data for the regression analysis. This transformation was done for two reasons. First, it was necessary for reducing the number of predictors in the regression analysis, as the number of predictor variables that can be submitted to a stepwise regression analysis (n) is restricted by the number of observations of a dependent variable required for the analysis (n + 1). Second, it offers a measure of the variability of each marker’s movements more generally, rather than its movement in two dimensions, while preserving the underlying dynamics of the data set (Charles Webber, personal communication, October, 2011). Data sets were transformed by converting the two dimensional time-series of each marker into a single time-series, the same length as the original two, such that the original 26 ×7200 matrix data set for each model was reduced from 26 trajectories (one for each marker in both the x and y directions) to a 13 ×7200 matrix data set of 13 trajectories (one for each marker). These new trajectories characterized the movement of each marker as the distance (in mm) from an origin of zero, each marker's movement now represented as a vector in only one dimension. PCA was then applied separately to the transformed motion data set of each model.
Each PCA, then, included 13 input variables (the one-dimensional movement trajectories of 13 markers), producing 13 principal components, each with 13 loading values (one loading value per input variable).

Next, stepwise regression was performed using the 13 loading values corresponding to the first principal component of each marker as predictor variables \((n = 13)\) and maximum RWJ height as the dependent variable. Using this method, a significant model emerged, \(F (5, 8) = 5.18, p = .02\), adjusted \(r^2 = .62\). Of the 13 loading values, five were included in the model and explained 62\% of the variance in RWJ height, including the left shoulder \((\beta = -1.21, p = .002)\), right elbow \((\beta = -4.09, p = .003)\), wrist \((\beta = 1.52, p = .009)\), knee \((\beta = -3.47, p = .002)\), and ankle \((\beta = 1.04, p = .040)\). The markers corresponding to these five loading values were selected as relevant markers, whose movement trajectories would be modified when generating new modified relevant point-light stimuli.

Of the eight loading values excluded from the model, the five loading values with the highest \(p\)-values (i.e., those with the least predictive power) were selected for modification in order to have an equal number of markers modified in each new video type. These included the left elbow \((p = .553)\), wrist \((p = .882)\), and knee \((p = .428)\), the right shoulder \((p = .411)\), and the head \((p = .579)\). The markers corresponding to these five loading values were selected as the non-relevant markers, whose movement trajectories would be modified when generating new modified non-relevant point-light stimuli.

To be clear, the Euclidean transformation served solely as a dimensionality-reduction technique for identifying significant marker movements, and was done prior to (and independent from) any modifications made to the original kinematic data sets created in Experiment 1 while generating new stimuli. Once relevant and non-relevant markers had been selected, the
transformed data sets as well as their corresponding PCA loading values were discarded and the
original time series for both x and y directions (and their corresponding PCA loadings) were
used for the manipulations of the kinematic data sets in Experiments 2A and 2B.

**Generation of point-light stimuli.** The original motion data sets and PCA results (from
Experiment 1) for models A and B were used for generating new stimuli. Each data set included
the two-dimensional movement trajectories of 13 markers, and PCA results included the loading
value for all 26 time-series (13 markers, each represented by two trajectories – movement in the x
and y directions) corresponding to the first principal component.

The first type of video was created after modifying the loading values of the five relevant
markers. These loading values for both the x and y trajectories of the relevant markers for Model
A (low jumper) were replaced with the corresponding loading values for both the x and y
trajectories of the relevant markers of Model B (high jumper); likewise, the loading values of
these markers for Model B were replaced with the corresponding loading values of Model A.
The second type of video was created by following the same method, however this was done
using the modifying the loading values for both the x and y trajectories of the non-relevant
markers of each model. New data sets were then generated by projecting the principal
component scores for each model onto their corresponding (now modified) variable loadings,
producing four new kinematic data sets and thus four new video types in addition to the original,
non-modified stimuli. This resulted in six point-light video displays: Model A (low-jumper)
original, Model B (high-jumper) original, Model A modified relevant, Model B modified
relevant, Model A modified non-relevant, and Model B modified non-relevant.

