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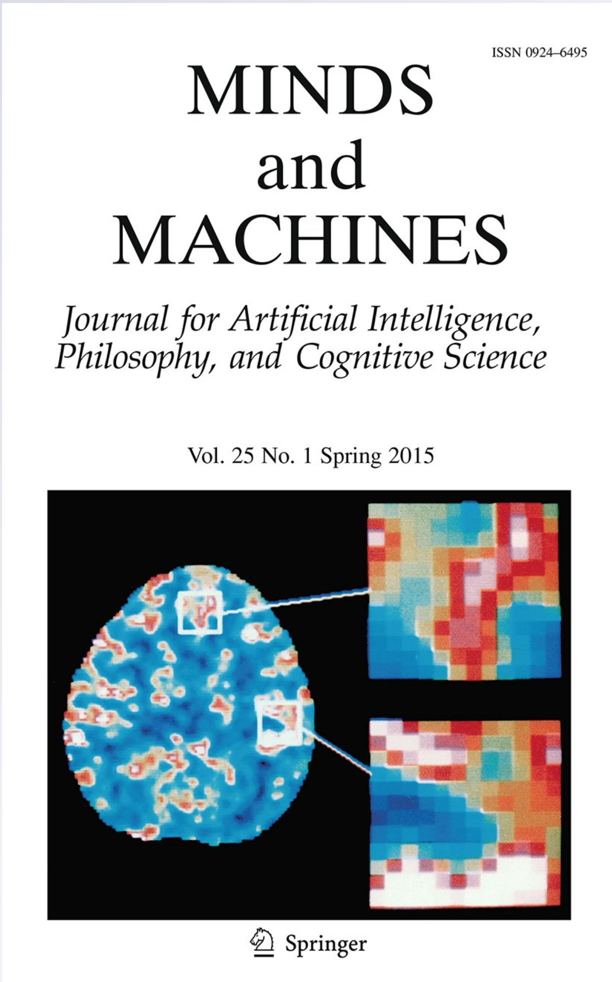

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Cognitive Representation of a Complex Motor Action Executed by Different Motor Systems

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Abstract The present study evaluates the cognitive representation of a kicking movement performed by a human and a humanoid robot, and how they are represented in experts and novices of soccer and robotics, respectively. To learn about the expertise-dependent development of memory structures, we compared the representation structures of soccer experts and robot experts concerning a human and humanoid robot kicking movement. We found different cognitive representation structures for both expertise groups under two different motor performance conditions (human vs. humanoid robot). In general, the expertise relies on the perceptual-motor knowledge of the human motor system. Thus, the soccer experts' cognitive representation of the humanoid robot movement is dominated by their representation of the corresponding human movement. Additionally, our results suggest that robot experts, in contrast to soccer experts, access functional features of the technical system of the humanoid robot in addition to their perceptual-motor knowledge about the human motor system. Thus, their perceptual-motor and neuro-functional machine representation are integrated into a cognitive representation of the humanoid robot movement.

Keywords Neuro-functional machine representation · Perceptual-motor representation · Expertise · Motor system · Humanoid robot · Human movement

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Introduction

For social interaction in general, one needs to single out relevant information from the steady stream of information influx to infer others' intentions and mental states and to coordinate one's own action with the actions of other people based on specific representations (Knoblich and Jordan 2003; Schack and Ritter 2009). When humans have task-related interactions with one another (e.g., driving instructors teaching their students how to drive) both agents develop representations of the specific situations, the partner, and the task to be solved. However, it is yet to be studied how individual and shared mental models of environmental settings, motor actions, or task contexts are established in task-related interactions (Sebanz et al. 2006). The current study is designed to shed light on the question of how people engage in collaborative interactions with other humans and/or with robots, by investigating the underlying mental representations and how these can facilitate human–human and human–robot-interaction (HRI).

To gain a better understanding of representation and categorization in action and interaction, it is fundamental that researchers understand how movements are represented in long-term memory. It is hypothesed that human motor control requires that actions are planned and represented in terms of *intended perceptual effects* and that experts require a well-structured mental representation of the task in order to carry out their movements successfully (Jeannerod 2001; Pulvermüller 2005). A number of studies provided evidence that motor representations in humans not only integrate perceptual effects but furthermore encode *biomechanical information* (e.g., speed and velocity) of human motion (Knoblich and Prinz 2001; Flach et al. 2004; Schack 2003).

