Biological Motion for Gestural Communication in Social Robots

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***Abstract*—This extended abstract describes a research project that implements non-verbal gestures on a social robot using biological motion and investigates how humans perceive the robot's resultant behaviour. We show that incorporating biological motion significantly increases the perceived warmth of robotic gestures and improves the overall interaction experience. These findings highlight the importance of biologically inspired movements in creating engaging social robots.**

***Index Terms*—Biological motion, human-robot interaction, gestures**

I. Introduction

Nonverbal communication constitutes a fundamental aspect of human interaction, encompassing a rich array of cues such as body language, vocal intonation, gestures, and facial expressions. These subtle signals significantly enhance interpersonal communication by conveying nuanced information, emotions, and intentions beyond the explicit content of spoken language [1], [2]. While the importance of nonverbal cues in human-robot interaction is increasingly recognized, existing approaches often fall short in replicating the fluidity and expressiveness of human gestures.

Biological motion is a fundamental characteristic of human and animal movement, characterized by its fluidity, coordination, and expressiveness. By incorporating these organic qualities into robotic motions, researchers aim to create more natural and engaging human-robot interactions [3]

II. Models of Biological Motion

There are two principal approaches to modelling biological motion: the Two-Thirds Power Law and the Minimum Jerk model. We discuss both approaches in the following.

A. Two-Thirds Power Law

The Two-Thirds Power Law, a widely accepted principle governing human upper-limb movement [4]–[7], has been extensively documented across various motor behaviours. This law has been observed in locomotion [8], ocular motion [9], and other forms of human motion. The Two-Thirds Power Law is expressed as follows:

$$V(t) = K(t)\left(\frac{R(t)}{1+\alpha R(t)}\right)^{\beta} \tag{1}$$

where V(t) is the tangential velocity at time t and R(t) is the radius of curvature at that same instant.
The value of the β exponent has been empirically demonstrated to be in reasonable agreement with the value of $\frac{1}{3}$ over a large class of human motion [6], [10], [11].

In case α = 0, the law can be simplified as:

$$V(t) = K(t)R(t)^{\beta} \tag{2}$$

from which we can derive the alternative formulation

$$A(t) = K(t)C(t)^{1-\beta} = K(t)C(t)^{\frac{2}{3}} \tag{3}$$

hence, the two-thirds power law formulation, where $A(t) = \frac{V(t)}{R(t)}$ is the angular velocity, while $C(t) = \frac{1}{R(t)}$ is the curvature.

B. Minimum-Jerk Model

The Two-Thirds Power Law presupposes a pre-planned trajectory and is primarily concerned with the execution and/or recognition of the planned or complete trajectory rather than its formation [12]. Consequently, it does not explicitly address the mechanisms underlying trajectory generation, and we exploit an alternative formalization of biological motion based on minimizing a global cost function. This cost function, expressed in Equation 4 below, prioritizes smoothness when generating movement trajectories [13].

$$CF = \frac{1}{2}\int_{t_1}^{t_2}\left[\left(\frac{d^3x}{dt^3}\right)^2 + \left(\frac{d^3y}{dt^3}\right)^2\right]dt \tag{4}$$

To enhance the social expressiveness of robots, Huber et al. [14] proposed a decoupled minimum-jerk model that incorporates a curvature parameter which allows the robot to approach the target from different angles. Thus, the decoupled approach offers greater flexibility in generating diverse and contextually appropriate motions. The decoupled minimum jerk trajectory is described by:

$$\begin{aligned} r_z(t) &= \sum_{k=0}^{5} a_{kz}t^k \\ r_{xy}(t) &= \sum_{k=0}^{5} a_{kxy}t^k \end{aligned} \tag{5}$$

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where $r_z(t)$ is the trajectory in the z direction, with duration t_z, and $r_{xy}(t)$ is the trajectory in the xy plane, with duration t_{xy}.

III. Biological Motion Trajectory Generation

The form of the motion trajectory that minimizes jerk is a fifth-order polynomial in time [15] expressed in Equation 6 below:

$$\theta(t) = a_0 + a_1 t + a_2 t^2 + a_3 t^3 + a_4 t^4 + a_5 t^5 \tag{6}$$

where $a_0, ..., a_5$ are constants.

The boundary conditions consist of the position (θ), velocity ($\dot{\theta}$), and acceleration ($\ddot{\theta}$) at the start of the movement (time = 0) and at the finish (time = d). The chosen boundary conditions are as follows:

$$\begin{aligned} \theta(0) &= p_s; \qquad \dot{\theta}(0) = 0; \qquad \ddot{\theta}(0) = 0 \\ \theta(d) &= p_f; \qquad \dot{\theta}(d) = 0; \qquad \ddot{\theta}(d) = 0 \end{aligned} \tag{7}$$

where p_s is the start position, p_f is the final position of the trajectory.