**Experimental task.** Point-light videos were displayed on a 127 cm (50 inch) Panasonic
high-definition plasma television (model number TC-P50S2; see Figure 1). Participants sat in a
chair approximately 130 cm away from the television screen. Point-light videos appeared from a sagittal view in the lower center portion of the screen, with the walker facing leftwards. Participants were instructed to watch each video, then use a wireless mouse situated on the armrest of the chair to move a small star on the screen to the maximum height they believed the model could reach with their fingertips while jumping vertically from a standing position. The initial screen position of the star was randomized, and its final location could be adjusted by participants before moving to the next trial. After completing the experiment, participants’ demographic information and sports history were collected.

Perceptual reports were provided four times for each of the six point-light videos, yielding a total of 24 trials. Trial order was randomized across participants.

![Screen display for experimental task](image)

*Figure 1.* Screen display for experimental task. The point-light walker in each video was approximately 18 cm in height when displayed on the screen (which measured 62 × 112 cm). Walkers remained stationary in the lower center of the screen during animation.

**Results**

Accuracy of perceptual reports for original videos was evaluated using the ratio of the average report provided by each participant divided by the actual affordance boundary of each
respective model. Ratios of 1 indicate perfect accuracy; ratios greater than 1 indicate an overestimation in affordance reports and ratios less than 1 indicate an underestimation. Ratios were submitted to a 2 (observer type: basketball players vs. non-player controls) × 2 (model: A [low jumper] vs. B [high jumper]) mixed ANOVA with observer type as a between-subjects factor and model as a within-subjects factor. A main effect of model was found, $F(1,32) = 161.17, p < .0001, 1 – \beta = 1.00, \eta_p^2 = .83$, such that mean ratios of reports for the low-jumper (1.25 ± 0.15) were significantly greater than mean ratios of reports for the high-jumper (1.12 ± 0.15): in other words, participants over-estimated more for the low-jumper than the high-jumper.

There was no main effect of observer type, $F(1,32) = 3.31, p = .08, 1 – \beta = .41, \eta_p^2 = .09$, nor an interaction between the two variables, $F(1,32) = 3.14, p = .09, 1 – \beta = .39, \eta_p^2 = .09$.

Participants’ raw RWJ perceptual reports (e.g., the screen-location of the star’s final position) were then analyzed. Mean report values were submitted to a 2 (observer type: basketball players vs. non-player controls) × 2 (model: A [low jumper] vs. B [high jumper]) × 3 (video type: original vs. modified relevant markers vs. modified non-relevant markers) mixed ANOVA with observer type as a between-subjects factor and model and video type as within-subjects factors.

Mean raw report values are displayed in Figure 2. A main effect of model was found, $F(1,32) = 22.15, p < .0001, 1 – \beta = 0.99, \eta_p^2 = .41$, as well as a two-way interaction of model × video type, $F(2,64) = 3.65, p = .031, 1 – \beta = 0.65, \eta_p^2 = .10$. However, all three factors also interacted, $F(2,64) = 3.75, p = .029, 1 – \beta = 0.66, \eta_p^2 = .11$. Simple effects analyses of perceptual reports for each observer type revealed a simple main effect of model both for basketball players [$F(1,16) = 11.63, p = .004, 1 – \beta = 0.91, \eta_p^2 = .40$] and non-player controls [$F(1,16) = 10.54, p = .005, 1 – \beta = 0.88, \eta_p^2 = .40$]. This was expected, as perceivers are
accurate at differentiating the action capabilities of two different actors (Ramenzoni et al., 2008a; Weast et al., submitted). For basketball players, there was no main effect of video type and no interaction ($F$s < 1). For non-player controls, there was no main effect of video type ($F < 1$); however, a significant interaction between model and video type was found, [$F(2, 32) = 6.03, p = .008, 1 – \beta = 0.86, \eta^2_p = .29$]. Simple effects analyses of perceptual reports were performed as separate one-way ANOVAs for each model, and revealed a simple main effect of video type both for Model A [$F(2,16) = 3.49, p = .043, 1 – \beta = 0.60, \eta^2_p = .17$] and Model B [$F(2,16) = 3.86 p = .031, 1 – \beta = 0.66, \eta^2_p = .19$]. Fisher’s post-hoc tests revealed that, for both models, reports for modified-non-relevant videos were significantly different from reports for both original videos and modified relevant videos ($ps < .05$); however, modified relevant videos were not significantly different from reports for original videos ($ps > .05$).