Due to current advances in robotic technology, highly developed humanoid robots are able to perform manual and complex motor actions similar to humans. However, current robot control is largely focused on a very low level of abstraction that is closely focused on sensors and actuators. In contrast, human actions are strongly influenced by the knowledge about the characteristics of the manipulated objects, about action goals, and about disturbances and mishaps that usually occur during even moderately complex movements. Therefore, shaping the movements of advanced humanoid robots, or more ambitiously, shaping their interaction in the complex real-world environment, raises a substantial number of non-trivial research questions (Pfeifer and Bongard 2007; Schack and Ritter 2009, 2013). One of these questions is concerned with humans' cognitive representations of humanoid robot movements. Because of the significant differences in sensory and biomechanical organization between humans and humanoid robots, humans cannot represent the perceptual and biomechanical movement effects of the robots. Thus, it is unclear whether humans simulate robotic movements based on their own motor representation, or based on a technical understanding of humanoid robot movement production. In the first simulation, they preferably use their representation of the own motor system. In the second simulation, they preferably generate and use a neuro-functional machine representation. Until now, there is no trivial answer to that question.

It has been demonstrated that the motor execution of a simple arm movement is impaired while observing another human executing an incongruent arm movement. This is not the case when a humanoid robot motor system is executing the same incongruent arm movement instead (Kilner et al. 2003). This finding indicates that the observation of a humanoid robot movement and the observation of a human movement are based on different representation structures. Thus, it can be speculated that interfering cognitive processes are influencing the perception and simulation of human and humanoid robot movements. Some of these mechanisms are simultaneously involved in the perception, simulation and execution of motor actions. The mechanism to observe movement intentions of other humans is based upon the functional equivalence of the cognitive representations involved in action execution, motor simulation, and action observation (Blakemore and Decety 2001; Grezès and Decety 2001). Thus, expert sport performance can be characterized by the advanced abilities and skills of athletes, in particular by the ability to predict other players' behavior (Ward and Williams 2003).

Advanced basketball players, for instance, are able to predict the success of free throws earlier and more accurately than novices, and more accurately than people with comparable visual expertise (e.g., sports journalists). These differences are already observed for movement phases before the ball left the hand. Experts are able to interpret body kinematics more accurately and more easily. To this end, they develop sport-specific anticipatory mechanisms (i.e., perceptual resonance) that enables them to predict others' actions ahead of their realization (Aglioti et al. 2008). Hence, the understanding of observed actions results from a mechanism that maps an observed action onto existing representations of that action in observers' long-term memory (Gallese et al. 1996). Supporting evidence for this 'direct matching hypothesis' is provided by a study involving participants in a block stacking task under two different conditions. In the first condition the participants only observed the blocks getting stacked, while in the second condition they executed the task by themselves. Interestingly, the eye movements were identical under both conditions. The authors concluded that the eye movements are controlled based on motor representations of the corresponding actions (Flanagan and Johansson 2003). Thus, perception is controlled by motor representations even when a task is observed and not executed. Moreover, when athletes were shown similar movement patterns from classical ballet and Capoeira, activation in premotor and parietal areas was higher while observing the movements that corresponded to their area of expertise (i.e., classical ballet or Capoeira). Vice versa, the effect was much smaller when the perceived motor action did not belong to their area of expertise. This finding indicates that the observation of a movement initiates a covert simulation of the corresponding action (Calvo-Merino et al. 2005, 2006).

In general, it can be stated that humans are able to perceive the effects of motor actions executed by other humans based on their cognitive representation of that motor action. These cognitive representations help humans to interact in a proper way with other humans. The present study tries to elucidate the influence of the executing motor system (e.g., human or humanoid robot) on the corresponding cognitive representation. Specifically, we ask whether such cognitive representations are sensitive to the executing motor system, i.e., when a humanoid robot executes a comparable motor action instead of a human motor system. It is hypothesed that humans, when perceiving a humanoid robot movement, activate cognitive representation structures of the corresponding human movement related to their motor-system-specific expertise. Furthermore, we hypothesize that humans with a particular knowledge about either the motor system or the movement will activate all accessible knowledge.

