Visual Perception of Humanoid Movement

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Abstract

We examined similarity judgements of arm movements generated by different control strategies with the goal of producing natural looking movements on humanoid robots and virtual humans. We examined a variety of movements generated by human motion capture data as well as fourteen different synthetic motion generation algorithms that were developed based on human motor production theories and computational considerations. In experiments we displayed motion clips generated by these 15 different methods on both a humanoid robot and a computer graphic character and obtained judgements of similarity between pairs of movements. Experimental results reveal that for movements with obviously different paths as occurred with two production techniques then, as expected, hand paths dominated in the perception of similarity. However, for roughly similar paths as occurred for the other techniques then judgements about fast movements appeared to be based on their velocity profile while judgements to slow movements were based on a more detailed representation of the movement.

1. Introduction

The generation of natural appearing motion for humanoid figures is a significant and challenging problem in humanoid robotics and computer animation. We tackle this problem by drawing on the visual perception of human movement, motor production in humans, and through the simulation of motion. We have developed fourteen synthetic motion production algorithms based on human motor production and computational considerations, and have tested these in two visual perception experiments using motions displayed using a computer generated figure and recordings of a humanoid robot. From the results of observers pairwise similarity judgements we reason about what properties of human movement are salient and speculate as to the possible perceptual mechanisms that could explain these results.

In Section 2 we discuss the visual perception of human movement and its relevance to motion generation. In Section 3 we discuss motion production, theories of human motor production, describe the implementation of fourteen synthetic motion algorithms, describe motion capture and explain how we produced a collection of motion clips for use as experimental stimuli. The experiments are described, along with results in Section 4 and a summary and conclusions are presented in Section 5.

2. Visual perception of human movement

From the standpoint of epigenetics robotics it is useful to start with consideration of the development of our ability to perceptually organize and understand the actions of others. Early studies into the perception of human movement using movies of point-lights attached to the limbs of actors moving in a dark room revealed that infants as young as 4 months of age were sensitive to human movement (Fox and McDaniel, 1982). Further studies, reviewed by Bertenthal (Bertenthal, 1993), suggest that infants' sensitivity to human movement arises from the same processing constraints as used by adults, and with the exception of knowledge-based constraints there is no clear lower-bound on the age at which they are first implemented. Indeed, studies of 1-year old infants have shown a significant viewing preference for infants of the same sex

(Kujawski and Bower, 1993) and studies of 3 and 5 year olds have shown that both can perform reliable recognition of human and nonhuman forms at 3 years of age with the 5-year-olds exhibiting ceiling levels of recognition. Moreover, there is evidence to suggest that 2-year-olds can utilize subtle distinctions in the kinematics of movement styles to determine the difference between real and pretense movements (Lillard and Witherington). Thus, we can consider the abilities of adults to exhibit a fine-tuning and elaboration of the extremely sophisticated mechanisms already evident in the youngest infants.

Besides its development, there are various other aspects of human movement perception which suggest that human movement is a special class of motion with specialized mechanisms devoted to its processing. One question which has addressed the issue of what is special about human movement has been whether the critical mechanism for the perception of human movement relies on specialized low-level motion detectors (Mather et al., 1992, Neri et al., 1998) or on higher-level mechanisms which organize the results of low-level motion detectors (Shiffrar and Freyd, 1990, Thornton et al., 1998). The resolution of this question has relevance for the development of motor production techniques for humanoid robots. For example, any systematic change between when a movement is evaluated against low-level physical properties and when a movement is evaluated against more cognitive aspects would be relevant. One example of such a systematic change in perception is demonstrated by the perception of two-frame apparent motion sequences of human movement. If the timing between frames is short then observers report seeing impossible movements where limbs appear to interpenetrate each other during a movement. As the timing between frames increases a solidity constraint is imposed and the movement is perceived as two limbs moving around each other (Shiffrar and Freyd, 1990). It is hoped that studying the perception of humanoid movement might reveal unique aspects of human visual perception and visual cognition.

3. Production of humanoid movements

In this section we introduce the relevant theories of motor production, discuss their implementation and then present how stimuli were obtained for use in the perceptual experiment.