![Figure 2. Mean values for reach-with-jump reports provided in Experiment 2A.](image-url)
Discussion

In order to determine whether athletes are more sensitive than controls to changes in local kinematic information, the walking kinematics of point-light stimuli were manipulated by modifying the movements of selected markers hypothesized to be both relevant and non-relevant to perception of RWJ.

Both types of observers were able to differentiate the jumping abilities of each model in the original, non-modified videos; that is, each group correctly reported higher RWJ heights for the high-jumper than for the low-jumper. This is consistent with similar research that has demonstrated movement kinematics provide information that is useful for differentiating the jumping height of different actors (Ramenzoni et al., 2008; Weast et al., submitted). However, evaluation of the accuracy of perceptual reports revealed that, unlike previous research (Weast et al., 2011; Weast et al., submitted), basketball players were not more accurate than controls in reports for original videos of each model. One possible reason no difference was found in accuracy of reports for basketball players and controls is the drastic overestimation of RWJ heights for each model by both observer types: this is described in more detail in the general discussion.

I expected RWJ reports for both models to be affected by modifications to the movements of relevant markers, more so for basketball players than non-players. Unexpectedly, neither group was influenced by these modifications; reports from both basketball players and non-players for modified relevant videos were not significantly different from reports for original videos. I hypothesized RWJ reports for both models would not be affected by modifications to the movements of non-relevant markers. This was supported by reports from basketball players, which were not significantly different from reports for original videos; however, non-player
controls were influenced by these modifications. For controls, the modified movements of non-relevant markers in the low-jumper video specified a high RWJ height, and the modified movements of non-relevant markers in the high-jumper video specified a low RWJ height.

There are several potential explanations for these unexpected findings. It is possible that the modifications to movements of relevant markers were too subtle to impact perceptual reports from either observer group. Only the information captured by the first principal component was manipulated; perhaps if the loading values corresponding to all principal components were modified for the relevant markers, this would produce an interruption in the kinematics strong enough to impact perception of RWJ. In spite of the present unexpected pattern of results, the results are not inconsistent with my hypothesis that athletes rely on information that is relevant to action prediction, while controls do not, presuming that the proper information specifying maximum RWJ height was not captured by the local body segments I identified. That is, if controls rely on structure in the point-light displays that is not relevant to action prediction, e.g. the movements of non-relevant markers, their perception of RWJ may be affected by modifying these movements, and indeed, reports from controls for the modified non-relevant videos were significantly different from their reports for both the original and modified relevant stimuli.

Additionally, the marker movements modified in each video were manipulated independently for each side of the body. For example, in the modified-relevant videos, shoulder movements were asymmetrically manipulated as movements of only the left shoulder marker were modified. Modifications to the movements of only one side of the body could disrupt any functional symmetries or asymmetries in body movements that may be useful for perception of affordances. Research has demonstrated, for example, that gait patterns of healthy adults are asymmetric due to differences in the contribution of each leg while walking; one lower limb is
typically responsible for postural support and the transfer of body weight whereas the other limb is primarily responsible for propulsion (Sadeghi, Allard, Prince, & Labelle, 2002).

