# Reading Motor Intentions

**Lewkowicz Daniel (daniel.lewkowicz@etu.univ-lille3.fr)**
URECA laboratory, Univ Lille Nord de France, F-59000 Lille, France

**Delevoye-Turrell Yvonne (yvonne.delevoye@univ-lille3.fr)**
URECA laboratory, Univ Lille Nord de France, F-59000 Lille, France
MESHS, USR 3185, F-59000 Lille, France

**Abstract**

Some evidence in very recent psychological studies have demonstrated that motor simulation ability is crucial for the correct understanding of social intentions. The present study was conducted first to confirm that the nature of the motor intention leads to early modulations of movement kinematics. Then, we tested whether humans could read an agent's intention when observing the very first element of a complex action sequence. Results revealed early variations in movement kinematics and further showed that human agents can use these deviants to distinguish above chance level between three different social actions. Similar performance levels were found using an artificial classifier (Neural Network) and this procedure demonstrated furthermore that decisions could be taken on the basis of information contained in the first 500ms of movement kinematics. Taken together these results confirm the importance of motor simulation for adapted social interaction, and suggest how robotic adaptive controllers may use as input low-level motor information (e.g. kinematics) to afford biologically inspired social behaviors.

**Keywords:** Classifier; kinematics; sequences; motor control; intentionality: social interaction; internal models; prediction; motor planning; biological movement.

## Introduction

In everyday activities, the grasping of an object might be performed with different prior intentions: e.g. touch, move, throw or pass. Ansuini et al. (2008) have measured the prior-to-contact grasping kinematics for reach-to-grasp movements performed toward a bottle filled with water. By comparing hand shaping across tasks involving different subsequent actions - pour the water into a container; throw the bottle; move the bottle from one spatial location to another - the authors demonstrated how the prior intention in grasping the object strongly affected the positioning of the fingers during the reaching and the contact phase of the action (Ansuini, Giosa, Turella, Altoè, & Castiello, 2008). In another series of studies, Becchio and collaborators investigated the effects of social context on reach-to-grasp actions. They found initial adjustments reflecting specific planning strategies (Becchio, Sartori, Bulgheroni, & Castiello, 2008a) as well as online adjustments (Sartori, Becchio, Bulgheroni, & Castiello, 2009) when performing under social context (see : Becchio et al., 2010 for a review).

More recently, researchers have gone one step further to suggest that not only end-point constraints and social contexts affect movement kinematics, but that these deviants may be used to read motor intention. For example, when observing actions performed under social context or not, Castiello and collaborators demonstrated that humans can successfully use kinematic cues of reach-to-grasp movements to predict the final goal of the action (Sartori, Becchio, & Castiello, 2011). Similar results were also found using point-light displays of simple reach to grasp movements (Manera, Becchio, Cavallo, Sartori, & Castiello, 2011). However, in these studies, the classification rates were obtained under a forced two-choice paradigm, and for the most subtle differences (cooperative vs individual preferred speed or competitive vs fast speed) the classification rates were very small (near 50%).

In the present work, we wanted to study the capacity of humans to read motor intention in a sequence of 2 motor elements. One novelty of this study is that the sequences were performed entirely during an interactive situation with a con-specific, without any interruption or verbal instruction between the sequences. As such, we recorded sequential actions during an ecologically inspired task (*Jungle Speed*), a simple face-to-face game using a unique manipulated object. Our main focus was to compare human and artificial categorization performances for three different sequential actions that took part during the game. To test the hypothesis that kinematics alone is sufficient to read social intention, we fed the artificial classifier with movement kinematics only.

Confronting Jacob & Jeannerod's (2005) *reading motor intention* hypothesis, we hypothesized that human agents are able to read motor intention through the simple observation of arm kinematics of the first element of a 2-sequence action. This is possible due to the fact that arm kinematics of the reach to grasp movements reveal specific deviants in function of goal intention from an ideal optimized trajectory. Finally, if motor simulation is sufficient, then an artificial neural network should be able to learn from the deviants and predict as well as humans, the motor intention of an observed agent. In the following section, we first describe the methods we used to make the observation videos (Part A), which were then played to human agents (Part B) and used as input parameters to an artificial neural network (Part C).