Solving for the constants $a_0, ..., a_5$, the position (θ), velocity ($\dot{\theta}$), and acceleration ($\ddot{\theta}$) are expressed as:

$$\begin{aligned} \theta(t) &= p_s + k\left[10(t/d)^3 - 15(t/d)^4 + 6(t/d)^5\right] \\ \dot{\theta}(t) &= \frac{k}{d}\left[30(t/d)^2 - 60(t/d)^3 + 30(t/d)^4\right] \\ \ddot{\theta}(t) &= \frac{k}{d^2}\left[60(t/d) - 180(t/d)^2 + 120(t/d)^3\right] \\ & \qquad\qquad\qquad\qquad 0 \le t \le d \end{aligned} \tag{8}$$

where k is the movement amplitude given by $k = p_f - p_s$.

IV. Gesture Execution and Control

Based on the expressions for joint angle position, joint angle velocity and joint angle acceleration in Equation 8 above, a trajectory generation module computed desired joint angle trajectories based on the selected gesture and its parameters. These trajectories were subsequently transformed into joint-level commands through inverse kinematics and motion control, ensuring smooth execution by a Pepper robot. The architecture of the gesture control system is shown in Figure 1.

The implementation of the biological motion for gesture execution on the Pepper robot is realised as a ROS node that provides a ROS service which listens for requests to the gesture service and executes the requested gesture based on the parameters provided. These include the gesture type, duration, angles of bowing and nodding, as well as the target coordinate for pointing in the world. To interact with the gesture service, a client node sends requests to the service with the required gesture parameters.

V. Experimental Design

A controlled within-subjects experiment was conducted to assess the impact of gestures executed using biological motion on human perceptions of the Pepper robot's social attributes. Participants were exposed to two experimental conditions without prior knowledge of the variations in the gesture execution principle in each condition.

Condition 1: Non-biological (control) gestures
In the control condition, participants observed the Pepper robot performing a set of gestures generated without the incorporation of biological motion principles. These gestures were executed using a trapezoidal motion profile, which lacked the natural fluidity and expressiveness of the biological motion profile.

Condition 2: Biological motion profile
In this condition, participants observed the Pepper robot performing a similar set of gestures using the biological motion model implemented in this research. These gestures included deictic (pointing) gestures, as well as body gestures such as bowing and nodding were designed to exhibit the principles of biological motion, which encompasses smooth, coordinated movements and natural velocity profiles.

To assess the impact of biologically inspired gestures on perceived social attributes, participants completed the RoSAS scale following exposure to both experimental conditions. This 19-item questionnaire, adapted from the original RoSAS scale [16], measured warmth and discomfort on a 7-point Likert scale. By focusing on these dimensions, the study aimed to quantify participants' immediate impressions of the robot's gestures, allowing for quantitative analysis of the potential differences between the biological motion and non-biological motion conditions

VI. Results

A. Warmth Dimension Analysis

The warmth dimension of the robot was evaluated across four criteria: naturalness, fluidity, expressiveness, and perceived friendliness. The linear velocity profile yielded a mean warmth score of 4.4973 (standard error = 0.2015, standard deviation = 0.83079), while the biological motion profile achieved a significantly higher mean warmth score of 5.4920 (standard error = 0.2007, standard deviation = 0.8276).

These results provide insights into how participants perceived the robot's gestures in terms of warmth, highlighting the effectiveness of the biological motion profile in conveying warmth in human-robot interaction scenarios. These results suggest that leveraging biological motion principles can enhance positive user experiences during human-robot interactions. Higher ratings of fluidity and naturalness indicate that biological motion helped the robot's movements appear more aligned with human motion patterns. This increased sense of familiarity and biomimicry can reduce the perception of robots as mechanical, unfamiliar entities, potentially mitigating feelings of discomfort during interactions.