Another potential explanation is that relevant marker movements, while identified in the regression analysis as being significant predictors of RWJ, may not capture the information used by observers for perceiving RWJ. That is, athletes may not rely on the movements of individual markers when anticipating the action capabilities of others, thus modifications to these local sources of kinematic information would have no impact on perceptual reports of RWJ. Instead, perceivers may rely on the global movements of the body (or some relation among all major segments) for action anticipation; for example, eye-tracking research has shown skilled tennis players scan the entire body of a point-light actor before predicting the direction of a shot (Ward et al., 2002). The global kinematic structure of point-light walkers must be manipulated to determine whether athletes are more sensitive to these manipulations than controls, which may implicate distributed kinematic information as the specifying variables to which athletes are attuned.
Experiment 2B

Rather than relying on localized kinematic information available in the movements of specific body regions, it is possible that global movement of the body in motion serves as the informational variable that specifies RWJ. Diaz et al. (2012) demonstrated inexperienced observers rely on combinations of both local and distributed sources of kinematic information when predicting the direction of soccer penalty kicks, but found evidence that kick direction could be accurately predicted by athletes using distributed information alone. Perhaps athletes rely solely on distributed information, whereas non-athlete controls rely on combinations of local and distributed sources of information. This would account for the unexpected results in Experiment 2A; only controls were affected by modifications to local kinematic information (e.g. the movements of non-relevant markers), suggesting they (at least partially) rely on local sources of information for action prediction.

Athletes, then, may be better attuned to more global kinematic information (e.g., higher order relations that are not captured by one (or more) specific body segment(s) alone) available in the dynamic spatiotemporal organization of the moving body when anticipating the actions of others. For example, skilled tennis players are able to predict the direction of a filmed shot more quickly than controls while visually scanning a larger portion of the unfolding action displayed (Williams et al., 2002). In Experiment 2B, point-light stimuli were manipulated by modifying the movements of all markers to determine whether athletes are sensitive to changes in the global kinematic information distributed across movements of the whole body.

One new video was generated for each model after modifying the loading values of all 13 markers, such that the global kinematic structure in the low-jumper video specified a high RWJ height, and the global kinematic structure in the high-jumper video specified a low RWJ height.
If the global movement patterns of all markers capture the information that specifies RWJ height, basketball players may be more sensitive to these movements, thus their perception of RWJ may be influenced by modifications to movements of all body segments more so than controls. It was hypothesized that modifications to the movements of all markers would influence perception of RWJ for both models, more so for basketball players than non-players.

**Method**

**Participants**

Thirty-four male undergraduate students at the University of Cincinnati participated in the study for course credit (mean age = 19.59 years ± 1.90). Participants included 17 basketball players (all had played on an organized basketball team within two years prior to the study) and 17 non-player controls (none had ever played on a basketball team).

**Materials and Procedure**

**Generation of point-light stimuli.** The original motion data sets and PCA results (from Experiment 1) for models A and B were again used for generating new stimuli. Videos were generated after modifying the loading values of all 13 markers. These loading values for both the x and y trajectories of markers for Model A (low jumper) were replaced with the corresponding loading values for both the x and y trajectories of markers of Model B (high jumper); likewise, the loading values of the markers for Model B were replaced with the corresponding loading values of Model A.

New data sets were generated by projecting each model’s principal component scores onto their corresponding (now modified) variable loadings, producing two new videos in addition to the original, non-modified stimuli. This resulted in four point-light video displays: Model A
(low-jumper) original, Model B (high-jumper) original, Model A modified, and Model B modified.

**Experimental task.** Experiment 2B followed the same experimental procedures used in Experiment 2A. Perceptual reports were provided four times for each of the four point-light videos, yielding a total of 16 trials. Trial order was randomized across participants.