## Creating Stimuli

Two adults participated in the study, one experimenter and the other as subject. Both participants were right handed as verified with the Handedness questionnaire (Oldfield, 1971). They had no prior knowledge of the experiment and provided informed consent before participating in the experimental session that lasted approximately 90 minutes. The subjects' movements were recorded using a (1) a video camera (Sony Handycam) and (2) 4 Oqus infrared cameras (Qualysis).5 infrared reflective markers were placed on the thumb (tip), index (base and tip) and the wrist (scaphoïd and pisiform). Cameras were calibrated before each session, allowing the system to reach a standard deviation smaller than 0.2 mm, with a 200 Hz sampling rate

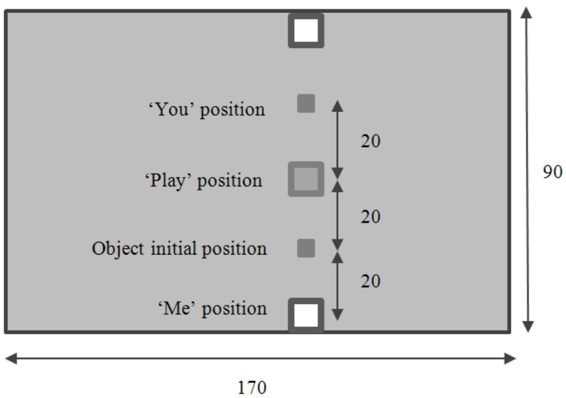


Figure 1. Schematic representation of the experimental setup.

***The game.*** The object that was to be manipulated by the subject was a wooden dowel of width 2 cm and height of 4 cm that was placed precisely 20 cm in front of the starting position ('pick' position). The subject started each trial by pinching index and thumb together at the starting position (see *Figure 1*). Each trial, the subject's task was to reach and grasp the dowel between thumb and index finger in order to move it from the initial position to one of the three 'place' positions during an adapted version of the *jungle-speed* game. The game consisted in 4 blocks of approximately 40 rounds. First, the subject's task was to pick and place the dowel at the 'Play' position in order to set the initial condition of the game. Then, at the 'go' signal (high pitch) both participants reached for the dowel as quickly as possible. The competitive move was not recorded and is not part of this study, although, this was indeed intentionally omitted during instructions given to the subject. During competitive move, the first who have grasped the dowel, won the round and scored a point. The second phase consisted in a *rewarding* phase. The dowel was first always repositioned at pick position and the subject wait at starting position for the next audio tone (low pitch). During the rewarding phase just after the competitive move, the subject has to reach to grasp the dowel and place it either at the 'You' position if the experimenter scored during competitive move, or at the 'Me' Position if the participant scored during competitive move. The game went on until one of the two players reached 20 points. Thus, we recorded twice as much 'Play' moves than 'You' or 'Me' moves during the game. Nonetheless, after 5 rounds of training to set up the game rules, no other verbal instructions were given during the blocks. The three different positions ('Play'; 'Me'; 'You') where the dowel had to be placed were delimited by visual marks directly placed on the tabletop.

***The recordings.*** The best 16 recordings of each category ('Play', 'Me' and 'You') were extracted using VirtualDub and kept for future use as stimuli. Each sequence was delimited with a 1-second pre-trial, i.e., before the initial movement onset, and was cut exactly one frame before the index finger contacted the object. Movies were compressed with FFdshow codec (MJPEG) at 50 frames per seconds with a screen resolution of 720x576. Video clips were coupled with the recordings of the arm kinematics using 4 Oqus infrared Cameras (Qualisys). Infrared reflective markers were placed on the index (base and tip), the thumb (tip), the wrist (scaphoïd and pisiform) of each participant, as well as on the object. Cameras were calibrated before each recording session, allowing the system to reach a standard deviation smaller than 0.2 mm for all three absolute positions at a 200 Hz sampling frequency. Care was taken as to provide no contextual information within the video clips (torso, gaze, face expression), i.e., only the hand and the target object were fully in view. Velocity profiles are presented in Figure 2 and show that play, me or you sequences show deviations during both first and second motor element (amplitude and the width of the bell-shaped curves, first and second peaks of velocity, time position for local minima).