3.1 Theories of motor production

There are a large number of theories regarding the way in which the brain plans and orchestrates physical movements of the body. Theories vary according to the space in which planning occurs (intrinsic body coordinates or extrinsic environment coordinates), whether planning is purely kinematic or dynamic, and to what the level the theory of motor production incorporates the physical interaction of the body with its environment through biomechanical and physiological principles. A consideration of extrinsic kinematic trajectory planning lead to the minimum jerk hypothesis (Flash, 1983, Hogan, 1984, Flash and Hogan, 1985) according to which motions are planned as trajectories in the physical environment satisfying minimization of the third derivative. Snap minimization was also investigated (Flash, 1983) but a general property of extrinsic kinematic planning is that point-to-point motions yield straight paths inconsistent with some empirical findings which have detected a curvature in point-point reaching motions (Atkeson and Hollerbach, 1985, Uno et al., 1989a, Haggard and Richardson, 1996). The minimum kinaesthetic jerk model (Wann et al., 1988) circumvents this complaint by modeling the instantaneous stretch and limb's centers of mass yielding dynamically planned motion with minimal internal and external jerk. Alternatively, the minimum jerk virtual trajectory model (Flash, 1987) proposes that motion is planned using a minimum jerk trajectory but that this virtual trajectory acts as a guide for the actual limbs in the form of a spring-damper system between actual and target joint angles. Other researchers have attempted to explain the curvature of hand trajectories, proposing that motion is planned in intrinsic kinematic space according to straight paths in joint-angle space (Soechting et al., 1986), or that motion is planned as a straight path in perceptually distorted visual space (Wolpert et al., 1994). While animators have used the intrinsic dynamic method of minimum torque (Rose et al., 1996), it has been proposed that motions are indeed planned according to the minimization of torque change throughout motion (Uno et al., 1989a). Higher level models have extended this concept by proposing the motion is planned according to the minimization of muscle tension change (Uno et al., 1989b) or neural activation change. It has also been proposed that planning occurs as an optimization at the control signal level with a signal noise component proportional to the activation level and that the constraint is minimum end-point positioning error (Harris and Wolpert, 1998). Finally, a class of theories based on the equilibrium point hypothesis (Feldman, 1966) suppose that the body is controlled using equilibrium positions at which the forces generated by the muscles supporting a given joint are in balance while the actual muscle force results from a lower level of control based on these equilibrium parameters (Bizzi et al., 1976, Abend et al., 1982, Latash and Gottlieb, 1991).

3.2 *Implementation of motor production strategies*

We implemented 14 motor production algorithms. These included trajectories planned kinematically in Cartesian world space and joint angle space, dynamically simulated virtual trajectories, dynamics based optimization and hybrid kinematic/dynamic methods. The models were either based on or inspired by existing motor production theories, and were intended to generate motions in the form of joint angle trajectories given specific Cartesian hand-point targets and a fixed duration for the motion. We based our algorithms on a 30 DOF humanoid corresponding to a robot called DB (Atkeson et al., 2000). A sequence of more than two target points is unconstrained regarding the passage time of any internal target points, and the target points may also be cyclic in which case the passage times of all but the first target (which is also the last target) are unconstrained. Four models, minimum velocity (MV), acceleration (MA), jerk (MJ) and snap (MS) were based on extrinsic kinematic trajectory planning in Cartesian space. The 3D space-line trajectory of the hand was calculated using a three dimensional piecewise polynomial spline. The coefficients were calculated using a general derivative minimization strategy of arbitrary dimensionality (Hale and Pollick, 2002). The hand coordinates were then used to derive postures using the extended Jacobian inverse kinematics method (Tevatia and Schaal, 2000). Four models, minimum angular velocity (MAV), angular acceleration (MAA), angular jerk (MAJ) and angular snap (MAS) were based on intrinsic kinematic trajectory planning in joint angle space. The joint angles were represented by 30 dimension piecewise polynomial splines. The coefficients were calculated using the same algorithm as above. A minimum jerk virtual trajectory model (MJVT) was implemented using the MAJ trajectory as a virtual trajectory guiding a dynamic simulation of a 30 DOF humanoid using spring-dampers acting at each joint. One model was based on the equilibrium point hypothesis (EPH), and was implemented by calculating target postures satisfying each hand positioning target, and then calculating lambda parameters for each joint by inverting the exponential lambda force equation. Postures throughout the motion were then generated by dynamically simulating the motion, and calculating joint forces using the exponential force equation with lambda parameters linearly interpolated between the postures. Two models based on dynamic optimization, minimum torque (MT) and minimum torque change (MTC) were implemented using a time consuming gradient descent algorithm. A minimum jerk trajectory was used as a starting point for the optimization since minimum jerk is expected to approximate minimum torque change. Finally, two algorithms were designed with both optimal dynamics and computational efficiency in mind, the minimum torque postures (MTP) and minimum torque postures virtual trajectory (MTPVT). The MTP model calculated postures satisfying each hand positioning target with a minimal torque requirement to maintain the posture statically and minimum torque change between successive postures. A minimum angular jerk trajectory through these postures yielded the final motion. The MTPVT algorithm extended MTP by using the MTP motion as a virtual trajectory guiding a dynamically simulated humanoid using spring-dampers and each joint.