**Results**

Accuracy of perceptual reports for original videos was again evaluated using the ratio of the average report provided by each participant divided by the actual affordance boundary of each respective model. Ratios were submitted to a 2 (observer type: basketball players vs. non-player controls) × 2 (model: A [low jumper] vs. B [high jumper]) mixed ANOVA with observer type as a between-subjects factor and model as a within-subjects factor. A main effect of model was found, $F(1,36) = 244.37, p < .0001, 1 – \beta = 1.00, \eta_p^2 = .87$, such that mean ratios of reports for the low-jumper (1.26 ± 0.15) were significantly greater than mean ratios of reports for the high-jumper (1.08 ± 0.13): in other words, similar to Experiment 2A, participants over-estimated more for the low-jumper than the high-jumper. There was no main effect of observer type ($F < 1$), nor an interaction between the two variables, $F(1,36) = 2.61, p = .11, 1 – \beta = .33, \eta_p^2 = .07$.

As in Experiment 2A, participants’ raw RWJ perceptual reports (e.g., the screen-location of the star’s final position) were also analyzed. Mean report values were submitted to a 2 (observer type: basketball players vs. non-player controls) × 2 (model: A [low jumper] vs. B [high jumper]) × 2 (video type: original vs. modified) mixed ANOVA with observer type as a between-subjects factor and model and video type as within-subjects factors.
Mean report values are displayed in Figure 3. A two-way interaction of model \times video type was found, $F(1, 36) = 10.87, p = .002, 1 - \beta = 0.91, \eta_p^2 = .21$. However, all three factors also interacted, $F(1, 36) = 6.03, p = .019, 1 - \beta = 0.67, \eta_p^2 = .15$. Simple effects analyses of perceptual reports for each observer type revealed a significant interaction between model and video type for basketball players, $F(1,19) = 13.03, p = .002, 1 - \beta = 0.94, \eta_p^2 = .39$. Planned pair-wise comparisons were performed to determine whether reports were different between video types for each model, and whether reports for original videos of each model were no different from reports for modified videos of the other model (i.e., if the modified kinematics for Model B yielded perceptual reports that were statistically identical to the perceptual reports corresponding to the original kinematics of Model A, and vice versa). As predicted, perceptual reports were significantly different between original videos from both models ($p = .04$) and modified videos from both models ($p = .0012$), as well as between the original and modified videos for both Model A ($p = .03$) and Model B ($p = .005$), and were not significantly different between the original video for Model A and the modified video for Model B ($p = .87$) nor the original video for Model B and the modified video for Model A ($p = .88$). No other effects were significant for reports provided by basketball players, and no significant effects were found for non-player controls (all $Fs < 1$).
Figure 3. Mean values for reach-with-jump reports provided in Experiment 2B.

Given that, unlike Experiment 2A, control participants were unable to differentiate Model A from Model B for the original (i.e., un-manipulated) point-light displays, I performed a follow-up analysis. Inspection of individual data sets indicated an unusual amount of variability in the pattern of reports for participants in the control group. Unlike Experiment 2A, nearly half of the control participants identified Model B as having a higher maximum RWJ height than Model A. In order to evaluate the possibility that a subset of the control participants were attuned to the same perceptual information as basketball players, the subset of controls that identified Model B as having a higher maximum RWJ height than Model A for original point-light displays were selected for the same analysis of the original data set along with the same number of randomly selected basketball players. A two-way interaction of model × video type was the only significant effect found, $F(1, 16) = 10.76, p = .005$, $1 - \beta = .88$, $\eta_p^2 = .40$. When perceptual reports were analyzed separately for each observer type, a pattern of results identical to the original analysis was found for basketball players; that is, the interaction between model and
video type was again significant for basketball players, \( F(1,8) = 5.50, p = .040, 1 - \beta = 0.54, \eta_p^2 = .38 \). Pair wise comparisons again revealed perceptual reports were significantly different for original videos from both models (\( p = .004 \)) and modified videos from both models (\( p = .007 \)), as well as the between the original and modified videos for both Model A (\( p = .015 \)) and Model B (\( p = .014 \)), and were not significantly different between the original video for Model A and the modified video for Model B (\( p = .91 \)) nor the original video for Model B and the modified video for Model A (\( p = .89 \)). The pattern of results from controls, however, was not identical to the original analysis; perceptual reports were significantly different only between the original videos from both models (\( p = .0007 \)); no other comparisons were significant (all \( ps > .11 \)). In other words, in spite of the fact that a subset of controls showed the same pattern of results as basketball players for original point-light displays, the same pattern was not shown for the modified point-light displays (see Figure 4).