Methods

Participants

Thirty-five participants (male, mean age 26.4 years, $SD = 4.56$) gave informed consent to participate in this study. The study was performed in accordance with the ethical standards described in the 1964 Declaration of Helsinki. Additionally, one high level expert (29 years old) from the field of soccer was investigated. This high-level expert was a former member of the German A—National Team.

The participants ($N = 35$) were subdivided in two groups according to their soccer-specific expertise. The first group ($n = 18$) consisted of experienced soccer players and served as experts for the human movement. They had on average a soccer experience of 17.53 years ($SD = 3.12$) with 9.31 h ($SD = 2.99$) of organized training per week, and played in the fourth league (i.e., highest amateur level) in Germany. These participants had no experience in handling with a humanoid robot. The second group ($n = 17$) consisted of humans experienced in handling a humanoid robot platform. They worked with humanoid robots on average for 4.63 years ($SD = 2.57$) in a full time job at a scientific research institute. This group served as experts for the movement executed by humanoid robot model. They had on average a soccer experience of 2.12 years ($SD = 2.49$) received at non-organized leisure time activities or at school.

Stimuli

An instep kick from soccer was investigated in this study. This movement was chosen because both motor systems (human and humanoid robot) were able to execute it in a comparable manner. For example, the kicking movement of the humanoid robot is extensively used at soccer RoboCup competitions. The investigated humanoid robot platform was the NAO robot. The NAO robot is a humanoid robot platform built by Aldebaran Robotics. It has a 52 cm tall body integrating electric motors and actuators with 25 degrees of freedom. This humanoid robot is used at the RoboCup World Cup as the state-of-the-art technical platform. The human model was a soccer expert, and former player in the 1st Bundesliga (i.e., highest soccer division in Germany). He possessed a very good soccer specific demonstration technique.

To study the cognitive representation, the investigated movements were broken down into relevant basic action concepts (BAC). BACs were defined in correspondence to the well-known conception of basic concepts in the field of object categorization described by Mervis and Rosch (1981). BACs were characterized by recognizable movement features, and they were treated as functionally essential components of complex motor actions (Schack 2011; Schack and Mechsner 2006). Before the study commenced, an evaluation study was conducted to verify the relevant BACs. The pre-defined BACs for an instep kick in soccer were judged by experienced coaches ($N = 5$, holding at minimum an A-license from the Deutscher Fußball-Bund or the Union des Associations Européennes de Football). These coaches were asked to state how relevant all the described BACs were for an appropriate movement execution (in a percentage between 0 and 100, $N = 25$). The final set of most important BACs ($n = 12$) were defined on the basis of an item fit analysis integrating the coefficient of variation. An overview of the used BACs and the item fit analysis is provided in Table 1.

The BACs were depicted as static images. Thus, the images served as stimuli in the experiment. Figure 1 presents the static images of BAC 9 for the human and the humanoid robot movement.

Task and Procedure

To analyze the cognitive representation of the participants for both movements, the Structural-Dimensional Analysis of Mental Representations (SDA-M; Schack 2004, 2011) was applied. The SDA-M measured the cognitive representation of the movement (executed once by the human and once by the humanoid motor system) with the corresponding BACs described in Table 1 in two separate experiments. The order of both experiments was counter-balanced across participants in each group.

Both experiments were conducted in the identical manner except the stimuli were aligned to the corresponding movement. Participants had to perform a splitting procedure. Two BACs were presented on the screen simultaneously. The BAC presented in the upper position was in an anchoring position. Participants were asked: Please decide whether the BAC presented in the lower position is similar to the BAC in the anchoring position during movement execution. To answer that question the participants were implicitly requested to determine a similarity criterion from their own memory (i.e., referring to their own knowledge base about that movement). If both BACs were related to each other during movement execution, participants sorted the BAC in the lower position into a positive subset. If not, they sorted it into a negative subset. Afterwards, the next BAC was presented in the lower position, and again compared to the BAC in the anchoring position. When all decisions related to the BAC in the anchoring position were made, the next randomly chosen BAC was presented in the anchoring position. This process was repeated until every BAC was once in the anchoring position and, thus, had been compared with every other BAC.