3.3 *Human motion capture*

In addition to implementing synthetic motion production models, genuine human motion data was also recorded. The motion of a human subject was captured using three Optotrak camera arrays and a total of 22 strobing infrared markers distributed over the upper half of the body. The subject was instructed not to move their feet. Motions were specified using physical reaching targets and obstacles. The subject was instructed to perform motions slowly or quickly and each motion was repeated five times to ensure good quality capture data was obtained. The marker locations were logged by the Optotrak system, and the position of the markers on the body was recorded in a fixed posture with the arms by the sides. It was then possible to locate the markers on a synthetic humanoid of similar kinematic dimensions, and derive joint angles from marker positions using a least-squares Gaussian optimization algorithm.

3.4 *Generation of movement stimuli*

Animation clips were generated using the 14 synthetic models and the motion captured human movements (a total of 15 motion models). Two different motions ((a) & (b)) were performed yielding a total of 30 clips. The two motion specifications were designed to represent via-point trajectories with fixed start and end points, and an intermediate passage point. The motions were slow and fast, performed in 4.4s and 0.5s. A brief period was included at the start and end of the clip to facilitate perception of the onset and termination of motion so that the clip durations were 5s and 1.5s. The motions were prepared offline and stored as posture (complete joint-angle) samples taken at 70Hz. Clips showing a computer generated synthetic humanoid were generated by converting the motion logs to BVH format and importing the motions into MetaCreation's Poser software which was used to render AVI files. Clips showing a humanoid robot performing the motions were generated by having the robot perform the motions and recording them using Digital Video. The recordings were subsequently cropped to the appropriate durations and stored as AVI files using Adobe Premiere. Examples of the movies can be found at http://www.dcs.gla.ac.uk/ halej/biomimetics.htm.

4. Experiments

Two experiments were performed that examined pairwise similarity comparisons of all elements of the set of movements including motions generated by the 14 different motor control strategies as well as the captured human movement. In Experiment 1 these movements were played back on both a humanoid robot and a computer graphics (CG) character. Analysis of the data was obtained through multidimensionsal scaling (MDS) (Kruskal and Wish, 1978) and indicated the presence of outliers that dominated the MDS solution. In an attempt to more closely inspect the fine structure of responses, Experiment 2 examined responses to the CG character when the outliers were removed.

General methods. In Experiment 1 we examined pairwise similarity judgements to sets of movements generated by the 15 production techniques. Excluding self-comparison, a set of 15 elements affords 105 comparisons between pairs. Thus, for each condition a set of 105 stimuli were constructed. In Experiment 1 there were 4 sets of 105 pairs corresponding to the combination of 2 modes of presentation (humanoid or CG character) and 2 movements ((a) or (b)). Experiment 2 used half of these stimuli, including only movements presented on the CG character. Pairs of motions for comparison were obtained by editing together individual video clips so that they played one after another separated by a brief black screen. Participants viewed a pair of movements displayed on a computer monitor and then gave a rating of how similar the movements were on a scale of 1 to 10. The MDS algorithim requires dissimilarity judgements so the similarity ratings were converted to dissimilarities for Experiment 1. However, for Experiment 2, to avoid this extra conversion we had participants directly rate how different pairs were.

The particular MDS algorithm used was the INDSCAL algorithm (Kruskal and Wish, 1978). It was chosen since it provides a solution unique up to reflections as well as measurements of the variance accounted for by the underlying dimensions. MDS works by taking a set of distance measurements between pairs of items, that for our case were assumed to be known up to their ordinal ranking, and computes a multidimensional metric representation of the items. This representation of the items is commonly termed the psychological space and gives insight into the relationship among the items. One important consideration with the use of MDS is that it doesn't automatically provide an interpretation of the underlying dimensions. For this further investigation is required to find properties that can explain the placement of items along the dimensions.