![Image](image.png)

**Figure 4.** Mean values for reach-with-jump reports provided by subset of nine basketball players and nine controls in Experiment 2B.
Discussion

In order to determine whether athletes are more sensitive than controls to changes in global kinematics, the walking kinematics of point-light actors were manipulated by modifying the movements of all markers. I expected RWJ reports for both models to be impacted by modifications to the movements of all markers, more so for basketball players than non-players. The results support this hypothesis; reports from basketball players for modified videos were significantly different from reports for original videos, whereas there was no difference between reports for each type of video from controls. In other words, only basketball players were affected by the modifications. This implicates global kinematic information as the informational variable specifying RWJ to which athletes are attuned; for basketball players, the modified marker movements in the low-jumper video specified a high RWJ height, and the modified marker movements in the high-jumper video specified a low RWJ height.

Unexpectedly, and in contrast to the results of Experiment 2A, only basketball players appeared able to differentiate the jumping abilities of each model in the original video; that is, only basketball players correctly reported higher RWJ heights for the high-jumper than for the low-jumper. Reports from controls were not significantly different for the high and low jumper in each original video. This was likely caused by the greater degree of variability in perceptual reports for control participants, suggesting a lack of attunement to specifying perceptual information. Basketball player reports for original videos had an average range of 0.20 for both models, whereas the average range for controls was 0.27, indicating a higher degree of variability when compared to basketball players. However, a subset of control participants were able to correctly differentiate the model’s jumping ability which raises the possibility that a significant number of the control participants may be attuned to the same perceptual information.
as basketball players. In order to evaluate this possibility, the subset of controls that correctly differentiated the models based on the original (i.e., un-manipulated) point-light displays were compared to a randomly selected subset of basketball players. Although the subset of basketball players showed the same pattern of results as was observed in the original analysis, the control participants were not affected by the kinematic manipulation in the same way. This result is consistent with the results of Experiment 2A, as well as previous research (Weast et al., 2011; Weast et al., submitted), which suggests that controls are not attuned to the same perceptual information as basketball players.

As in Experiment 2A, basketball players were not more accurate than controls in reports for the original videos of each model. This finding may be attributed to the increase in variability in reports from controls as described above, which could have washed out any differences between groups. The drastic overestimation of RWJ heights for each model by both observer types that was also observed in Experiment 2A could be another reason for the lack of observed differences between groups. This issue is discussed further in the general discussion.
Chapter IV

General Discussion

The goals of the present research included identifying the structure in walking kinematics that specifies the RWJ affordance for another person, as well as evaluating the effect of manipulations to this structure on perceptual reports of RWJ from both basketball players and non-player controls. In Experiment 1, PCA was applied to kinematic data from normal treadmill walking to evaluate which body segments contribute to the overall variability in a walker’s locomotion reliably predict maximum RWJ height. The loadings on body segments determined in Experiment 1 were used in Experiment 2 to modify the depicted motion of point-light displays of walkers in order to manipulate the information available in walking kinematics to perceivers. Experiment 2A evaluated the impact of modifications to movements of specific body segments to determine whether athletes are sensitive to changes to local kinematic information that was determined to be relevant to RWJ. In Experiment 2B, the impact of modifications to the motion of all body segments was evaluated to determine whether athletes were sensitive to changes in global kinematic information.