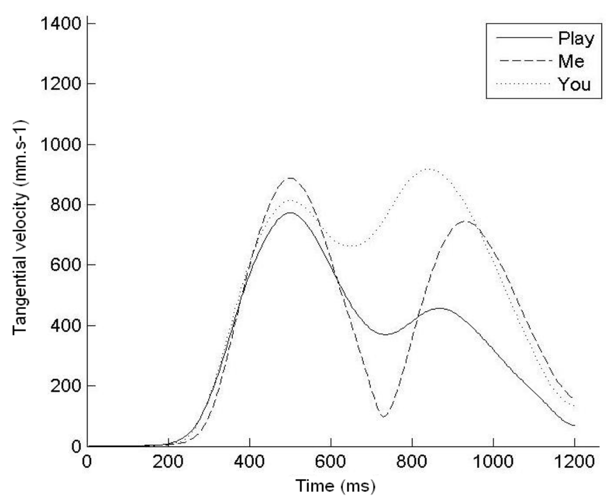


Figure 2. Mean velocity profiles for the three categories of sequences. Each bell-shape curve corresponds to a motor element. The first is the reach to grasp element, and the second bell-shape curve is placing element. The local minima are used to segment the two motor elements and compute movement times.

## Human Categorization Performance

The short video clips were presented to a panel of human subjects to test whether human agents were able to predict the goal of a sequential action when shown only the first sub-element of a sequence, i.e., the reach movement.

***Participants, Apparatus and Software.*** Twenty-six young adults (mean age: 21.82 ± 2.76 years, range = 18 - 29 years) participated in the study. All subjects were right handed (Oldfield, 1971) and had no prior knowledge of the experiment. Subjects provided informed consent before participating in the experimental session that lasted approximately 45 minutes. Participants were seated comfortably facing a table in a dark and silent room. For each trial, participants started by placing their hand on response keys that were delimited by tape placed directly on the keyboard keys. Stimuli were presented on a laptop computer with MATLAB software (Mathworks) with the PsychToolbox environment.

***Experimental Procedure.*** The participants' task was to answer on the keypad after each video clip presentation whether the social intention of the sequence was 'let's **Play**' (5 key), 'for **Me**' (2 key) or 'for **You**' (8 key). A 1-second blank screen was displayed in between two trials. Participants were instructed to give their answers as fast and as accurately as possible. They were obliged to provide an answer within a 4-second time window otherwise the trial was cancelled and presented at the end of the block. A feedback message was given to tell participants if their response was too slow. Each block consisted in the random presentation of a series of 48 stimuli, i.e., 16 different video clips for each of the three categories (Play; Me; You). After a 5-minute pause, the next block of 48 video clips was presented.

**Dependent variables and statistical analyses**. The number of correct responses (correct prediction of the ongoing action) and the response times were calculated for each category. The dependent measures were submitted to a repeated-measure ANOVA with *Block* and *Category* (Play; Me; You) as within factors. The participants' scores for each category were compared using a Chi-square between the observed scores and the random distribution between categories corrected by total the number of answer of that category. In other term, because the total amount of answer is not exactly the same between categories, we consider the guessing base-rate of each category separately. The alpha level of significance was set to 0.05.

***Response times.*** Results showed no effect of Block on response time, $F(2,50) = 1.401$, $p = .256$, indicating that participants answered with a similar response time in the first (M = 878, SD = 382 ms), the second (M = 848, SD = 315 ms), and in the third block (M = 944, SD = 316 ms). No effects of Category were found on response time, $F(2,50) = 2.621$, $p=.083$, indicating that participants answered within the same delay both for 'Play' (M = 900, SD = 294 ms), 'Me' (M = 866, SD = 294 ms), and 'You' categories (M = 905, SD = 300 ms).