4.1 Experiment 1 - Pairwise ratings of the humanoid and CG character

The goal of Experiment 1 was to see what underlying variables could be found to explain the pattern of participants' similarity ratings. In addition, since the human movement provides a standard of comparison we can examine results from the viewpoint of how the other movements are placed around the human movement.

Design and methods. A total of 20 volunteers participated in the study with half performing similarity ratings on the humanoid while the other half rated the CG character. For ratings of both the humanoid and CG character, trials were separated into two blocks of 105 trials based on the two different movements. Participants performed the two blocks of trials in a single session separated a by a brief rest.

Results. Similarity judgments were converted into dissimilarity values and entered into the INDSCAL algorithm for MDS. A first pass examined the number of dimensions appropriate for modeling the results and found that 2 dimensions was optimal in the sense that increasing the number of dimensions did not appreciably increase the variance accounted for by the solution. In Table 1 we present the results of the fits of the INDSCAL algorithm, including stress, r-squared - amount of variance accounted for, and the importance measures of the 2 dimensions. The importance of the dimension corresponds to the amount of variability in the data accounted for by that particular dimension and are ordered so that the first dimension corresponds to the dimension accounting for the larger amount of variance. The results of the 2D solutions are shown in Figure 1. Taken together, the results displayed in Table 1 and Figure 1 indicate that although stress and r-squared measures reveal that a good fit is obtained to observers' judgments it appears that this solution is dominated by the presence of outliers. This is evident in the plots of movement (a) where for movement (a) production technique MT is very far away from all the other production techniques for both the humanoid and the CG character. Technique MT yields different results most likely because MT optimizations over slow movements can produce unexpected types of motion (ie pendulous swing for slow point-point movements). A similar situation is observed for movement (b) where production technique EPH is far away from other production techniques for both the humanoid and CG character. Technique EPH yielded extreme motion most likely because the implementation, based on linear interpolation of the lambda parameters and an exponential force generation equation, did not include a velocity damping term so that motions tended to be unstable.

A final note is that we attempted to find an average solution which fairly represented the data. However, due to the distinctive nature of each of the outliers in the 4 different conditions, attempts at this revealed that the overall solution lost important characteristics of the individual solutions.

Discussion. Overall the results indicate that six movements account for most of the variability in the data. These are 1) MT for humanoid movement (a), 2) MT for CG movement (a), 3) EPH for humanoid movement (b), 4) EPH for CG movement (b), 5) MTP for humanoid movement (b) and 6) MTPVT for humanoid movement (b). Informal examination of the movies reveal that MT for movement (a) is unnatural due to several arm swings inititating the movement from start to endpoint; EPH for movement (b) is a very indirect path and MTP and MTPVT for movement (b) appear awkward on the humanoid due to apparent difficulty of the humanoid to obtain one of the intermediate postures. This awkwardness wasn't apparent on the CG character movement. For the first 4 cases the hand path was very different from the other movements and thus the dissimilarity results are consistent with even informal observation of the set of movements. However, for the other two cases it is not obvious what physical properties of the movements are making them appear distinct.

4.2 Experiment 2 - Pairwise ratings of the CG character with outliers removed

In Experiment 2 we examined ratings of dissimiliarity to CG character movements. We used the same two movements as used in Experiment 1 however for production techniques we excluded the EPH and MT technique since they dominated the MDS solution, precluding the possibility of other factors explaining participants' responses. We chose the CG character rather than the humanoid since, as indicated by MTP and MTPVT for movement (b), the humanoid appeared to demonstrate additional properties in the movement performed. Although just what additional properties the humanoid adds to the movement is of interest it is beyond the scope of the current work.

Design and methods. A total of 7 volunteers participated in the study. Each participant made pairwise dissimilarity judgements on the two sets of 78 motion pairs generated form the set of 13 versions of movement (a) and movement (b). Each set of 78 movements was presented together in a block and a small rest occurred between blocks.