Data Analysis

The SDA-M consists of three analysis steps: In the first step, the described splitting procedure reveals the proximity between the BACs for each movement separately. The splitting procedure results in a positive and a negative subset for each BAC in

Table 1 Overview of used BACs

No	Description of BAC	Mean	SD	Item fit
1	Look to the ball	88.00	21.68	63.36
2	Upper body leans forward	86.00	15.17	68.37
3	Bend knee of the supporting leg	72.00	20.49	43.54
4	Foot of the supporting leg points towards kicking direction	82.00	10.95	68.64
5	Kicking leg swings in kicking direction	90.00	10.00	78.89
6	Acceleration of the lower leg	87.00	12.04	73.16
7	Toehold points straight downward	94.00	08.94	84.48
8	Knee of the kicking leg is above the ball	72.00	16.43	49.18
9	Meet the ball with instep at the center	94.00	08.94	84.48
10	No hyperextension of the knee	72.00	23.87	38.84
11	Gaze follows the ball trajectory	66.00	31.30	18.57
12	Kicking leg swings through	62.00	16.43	35.50

The BACs are characterized by short complex phrases. The calculation of an item fit for each stimulus was based on coaches' decisions and formed the basis to choose for the 12 most relevant out of 25 adequate BACs for the instep kick in soccer applied in the experiment. BACs 1–4 describe the assisting phase (preparation), BACs 5–9 describe the main phase (kicking), and BACs 10–12 the assisting phase (follow through)

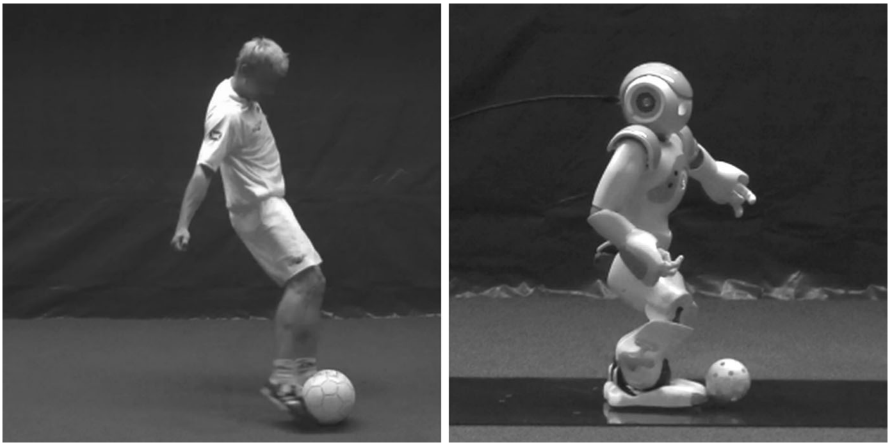

Fig. 1 BAC 9 describing the most important BACs in the execution of the instep kick in soccer for humans (*left*) and humanoid robots (NAO, *right*). Participants were confronted with similar static pictures taken out of the identical movement. All stimuli were matched regarding their visual appearance of both models (i.e., both models were dressed in *white* in front of a *dark same-colored* background). Both stimulus sets were aligned to match the models in size

the anchoring position. The BACs sorted into the subsets are assigned a score which reflects their similarity to the BAC in the anchoring position. The sign of the subset (positive/negative) and the number of elements within each subset form the basis for that score. This procedure results in a score vector for each BAC in the anchoring position. The concatenation of all score vectors creates a matrix in which each row corresponds to one BAC. The rows are then converted to a relative position of each BAC in multidimensional space by a z-normalization. From this normalized position matrix, a Euclidian distance matrix is calculated.

In the second step, the cognitive representations of the kicking movements (i.e., executed by the human and humanoid motor system) are calculated by applying an unweighted average-linkage hierarchical cluster analysis to the Euclidean distance matrix. The cluster analysis results in a dendrogram (e.g., Fig. 2). The Euclidean distance between a given pair of BACs can be read as the height of each conjunction on the y-axis. The smaller the Euclidean distance between BACs, the more similar the BACs are perceived by the participants, and the closer they are represented in the participants' long-term memory. Based on an error probability of $p = 0.01$, a critical Euclidean distance with a value of $d_{crit} = 4.55$ was calculated. All BACs connected below this critical value belong to a common cluster. By contrast, BACs connected above the critical value belong to statistically distinct clusters.

In the third step, the measure of invariance λ is calculated between dendrograms in order to test the generated representation structures for structural homogeneity. The measure of invariance value λ ranges between 0 and 1, whereas 1 indicates the highest accordance between two structures. The statistical threshold for accepting invariance between two structures is set to $\lambda = 0.68$ (Lex et al. 2012, 2014; Schack 2004).