***Number of correct responses.*** There was an absence of Block effect on classification performances, $F(2,50) = 0.102$, $p = .903$. However, a main effect of Category was obtained, $F(2,50) = 16.022$, $p < .001$, $\eta^2_p=.39$. Post-hoc Scheffé analyses further showed that participants were more accurate for trials in the 'Me' category (M = 57.53, SD = 13.02 %) than in the 'You' (M = 40.87, SD = 12.12 %) and in the 'Play' category (M = 47.27, SD = 13.04 %). More importantly, Chi-squared tests showed highly significant difference between observed frequencies and random guessing baselines for the 'Me' (guess rate = 36.98, $p<.001$), 'Play' (guess rate = 36.12, $p<.001$) or 'You' (guess rate = 26.90, $p<.001$). These results confirmed that performance was significantly greater than chance level.

## Categorization with Artificial Neural Networks

In the following section, we present the simple feedforward neural network that was developed to demonstrate the possibility to categorize on the only basis of motor kinematics.

***Architecture and Learning procedure.*** A simple classification Neural Network was constructed with N neurons (1-23 neurons) as inputs, 3 hidden layers and 3 output neurons (one for each category). The N size is the sub-selection of the total movement duration. Activation functions for the output layers were symmetrical and sigmoid, between -1 and 1.

With this NN, the instantaneous velocity in 3D was calculated between the recorded positions of the wrist for two subsequent frames. A threshold of 20 $mm.s^{-1}$ was then determined to compute the *reaction time* (RT) delay between the start of the recording and the actual beginning of the movement. Second, a *sampling* parameter was used to compute the average velocity across 10 frames. Third, the mean velocity values were converted from $mm.s^{-1}$ to $m.s^{-1}$ in order to get data within an overall range of 0 to 1. Finally, a training set (25%) and a test set (75%) were randomly picked from the 144 different kinematic recordings. 20 different networks were trained to obtain the classification performance for every specific target time widow (i.e. time window for kinematic recognition). The mean response and variance across the 20 networks are described in the result section as the NN success rate (this value is always lower than the best performing network). By varying the amount of data fed as input, we computed the classification performance from multiple time windows. The learning procedure was a back-propagation algorithm using the FANN library (Nissen, 2003). Target error (to stop the learning) was set to MeanStandardError < 0.001 with a maximum number of epochs set to 10 000, and 300 iterations between each test (evaluation of target global error.

***Classification results in function of time.*** Results revealed that the simple artificial classifier was able to converge in most cases. The classifier succeeded in discriminating between categories for input sizes above 9, i.e. with a time window of 450 ms. For the input size of 9, single sample t-tests confirmed that all categories were above chance level, $p < .001$: 'Play' ($M = 55.70$ $SD = 8.08$ %); 'Me' category ($M = 56.70$ $SD = 4.16$ %), and 'You' category ($M = 50.33$ $SD = 5.63$ %). Figure 3 presents the detailed results for 12 different input sizes, between 50ms to 1150ms with a step of 100ms. From the input size of 5 (250ms) to 9 (450ms), only 2 categories were successfully recognized while the other remained below chance level; Below 250ms, only one category was correctly classified. The crucial point to note here is nevertheless the fact that by 450ms all categories are classified above chance level; a point in time that occurs before the end of the first sub-element of movement sequence confirming the capacity of a simple network to predict motor intention by the use of low-level kinematics early on during motor execution.

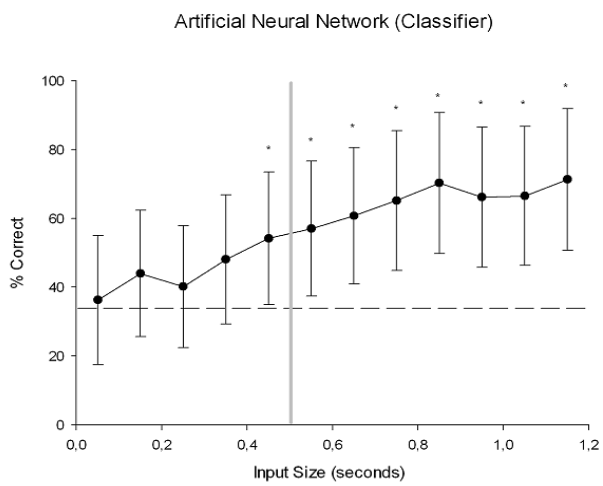


Figure 3. Results obtained with the ANN. Note that with an input size of 450ms, most of the networks classify the movements with a higher rate than chance level and before the end of the first motor element (vertical grey bar).