The central hypothesis was that walking movements include information about an actor’s maximum RWJ height, and that athletes would be affected by manipulations to that information more so than controls. This hypothesis was supported by the results of Experiment 2B; specifically, modifications to the global information available in walking kinematics influenced perceptual reports provided by basketball players as expected, implicating dynamic patterns of movement distributed across the body as the information specifying RWJ. This significantly extends previous research on the role of kinematic information on perception of affordances, as well as the influence of perceptual-motor experience on perceptual sensitivity in athletes.
Unlike previous research (Weast et al., 2011; Weast et al., submitted), basketball players were not more accurate than controls for reports based on original videos of each model in both Experiments 2A and 2B. One possible reason for this unexpected finding is the drastic overestimation of RWJ heights for each model by both observer types. Both Weast et al. (2011) and Weast et al. (submitted) found that participants, after viewing the walking movements of either a live or point-light walker, provided RWJ reports for which the ratios of the average reports to the actual RWJ height of the walker was approximately 0.93 in each study. The overestimation by both observer types in the current research may have eliminated any observable differences in accuracy between the two groups. Although it is not obvious why this pattern of results was obtained, one possibility is that the overestimation may have been caused by the relatively small size of the point-light walkers relative to the size of the television screen on which videos were displayed, as this difference was greater than in previous research with both live and point-light walkers.

**Identification of Relevant Body Segments**

It is clear based on the results of Experiment 2B that PCA captures the relevant structure for perceiving maximum RWJ height. Nonetheless, there are significant challenges associated with using a PCA regression strategy to identify the particular body segments that contribute to the perceptual information for maximum RWJ height. For example, PCA could be applied to dynamic movement patterns other than the two-dimensional marker trajectories used in the present study. Diaz et al. (2012), for example, used PCA to evaluate both marker movement trajectories as well as the pitch and yaw angles of relevant body segments while performing a shot in soccer as indicators of shot direction. These and other aspects of movement patterns...
could have yielded different predictive utility. Such an approach could reveal structure related to local kinematics (e.g. the pitch and yaw angles of body segments while walking) as well as global movement patterns distributed across multiple parts of the body (e.g. the relations among joint angles while walking).

Another strategy for identifying relevant body segments would include symmetric manipulations of marker movements. The markers identified in Experiment 2A as being significant predictors of RWJ height did not include any pairings of joints on opposite sides of the body; for example, only the left shoulder, but not the right shoulder, was found to be a significant predictor of RWJ height and thus movements of only the left shoulder were modified. This regression outcome was expected, as it is likely that the movements of (most) opposing body segments covary with one another; movements of a body segment on one side of the body are likely to contribute the same variance as the movements of the opposing segment, thus only one may be included as a significant predictor of RWJ height. If this is the case for most of the joints on the body, then asymmetric modifications to joint movements may not be an effective strategy for manipulating the relevant kinematic information. However, had both left and right body segments been modified for all markers that were determined to be significant predictors of RWJ height, then only the head marker would have been left as a non-relevant marker. Thus, it was not possible to create a local subset of symmetrically represented markers for manipulation.

An additional note about the present strategy is its reliance on PCA loadings that are determined by accounting for variance in walking movements, not jumping movements, as predictors of jumping height. Because these loading values are not directly determined based on their contribution to RWJ, there may be a more efficient approach that determines how walking kinematics are related to maximum RWJ height. Perhaps the loadings values for marker
movements during jumping rather than walking can be examined as predictors of RWJ height. The movements of those markers found to significantly predict RWJ heights could then be modified in point-light displays of normal walking to determine the effect of these modifications on perception on RWJ.

**Alternative Methods for Generating Biological Motion Displays**

The techniques used for the generation of stimuli in the present research are certainly not the only methods of manipulating the movement kinematics in point-light displays. An alternative method for identifying the informational variables that are useful for action prediction is to employ strategies similar to those used by Johansson (1973) and Kozlowski and Cutting (1977), in which the number of points displayed in point-light stimulus videos is reduced. Reducing the number of points restricts the available information and will likely constrain perception of RWJ more so than the strategies used in the current project. Displays featuring various combinations of points could be used, reducing the number of points displayed to the minimum number necessary for accurate perception of RWJ. This technique has been found to be effective for identifying the minimal number of points necessary for perception of certain characteristics of the point-light actor. For example, Kozlowski and Cutting (1977) found that gender classification is still possible when walking displays are reduced to only the points representing movements of the ankles. Additionally, this strategy may be useful for revealing differences between athletes and non-athletes in information pick-up (Abernethy et al., 2001).