Results

Figure 2 illustrates the cognitive representation of the high level soccer player. The cognitive representation of this expert for the human movement is comparable to the phase description of the instep kick in soccer (Lees and Nolan 1998). The cognitive representation consists of three distinct clusters. The first cluster (1–4) indicates an assisting phase (the preparation). The second cluster (5–9) indicates the main phase (kicking the ball), and the third cluster (10–12) is an additional assisting phase (follow trough). The single soccer experts' cognitive representation of the human movement is functionally aligned to relevant phases of the movement execution. That representation structure reveals a highly automated and internalized cognitive representation of the human kick movement.

The average cognitive representation, split by expertise (robot/soccer experts) and model (human/humanoid robot) are illustrated in Fig. 3. The soccer experts' cognitive representation of the human movement (Fig. 3a) is structurally identical to the cognitive representation of the single high level expert (Fig. 2), $\lambda = 1.0$. This representation structure is aligned to the functional demands of the movement execution for a kicking movement in soccer. The robot experts' cognitive representation of the human movement (Fig. 3c) is structurally dissimilar to the high level expert (Fig. 2, $\lambda = 0.57$), and consists of four particular clusters. The preparation phase of the movement is divided into two separate subphases. The robot experts' representation of the human movement shows an alignment towards the ball as a separate phase (1–2), and a separate cluster for the definition of the kicking direction combined with the shooting power (3–4). Nevertheless, the third

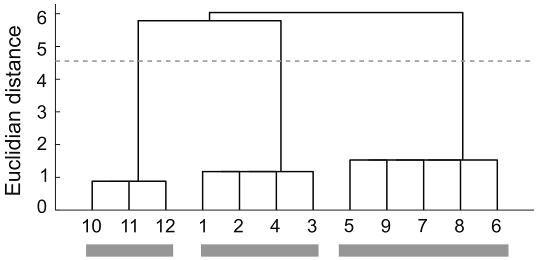

Fig. 2 The cognitive representation of the high level expert in soccer for the human movement. The numbers at the *bottom* refer to the BACs of the movement. The numbers at the *y*-axis refer to the Euclidian distances between the connected BACs. The *grey dashed line* signifies the critical Euclidean distance (d_{crit}) where all branches of the dendrogram were cut off. Everything connected to one branch below this value forms a common cluster. The emerged clusters are indicated by the *solid grey bars* at the bottom of the dendrogram

cluster (5–9) as well as the fourth cluster (10–12) indicate a functional organization of the human movement. The soccer experts' cognitive representation of the humanoid robot movement (Fig. 3b) consists of three clusters and one singled BAC (8). A first assisting movement phase indicates the alignment to the ball (1–2). A second assisting phase (3–7) describes the movement preparation. One specificity is the singled BAC 8 (i.e., knee of the kicking leg is above the ball). The last cluster (9–12) indicates the main movement phase (kicking the ball) together with the follow through phase within the humanoid robot movement. This representation structure is statistically different compared to the soccer experts' representation of the human movement, $\lambda = 0.57$. The robot experts' cognitive representation of the humanoid robot movement (Fig. 3d) is statistically different to their representation of the human movement ($\lambda = 0.55$), and to the soccer experts' cognitive representation of the humanoid robot movement ($\lambda = 0.51$). Four clusters designate the robot experts' cognitive representation of the humanoid robot movement. The first cluster (1–2) describes an assisting movement phase (alignment to the ball). The second cluster (3–6) indicates the movement preparation with the shifting of the weight towards the supporting leg. Cluster three (7–8) consists of the movement components which are related to the movement execution of the kicking leg. The fourth cluster (9–12) is integrating all movement components from the first contact with the ball until the end of the movement, including the follow through. Table 2 summarizes the results of the comparison of evolved cluster structures.