## Discussion

In the present contribution, we report experimental data confirming that motor intention can be read through the simple observation of movement kinematics. More specifically, we first showed that the three different motor intentions that were used in a simplified version of the *Jungle Speed* game (Asmodee eds.) modified the kinematics of the first (reach) sub-element of the sequential action. Second, human agents were able to classify rapidly (<1s) and above chance level (>40%), the trial category when observing a video-clip of the reaching movement only of the sequence. Third, a classic feedforward neural network was also able to categorize motor intention through the use of low-level kinematic information of, once again, the reaching sub-element only. In the following section, we discuss these findings in more detail and describe how this work can help advance the development of future cybernetic systems that will afford true human-robot interactivity.

***Kinematics reflecting motor intention.*** In the abundant literature of manipulating actions, the effects of end-point constraints on the early parts of movement kinematics have been investigated extensively in experimental psychology. In individualistic situations, multiple sources have been reported to modify and shape hand trajectory in two-element sequences such as second-target distance (Gentilucci, Negrotti, & Gangitano, 1997), end-target orientation (Haggard, 1998; Hesse & Deubel, 2010) or second-action type (Armbrüster & Spijkers, 2006; Marteniuk, MacKenzie, Jeannerod, Athenes, & Dugas, 1987). In social interactive manipulative tasks, final-goals have also been reported as having an effect on reach-to-grasp kinematics such as giving vs. placing an object (Becchio et al., 2008a), cooperative vs. competitive actions (Becchio, Sartori, Bulgheroni, & Castiello, 2008b; Georgiou, Becchio, Glover, & Castiello, 2007), absence vs. presence of social request (Ferri, Campione, Dalla Volta, Gianelli, & Gentilucci, 2011), verbal communicative vs. non-communicative intentions (Sartori, Becchio, Bara, & Castiello, 2009). The kinematic effects reported here are consistent with this literature and suggest that when planning a sequential action with multiple sub-elements, the requirements of the endpoint element are back-propagated to constrain the way the very first element of the sequence will be planned and performed. Thus, it is possible to suggest that low-level motor components may contain early indices that reflect the end-point motor intention of an agent.

***Reading intentions.*** In the present study, the first part of each movement was identical, i.e., the agents initiated their move with their hand placed on the starting pad of the playing area, and reached for and grasped the wooden-peg that was always at the same position on the table. However, the second part of the move was specific and directly related to the game intention: lift the wooden peg to take it ('Me' category), to give it ('You' category) or to place it on the table ('Play' category). Thus, any kinematic deviants observed on the first part of the sequence may be related to the social intention of the second part. By measuring two basic motor parameters (*peak velocity* and *movement duration*), we showed that it was possible to dissociate the three types of social interaction categories (*Figure 2*). We then tested the fact that human observers could use these deviants to classify observed actions above chance level. The video clips were created in order to show the first sub-element only, without any contextual cues; care was also taken to cut the end of the reaching action, one frame before object contact, in order to avoid providing any cues on movement direction of the second part of the sequence. Our findings demonstrate that classification is possible and that in certain cases, the participants' performance can be extremely precise (up to 67% of correct classification for the best of participants). But how is this possible?

***An alternative low-level hypothesis.*** It is nevertheless possible that the understanding of motor intention is based on more low-level cue readings. As suggested by the work of Perrett and al. (Perrett et al., 1989), the visual system definitely contribute to action recognition and the performance showed by humans could be interpreted as the resolution of an “inverse” problem (goal attribution) with a simple bayesian inference about which goal explain the best which action (Csibra, 2008). Indeed, despite a total absence of contextual cues within the video clips (body, head, eyes), we demonstrated in the present study that participants were able to read motor intention significantly above chance level. Hence, the subjects’ responses could be guided by the slight deviances from the optimal strategy (i.e. to grasp without any subsequent action) in the low-level motor kinematics. This confirms recent results presented by Stapel et al. (2012) who showed that in absence of contextual cues, kinematics could be a key source of information to predict intentions of ongoing actions. To go further in this low-level hypothesis, we conducted a second work for which we used a very simple artificial neural network classifier and we showed that this simple classifier performed as well as our human subjects in categorizing the three different social-intended video-clips. Further studies, namely brain imaging, are needed in order to determine whether the good performance reached in our human individuals was due to direct coding of the low-level kinematic parameters or whether the kinematics deviants are simple by products and that even for simple actions, human performances engage in a cognitive motor simulation to read motor intention (see e.g. Kilner, Friston, & Frith, 2007; Kilner & Frith, 2008).

