Motor Resonance as Indicator for Quality of Interaction - Does it Scale to Natural Movements?

Socially Interactive Agents Track

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1 INTRODUCTION

Detecting in an automatic manner whether a particular interaction between man and machine "works", is an unsolved problem in human-machine interaction. No computational technique exists by which the artificial agent could perceive whether the interaction works from the viewpoint of the human or whether interactional breakdown is likely to occur. In human-robot interaction (*HRI*) motor resonance has been proposed as a potential candidate for assessing what might be termed "quality of interaction" [3]. Chaminade et al. assert that "the measure of resonance indicates the extent to which an artificial agent is considered as a social inter-actor" [2], and call it "a plausible foundation for higher-order social cognition" [1]. Motor interference (*MI*) is often used as a metric for resonance [8]. While the above suggests that motor resonance might be suitable as general measure for the potential of an artificial agent to be conceived of as a social entity, the question remains whether it can be used as a measure for the quality of an ongoing interaction.

2 MOTIVATION

Previous research on motor resonance focussed on the identification and disentanglement of factors on part of the model for the evocation of motor resonance in the human interactor. While the current work still attempts to contribute to this line of research, a second research target is to assess whether motor interference is amenable to its use in more naturalistic interaction formats. For this to be the case it would need to 'scale up' along the following 3 'dimensions': Firstly, it would need to be applicable to motor actions more complex than linear intransitive movements. We address this by using transitive *grasp and translate* movements, grabbing an object and placing it somewhere else. Secondly, it would need to 'scale' in terms of how fast it can be detected, an issue not addressed in the present experiment. Thirdly, *MI* should be measurable beyond simultaneous interaction formats and extend to turn-based interactions as is the case for conversational interaction [11].

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3 MATERIALS AND METHODS

3.1 Experimental Design

The presented experiment constitutes a 2x2x2x2 repeated-measures design with between factor *prime*, and three within factors *congruency*, *interaction mode* (simultaneous / consecutive), and *movement direction* (left-right / forth-back). *Primed* participants, were told that Deechee, the robot, would be watching them during their performance of the instructed motor actions. *Non-primed* participants were given no such additional information. In *congruent* conditions participants and robot performed compatible movements, meaning both performed matching *left-right-left* or *forth-back-forth* movements. In *incongruent* conditions the participants' and the robot's movements were mismatched: participants performed *left-right-left* movements while the robot executed *forth-back-forth* ones or vice versa. In *simultaneous* conditions participants and robot performed their respective motor actions simultaneously. In *consecutive* conditions participants were told to wait until the robot had finished its turn. Participants performed the *grasp-and-translate* actions in both left-right-left and forth-back-forth directions.

The robot employed was an iCub humanoid [9] (Fig. 1). Participants were seated on the opposite side of a table facing the humanoid. Their arm movements were recorded using the *Polhemus Liberty* motion tracking system. 22 right-handed plus 2 ambidextrous participants were recruited from the university campus as well as the wider area surrounding it and randomly split into a primed and non-primed group. Participants performed 8 runs, each of which constituted an instantiation of the 8 possible factor combinations. For further details see [4].

The iCub's behaviour was scripted and semi-autonomous. It starts with the robot grasping and picking up the toy located in a fixed position in front of it. In *consecutive* runs the robot executes 15 left-right-left or forth-back-forth translation movements. It slightly lifts, moves, and lowers the object onto the table at a target position and subsequently moves the object back to the start position without relaxing its grasp. It repeats this movement cycle 15 times. In *simultaneous* runs the robot executes the movement cycle until it receives a stop signal. See [4] for more details.

3.2 Analytical Methods

MI is typically measured either in terms of variance with respect to the axis orthogonal to the main axis of movement (*standard analysis*) or in terms of movement curvature.