A last analytic step investigated the average cognitive representation over all participants for both movements. Figure 4a illustrates the average cognitive representation of the human movement over all participants, which shows three distinct clusters. Cluster one (1–4) indicates the assisting phase (preparation). The second cluster (5–9) indicates the main phase (kicking the ball), and the third cluster (10–12) the assisting phase (follow trough). This representation structure is identical ($\lambda = 1.0$) to the cognitive representation of the soccer experts (Fig. 3a) and the single soccer experts' cognitive representation (Fig. 2) of the human movement. Figure 4b illustrates all participants' cognitive representation of the humanoid robot

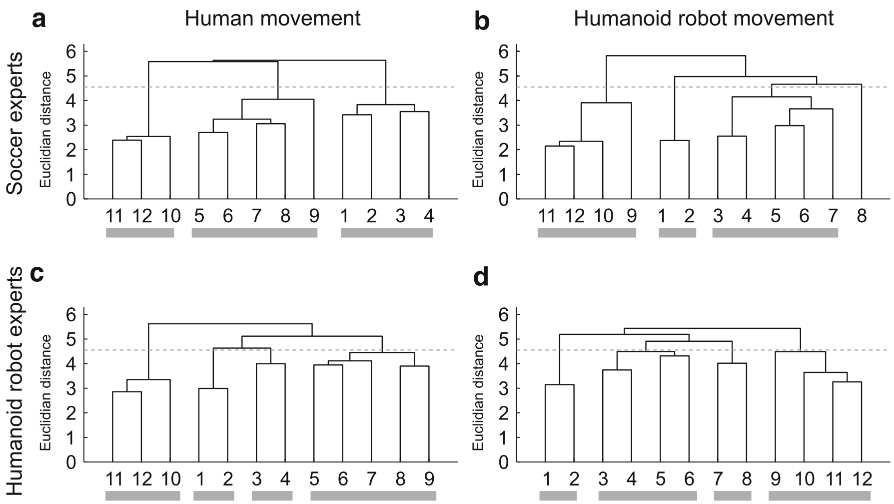

Fig. 3 Cognitive representation structures for the soccer experts of the human (**a**) and the humanoid robot (**b**) movement, as well as the cognitive representation structures for the robot experts of the human (**c**) and the humanoid robot (**d**) movement. The numbers at the *bottom* and at the *y*-axis are identical to Fig. 2

Table 2 Comparison of similarity between the groups (soccer/robot experts) for both motor systems (human/humanoid robot model)

Group 1	Group 2	λ value
High level expert—human model	Soccer experts—human model	1.00
High level expert—human model	Robot experts—human model	0.57
Soccer experts—human model	Soccer experts—humanoid robot model	0.57
Robot experts—human model	Robot experts—humanoid robot model	0.55
Robot experts—humanoid robot model	Soccer experts—humanoid robot model	0.51

The λ value is supposed to be between 0 (no similarity between the cluster structures) and 1.0 (identical cluster structures). Two cluster structures are regarded as similar to each other when $\lambda > 0.68$

movement indicating four distinct clusters. Cluster one (1–2) is representing the alignment of the humanoid robot towards the ball. The second cluster (3–6) is best be described by the backward movement of the kicking leg. The third cluster (7–8) focuses on the movement features of the kicking leg and their relevance for the movement execution. The main phase (9–12) combines the kicking of the ball with the movement parameters of the follow through (assisting phase). All participants' cognitive representation of the humanoid movement is statistically different to all participants' cognitive representation of the human movement, $\lambda = 0.47$. Further, all participants' cognitive representation of the human movement is identical to the soccer experts' cognitive representation of the human movement, $\lambda = 1.0$. Additionally, all participants' cognitive representation of the humanoid robot movement is identical to the robot experts' cognitive representation of the humanoid robot movement, $\lambda = 1.0$.

Discussion

The present study was designed to investigate the cognitive representation of a kicking movement executed by a human and a humanoid robot. The comparative performance of two groups was examined—a group of soccer experts and a group of humanoid robot experts. The implications of the results of the experiments are discussed with regard to certain fields of expertise of both groups, and with regard to a global perspective involving implications regarding cognitive representations in humans.

We asked whether humans would activate their own, movement-specific knowledge structures to understand the intended goals of an action while perceiving a humanoid robot performing a movement. The data of the current study supports this hypothesis. However, the activated representation structures are shaped differently based on the knowledge background of the observer. Three observations in this study support this assumption. First, the results showed a functionally organized cognitive representation of the human movement for the single high level expert in soccer. In comparison to studies from tennis (Schack and Mechsner 2006), dancing (Bläsing et al. 2009), or judo (Weigelt et al. 2011), additional evidence was delivered that the memory structure of a high-level expert is functionally organized. As well as the level of expertise (i.e., a certain league), the domain-specific experience (i.e., years of practice) contributes to an establishment of functionally organized cognitive representations (Ericsson et al. 1993). Thus, the representation structures between the single soccer expert and the group of soccer experts were statistically identical.