It is to note that correct classification of the three social categories was far from being perfect, reaching in the best of cases 60% of correct identification. Hence, kinematics can be used for predicting ongoing actions but cannot be the only source, used by human agents to judge motor intention. It has been shown that during natural sequential task (i.e. preparing a sandwich), eye movements are stereotyped and predictive (Hayhoe, Shrivastava, Mruczek, & Pelz, 2003). During the task, the eye precedes the hand movements in systematic way ensuring a good coding of object position for accurate planning of arm (Johansson, Westling, Bäckström, & Flanagan, 2001). This coordination between eye and hand movements during manipulative tasks have extensively been tested in experimental psychology and have demonstrated that e.g., eye movement onset is always faster than hand movement onset, and the peak velocity of both eye and hand movements are strongly correlated, suggesting that they possess a coupled function. It is thus possible that using both gaze position and the hand movements kinematics, an observer would be able to increase the efficiency of intention reading (see also : (Bekkering & Neggers, 2002).

***Perspectives for interactive and social robotics.***

The application of our work would be to develop robots that afford true interaction, i.e., being able (1) to read motor intention in human kinematics in order to adapt but also (2) to move with biological realistic kinematics, in order allow others to understand the intention of the robot. Following the data presented here, we hypothesize that a humanoid robot could become interactive if it moved following the laws of biological movement with action sequences that integrate back propagation of terminal intention. Such a phenomenon would provide the means for human agents to read intentionality and thus, gain in understanding the goal of the robot’s movements. Furthermore, including social deviants in the motor kinematics within early steps of motor sequences would also allow safe interaction with large industrial robots by affording humans the possibility of anticipating false moves in joint actions that share similar work spaces.

Implementing robots with the architecture necessary to “afford intentionality” would need to integrate the different brain regions that are known to play a role in motor planning and motor-sensory predictive mapping. De Rengervé et collaborators (de Rengervé, Hirel, Andry, Quoy, & Gaussier, 2011) have recently reported on such an architecture, which included amongst other areas, the cerebellum and the basal ganglia. Tested on both software and hardware, this neural architecture has demonstrated its efficiency on data collected in a hydraulic robotic arm. With a series of imitation trials, this system demonstrated the capacity to learn how to perform sequential actions that respected biological laws, i.e., to perform movements with kinematics that mirror those performed by human agents. As such, this robot arm has demonstrated increased interactivity with human agents affording augmented interaction both in time and in space (none published results). Ongoing studies are now being conducted to assess whether this interactivity is associated to an increase in the capacity of human collaborators to read the robot’s intention.

## Conclusion

We have here described experimental findings in humans demonstrating that it is possible to read motor intention through the simple observation of kinematic deviants. Classification capacities were significantly above chance level and provided human subjects the means to dissociate between three different socially oriented actions. We argue in the present study that reading intentionality may not depend on a high-level cognitive function as suggested in the psychological literature. Internal simulations may not be systematically required and understanding other intentions may in certain cases relate to a direct coding of those kinematic deviants that back propagate from end-point to early on during sequence execution; this direct coding would emerge through years of joint-action experiences, during interactions with adult con-specifics. As a first step to support this hypothesis, we report in the present study simple neural networks that were able, after learning the meaning of kinematic deviants, to classify the three categories of actions to the ***same degree of accuracy than***

***our human participants***. These preliminary results stresses the importance of further developing the optimal theories of motor control in order to include the effects on sequential actions such as, back propagation phenomena of social context.

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