Data Preprocessing: The data was segmented in a semi-automatic fashion into single movement segments. Due to the observation of

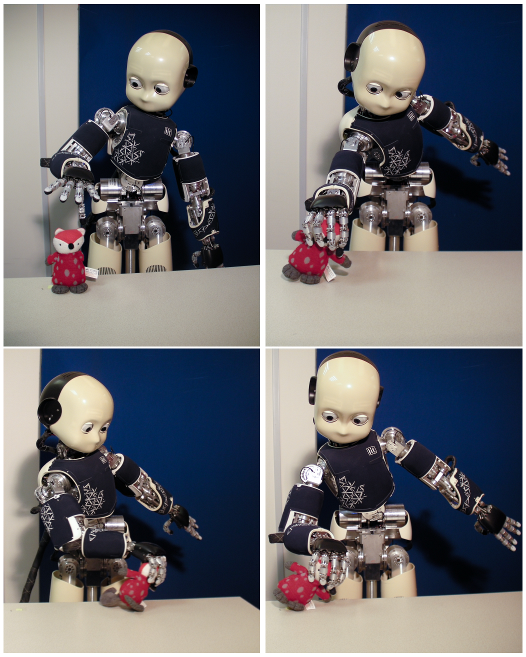

Figure 1: iCub humanoid robot in various phases of movement.

subjects resting their hands shortly on the table between changes of direction we generated two data sets: in the *no gaps* set we divided the border data between segments into equal halves and assigned the first half to the preceding and the second half to the subsequent segment. In the *clipped* data set we discarded all boundary data. Data from all three dimensions was separately low-pass filtered and leading and trailing motion segments from each run were discarded until only the central 10 motion segments were left (cf. [4, 5]).

Standard Analysis: In the "standard analysis"[7] standard deviation or variance on the orthogonal axis is used as base measure [5, 6, 12, 13]. See also [7] for an unpacking of this measure.

Curvature Analysis: We both adopted and modified the method described in [3, 10]. Curvature values are typically normalized in order to account for differences in movement lengths (cf. [10]). On top of the method described in [10] we developed our own type of normalization where the curvature of each movement segment is divided by the mean curvature of a reference condition. In addition to 'aggregation' by variance [3, 10], we aggregated segmental curvature data using the mean. We deem this more plausible and it is in line with the way segmental variances are aggregated in the *standard analysis*(cf. [4]).

4 RESULTS

The data was split along movement direction and analysed separately (see [4] for a discussion). Several statistical analyses were performed as our data analysis could be varied along several dimensions such as the removal or not-removal of outliers, or the type of normalization in the case of curvature, amongst others (see [4]). We performed both mixed ANOVAs as well as non-parametric tests as some of the data sets violated normality.

Standard Analysis: 3 out of 10 test configuration yielded the near-significant interaction *prime* × *congruency* on the *left-right* data with p-values between 0.05 and 0.084. Planned contrasts with fixed *prime* levels indicated that differences in variance due to *congruency* only approached significance for *primed* participants ($p = 0.074$, $\chi^2 = 3.20$), but not for *non-primed* ones ($p = 0.26$, $\chi^2 = 1.29$). Under this measure there is some evidence that motor interference has occurred for *left-right* movements, but not for *forth-back* movements, and that its occurrence was conditional on priming.

Curvature Analysis: When using curvature as base measure and variance as aggregating function as described in [3] the analysis yields a number of near-significant interactions *prime* × *interaction_mode* on the *left-right* data sets. On the *forth-back* data set the majority of test configuration indicates that *congruency* had either a significant or near-significant effect on the curvature measurements. While this would also be the case if motor interference had occurred, the effect here seems to be reversed: the mean curvature values in incongruent conditions is smaller than that of congruent ones across all test configurations.

When using curvature as base measure, but substituting variance with mean as aggregating function, the results look more like what one would expect: on the *left-right* data sets a number of configurations flag up *congruency* as significant or near-significant effect. A comparison of the means between congruent and incongruent conditions indicates that motor interference has taken place: the curvature is larger in incongruent conditions as compared to congruent ones. Also on the *forth-back* data sets congruency is flagged up as significant or near-significant by many test configurations, but, again, the effect appears to be counterintuitive: the mean curvature values of incongruent conditions are smaller than those of congruent ones.

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