In contrast, robot experts' cognitive representation of the human movement was statistically different to the soccer experts'. This difference is mostly related to the "preparation phase" of the kicking movement. The robot experts split the assisting phase into two subphases which is dysfunctional with regard to the execution of the kicking movement. Remarkably, a comparable splitting of the "preparation phase" is also found in robot experts' cognitive representation of the humanoid robot movement. This result indicates that the initiation of the kicking movement might be impaired in the robot experts. Nevertheless, their representation structure showed similarities regarding the main movement phases of "kicking the ball" and "follow through". This might be explained by the fact that the robot experts possess an extensive movement relevant experience with their own human motor system. It can be assumed that such a simple kicking movement is executed and experienced by almost every human. Interestingly, the cognitive representation of the humanoid robot movement shares common features between both expertise groups (e.g., the movement organization of the kicking phase for the BACs 9–12). This finding supports the idea that both groups try to access their knowledge about their own human motor system. They apply their perceptual-motor knowledge about the human movement (i.e., arm position, hip angle, etc.) to the humanoid robot

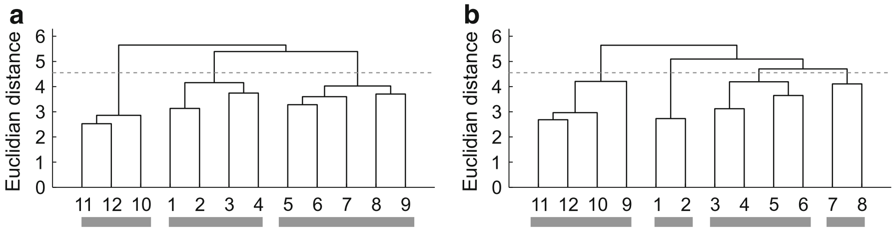

Fig. 4 All participants cognitive representation of the human (**a**) and the humanoid robot (**b**) movement

movement, and therefore to the humanoid robot motor system. However, statistical differences have been observed (e.g., regarding the movement organization for the assisting phases for the BACs 3–8) between the cognitive representations of the human and the humanoid robot movement within both groups. The soccer experts' cognitive representations of the human and humanoid robot movement showed a difference regarding BAC 8, which was singled out. BAC 8 (knee of the kicking leg is above the ball) is responsible for a steady and flat ball trajectory within a human kicking movement. One may speculate that, to soccer experts, it seems impossible that a humanoid robot can execute this movement in a comparable fashion and play, for instance, a long ball in the air. Therefore, soccer experts might not have integrated such a BAC into the movement phases of the humanoid robot movement. In addition, the assisting phase, "movement preparation," was subdivided into two phases: BACs 1–2 and BACs 3–7. BAC 1–2 represented an assisting phase which seems typical for humanoid robot movements. Thus, humans are unable to represent perceptual effects of humanoid robot movements. The movement phase (BACs 1–2) is observable within the robot experts' representation of the humanoid robot movement. The movement phase integrating the BACs 3–7 can be interpreted as directly associated with the preparation of the movement itself. Thus, movement phase one (BAC 1–2) represents the alignment of the body (i.e., meaning to be at the right place), and movement phase two (BACs 3–7) represents the specification of the lower limbs directly responsible for movement execution.

The robot experts' cognitive representations of the human and humanoid robot movement showed the largest differences regarding the representation of the BACs 3–8. The assisting phase (BACs 1–2, alignment of the body) is identical in the representation structure of both movements. It seems that robot experts start both movements with the alignment of the executing body towards the ball. However, they then separated the movement preparation into two phases. Phase one (BACs 3–6) seems to be representing the preparation of the essential movement-relevant specifications for the motor execution. In contrast, the BACs 7–8 seemed to be of marginal relevance for the movement execution. It can be speculated that the BAC 7 and BAC 8 are controlled passively during the motor execution of the NAO robot.