Results. The results of each individual participant was averaged together to form an estimate for each movement pair and the two resulting dissimilarity matrices were input to an INDSCAL algorithm to find a two dimensional solution. The solution obtained had a stress of 0.15 and r-squared value of 0.94 with dimension 1 having an overall importance of 0.72 and dimension 2 having an importance of 0.22. The results of this can be seen in Figure 2. An additional piece of information provided by the INDSCAL algorithm that is relevant to the current experiment is the weighting of dimensions for the two matrices. This revealed that movement (a) had a dimension 1 weight of 0.93 and a dimension 2 a weight of 0.25, movement (b) had a dimension 1 weight of 0.72 and a dimension 2 weight of 0.62. Indicating that the fast movement (movement (a)) was evaluated primarily along a single dimension while the slow movement (movement (b)) was evaluated equally along two dimensions.

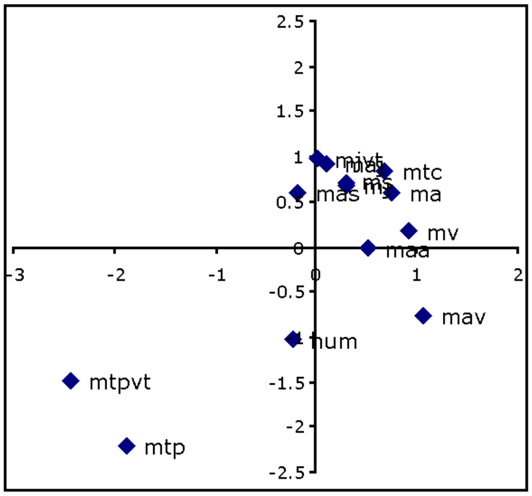

Figure 2: Results of the INDSCAL algorithm for the fits to participants pairwise dissimilarity judgments

Overall the structure revealed in Figure 2 indicates that the MTP and MTPVT production techniques were outliers on both dimension 1 and dimension 2. In addition the human motion capture movements appeared to not be grouped with any of the other production techniques. In the Discussion we will examine the implications of this as well as consider what physical properties might underly the two dimensions.

Discussion. MDS provides a useful technique for finding a compact description of a large set of measurements - reducing a large number of pairwise comparisons to the positions of the stimuli in a low dimensional space. However, it does not automatically provide an interpretation of the dimensions. Some obvious candidates to consider as explanatory vari-

	Stress	r-squared	Importance Dimension 1	Importance Dimension 2
Robot movement (a)	0.12	0.98	0.96	0.02
Robot movement (b)	0.20	0.90	0.53	0.37
CG movement (a)	0.13	0.97	0.93	0.04
CG movement (b)	0.17	0.95	0.88	0.07