The sources of kinematic information for perceiving RWJ can be evaluated in other types of biological motion as well. For example, the same strategy used in the current research can be employed using kinematic data sets of squatting instead of walking. Observers demonstrate high
degrees of accuracy in perceiving RWJ when provided kinematic information in walking (Weast et al., 2011) and in squatting (Ramenzoni et al., 2010; Weast et al., submitted). It is likely, therefore, that information other than that which specifies maximum RWJ height is present in both types of movement kinematics and so it is not clear the degree to which PCA is capturing only the structure relevant to jumping. In order to rule this possibility out, one strategy may be to determine if marker loadings for PCA performed on squatting that are significant predictors of maximum RWJ height are the same as those identified for walking. If they are the same, this supports the utility of the present strategy. If they are not the same, a more conservative strategy may be to use only significant predictors of RWJ that overlap for squatting and walking as relevant markers. That is, the other markers identified in PCA to be significant predictors of RWJ that are not in common for the two actions may be non-essential and/or may serve to specify different movement possibilities. In any case, both of these alternative approaches would rely on converging evidence to identify the relevant markers, which would be a more conservative approach than the present strategy.

**Theoretical Implications for Perception and Action in Sport**

The results of the current project contribute to the growing body of evidence that athletes rely on global, distributed kinematic information for action anticipation; however, further efforts are required to determine the degree to which affordance perception is based on global rather than local information (Diaz et al., 2012).

Eye tracking may be a particularly useful experimental method for evaluating the visual search patterns used by athletes during action anticipation. Visual displays could be created in which the movements of certain body segments are occluded, to determine if athletes remain
superior in their perception of affordances by shifting their focus to particular sources of local information. For example, when watching point-light displays of tennis players performing a shot, eye-trackers show that experts scan the entire body before they predict shot direction; when the arm movements are occluded, they spend more time scanning the trunk region; when the trunk region is occluded, they spend more time scanning the arms and legs; etc. (Williams et al., 2002).

Further research is required to determine whether basketball players remain more accurate than controls in action prediction when the affordance in question is not related to their sport. Biological motion perception is influenced by an observer’s familiarity with the observed action (Calvo-Merino, Grezes, Glaser, Passingham, & Haggard, 2009; Casile & Giese, 2006). Basketball players are more familiar with RWJ than controls, allowing more accurate perception of RWJ for others. However, the accuracy of their predictions for other actions not related to basketball should be considered. For example, Weast et al. (submitted) demonstrated basketball players were more accurate than controls in perceiving RWJ with exposure to kinematic information, but performed at the same level of accuracy as controls in perceiving maximum horizontal long-jump distance. Action prediction for actions that are not related to one’s sport must be evaluated to determine if athletic experience enhances accuracy for affordance perception generally, or whether this enhanced sensitivity to perceptual information occurs only when predicting actions specific to a sport.

Conclusions

The aim of this project was to explore informational constraints on affordance perception for others. I hypothesized that human walking kinematics carry information that specifies the
affordance of maximum RWJ height, and that athletes are more sensitive than non-athletes to the information available in walking kinematics. Two experiments tested these hypotheses. The first hypothesis was supported; global kinematic structure of walking was found to carry information that specifies maximum RWJ for an actor. This is evidenced by the fact that swapping the PCA loadings for high and low jumpers results in an inversion of the maximum RWJ height reported by perceivers for the model walkers. The second hypothesis was also supported; athletes were found to be more sensitive to manipulations to the global kinematic structure of walking movements, indicating they are better attuned to useful kinematic information as a result of their sports experience.

This research offers a new strategy by which PCA can be used for manipulating global patterns in human movement and investigating perceptual sensitivity to such patterns, however further research is needed to determine the most useful techniques for identifying the particular structure in human movement that serves as perceptual information for affordances for others.
References