The present data supports the hypothesis that humans activate cognitive representation structures if they perceive a humanoid robot movement. Both expertise groups (i.e., soccer and robot experts) try to apply their existing knowledge to different motor systems. The data suggests that the transferable knowledge differs between both groups. It can be assumed that soccer experts refer to their perceptual-motor knowledge about the execution of the human movement, and transfer their motor system representation onto the humanoid robot. Additionally, it can be assumed that robot experts activate their perceptual-motor knowledge of the human movement as well. However, they also access their representation of functional features of the humanoid technical system (i.e., functioning of the actuators within that humanoid robot). Their memory structure can be described as a neuro-functional machine representation. Of course, some researchers state that perceptual-motor skills and intellectual skills are "… as far apart, one might say, as gym lockers and libraries in a typical university" (Rosenbaum et al. 2001, p. 456). However, intellectual skills like the visual-spatial representation of a movement output (e.g., writing a word) can be generalized to untrained body parts such as writing with a foot (Meulenbroek et al. 1996). The general adjustability (Abeele and Bock 2003) between different sensorimotor adaptation tasks (i.e., transfer of intellectual knowledge about a distortion of the visual feedback from a pointing to a tracking task) delivers additional evidence that knowledge about task-specific features is combined with perceptual-motor knowledge. Thus, the robot experts' cognitive representation of the humanoid movement indicated how functional features of technical systems (i.e., knowledge about the operation mode of a humanoid robot) are involved in the structure formation of cognitive representations. Additional evidence is delivered by the mean representation structure of all participants for the human and the humanoid movement. Humans tend to integrate all knowledge resources about the humanoid motor system that are accessible. Thus, perceptual-motor knowledge about the own motor system and functional features of the technical system are merged to create a cognitive representation of a humanoid robot movement. Furthermore, it can be speculated with regard to the described findings of Kilner et al. (2003) that this kind of cognitive representation might influence the corresponding motor behavior. In contrast to the described findings of Calvo-Merino et al. (2005), the perceptual-motor knowledge of the human motor system is to some extent transferable onto a humanoid robot motor system. However, knowledge about the functional features of the technical system complement the perceptual-motor knowledge of the human motor system.

Despite the fact that the dynamic systems approach (Gibson 1977) and the motor approach (Schmidt and Lee 2005) are fundamental research areas in motor control, the cognitive architecture of complex motor action also plays an important role in the understanding of movement organization (Schack and Ritter 2013). Our results deliver further evidence in how far intellectual and motor-perceptual knowledge are integrated into the memory structure of a movement, and that both information resources have an impact on the integral cognitive structure formation. Thus, multiplexed experience in executing a specific motor action and in handling a humanoid agent might help humans to predict, interpret, and understand an observed motor action of a humanoid robot.

Finally, we would like to speculate about the integration of intellectual knowledge into a complex architecture of motor actions. This integration seems possible when a minimal perceptual-motor knowledge of the motor action is already established. We believe that further intellectual knowledge about actuators of a humanoid robot settles on an information base of the actual motor behavior. Such an information base is established as a cognitive representation integrating sensory potentials and produced environmental effects (Schack 2004). An effect-oriented storage of complex motor actions is assumed to consist of different sensory input signals (kinesthetic, visual, auditory, etc.) which are aligned to BACs. The corresponding internal model stores and combines all possible redundant multisensory information (Schack et al. 2014). Our results suggest that the intellectual knowledge about a motor system seems to be integrated into the corresponding internal model of a complex motor action as well. Thus, if humans have already built up a meaningful cognitive representation, they are able to integrate additional intellectual knowledge on subsequent organizational levels.

Presumably, a more intuitive interaction with humanoid robots would require the user to possess intellectual knowledge about their functionalities. Once this knowledge is acquired, the handling might become easier because the humanoid behavior becomes predictable and the understanding of a humanoid movement becomes more intuitive. However, such intellectual knowledge would not activate the specific action representations for human movements while perceiving a robot action. To this end, the robot would have to produce perceptual and biomechanical effects identical to the effects produced by humans (Press 2011). In addition to Press, it can be stated that the tuning of an action observation network is mainly influenced by the produced environmental effects and the intellectual knowledge about an observed agent. Thus, street performers showing a Robo-Dance routine can be sure to catch the attention of the crowd, simply by pointing at the mismatch between the performed motor actions and the motor potential of the performing motor system. To overcome such mismatches in humanoid robot design we need to engineer bio-inspired machines making it easier for humans to understand the intended action goals of such machines. But as Pfeifer et al. (2007) pointed out, it is still a long way to go to engineer bio-inspired machines for the real world, and a lot research is necessary to strengthen such bold claims.

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