Table 1: Results of INDSCAL algorithm fits to the participants responses

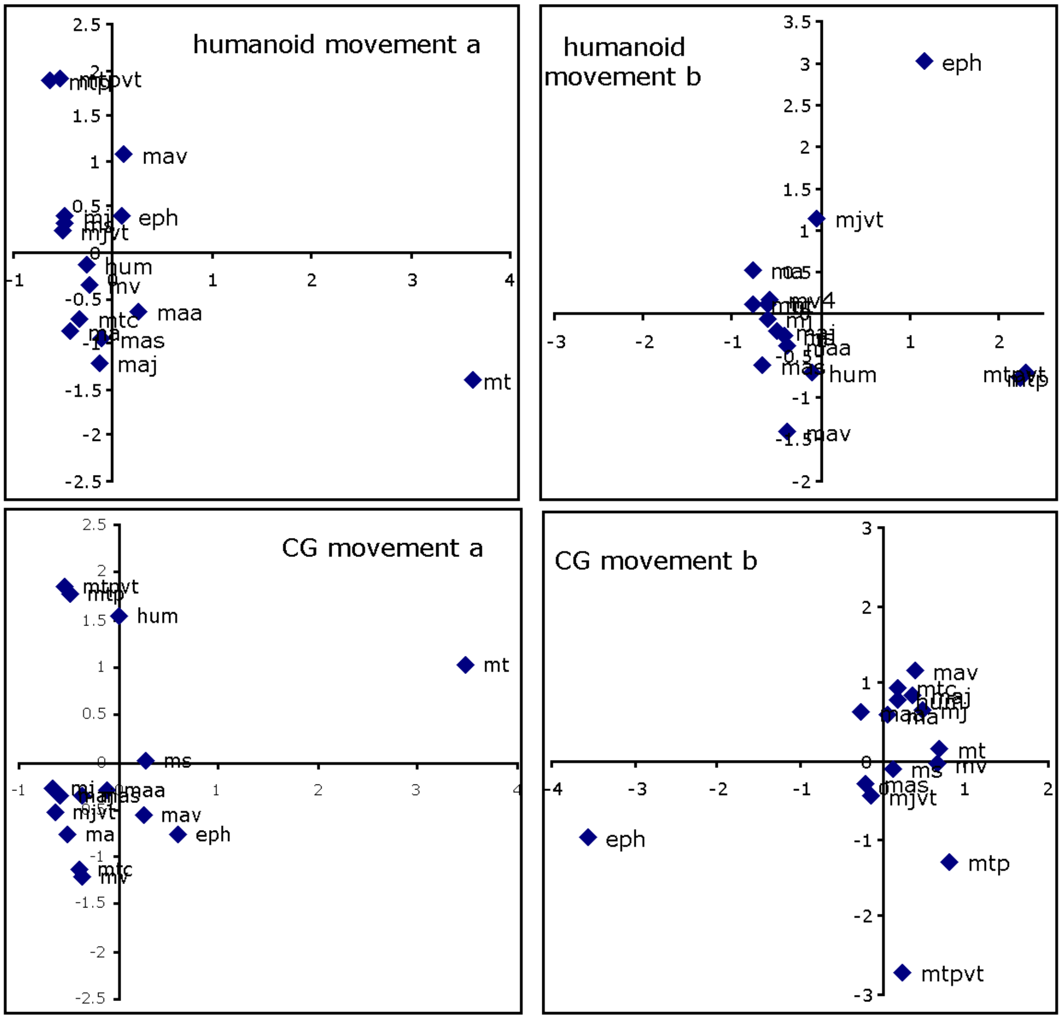

Figure 1: Results of the INDSCAL algorithm for the fits to participants pairwise dissimilarity judgments

ables underlying the dimensions are the velocity of the movement, the path of the hand and the postures of the entire body as the hand traverses a path. Though it might be difficult to separate these possibilities into independent components.

The fact that dimension 1 is used primarily for the fast movements raises the possibility that it is related to the velocity of the movement. Consistent with this is the observation that dimension 1 appears to separate movements according to qualitative properties of the velocity field. For example at the rightmost extreme are techniques MAV and MV that are known to create discontinuous velocity profiles, around the middle of dimension 1 are techniques which have bell shaped velocity profiles and at the leftmost extreme are the techniques MTP and MTPVT which have bell shaped velocity profiles that are skewed.

The fact that dimension 2 is involved for slow movements is consistent with the idea that it involves the processing of information such as postures that should be difficult to perceive for fast movements. In addition, if dimension 1 corresponds to sensitivity to the velocity profile then it can be expected that perceptual estimates of the velocity profile might become noisy and less reliable for slow movements. Thus, making dissimilarity ratings more reliant on factors other than the velocity profile.

5. Summary of the two experiments

Results of the two experiments can be used to reason what properties of movements are salient in the recognition of movement. In Experiment 1 it was seen that movements with distinctly different hand paths such as those generated by technique MT for movement (a) and technique EPH for movement (b) were seen as distinctly different. While this could have been expected based on casual viewing the result serves as baseline data and confirmation of a quantitative method for validating such informal observations. Experiment 2 discarded the outliers obtained in the previous experiment leaving a set of movements that were not distinctly different from one another in their hand path and tried to find what movement properties were used to distinguish between the movements. It was found qualitatively that the fast movements appeared to be distinguished from one another based on their velocity profiles. The slow movements appeared to be distinguished from their velocity profile and another factor. We conjecture that this additional factor is related to the posture of the body, but further investigation is necessary.

6. Conclusions

Of theoretical interest in the interpretation of the current results is the nature of the difference between the perception of the fast and slow movements. That there would be a difference is consistent with results that show that as more time is given to view a human motion sequence there is an increasing tendency for a cognitive interpretation to be given to it. In this light we can conjecture that the sensitivity to differences in velocity profiles is due to low-level perceptual processing of the movements and that for slow movements the addition of another dimension in the MDS solution is reflecting some cognitive analysis of the movements, although there are alternatives to this explanation. For example, it has been argued that the perception of human movement is mediated not through motion per se, but rather through the recognition of discrete postures (Beintema and Lape, 2002, Giese and Poggio, 2003). Such a mechanism might be more influential for slow movements.

Further research will probe this question, investigating which features of motion are salient for recognition excluding velocity, and when they become significant with respect to the influence of the velocity profile.

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