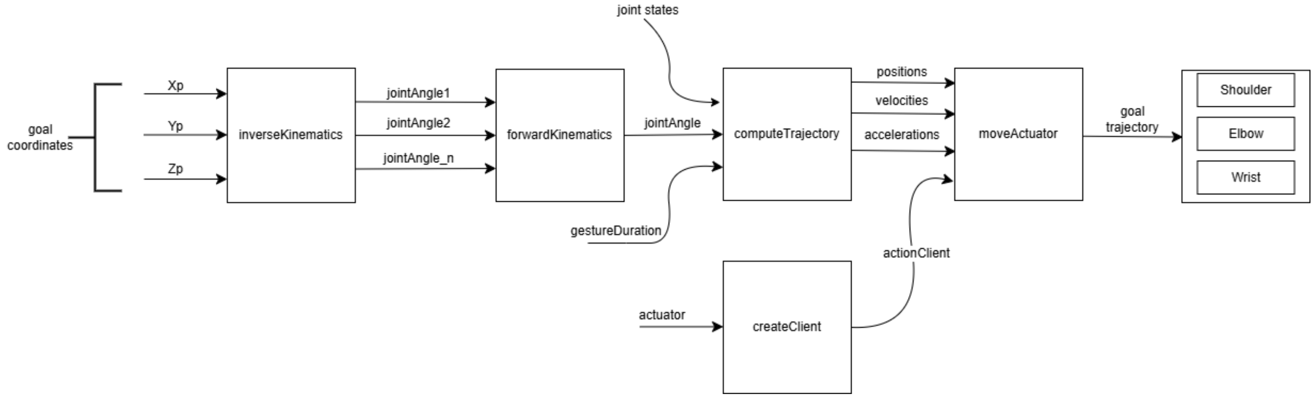

Fig. 1. Architecture of the Gesture Control System

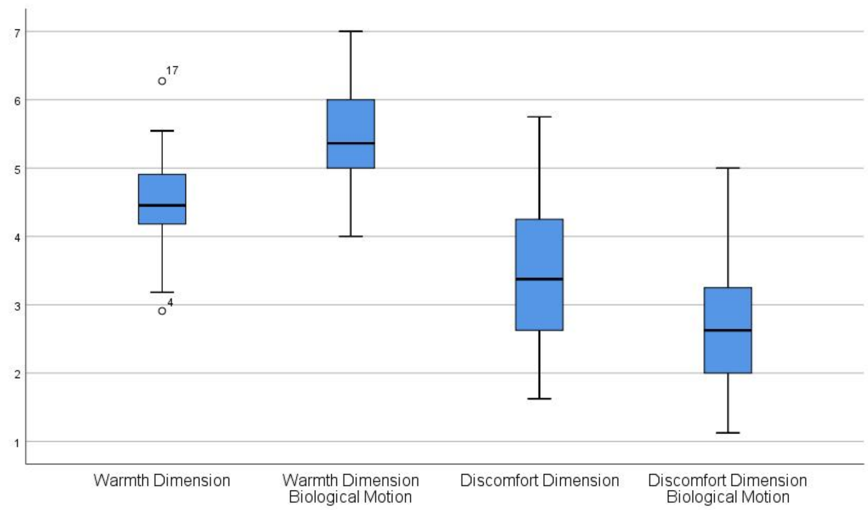

Fig. 2. Mean of Responses in the Warmth and Discomfort Dimensions of both Conditions

B. Discomfort Dimension Analysis

The discomfort dimension was assessed based on perceived unnaturalness, awkwardness, and unease. Participants rated the linear velocity profile with a mean discomfort score of 3.5147 (standard error = 0.2803, standard deviation = 1.1557), while the biological motion profile elicited significantly lower discomfort, scoring 2.5515 (standard error =0.2414, standard deviation = 0.9952). As lower scores indicate less discomfort, these results demonstrate that the biological motion condition led to a more comfortable interaction experience.

The overall comparison of the means obtained from the two conditions in both the warmth and discomfort is shown in Figure 2 above.

The findings underscore the significance of biological motion in mitigating discomfort during human-robot interactions. By reducing perceived awkwardness, unnaturalness, and uncertainty, biologically inspired gestures enhance user experience. This suggests that aligning robotic movements with human movement patterns fosters a sense of familiarity and reduces the uncanny valley effect, ultimately leading to more comfortable and engaging interactions.

VII. Discussion

This study demonstrates that using a biological motion profile, obeying a minimum jerk law, increases the perceived warmth of robot gestures compared to a linear velocity profile. Additionally, participants reported less discomfort during interactions with gestures performed using the biological motion profile. The finding that biological motion increases the perceived warmth of robot gestures aligns with previous research highlighting the importance of natural and human-like movements in enhancing the social attributes of robots.

Incorporating biological motion helps reduce the uncanny valley effect [17], a phenomenon that can lead to discomfort and aversion when robots appear almost human-like but not quite natural. By aligning robot movements with familiar human motion patterns, users are less likely to experience the unsettling feelings associated with the uncanny valley, promoting a greater sense of familiarity and reducing discomfort during interactions.

By effectively mitigating the uncanny valley effect, the integration of biological motion can enhance user experience. The resulting increased sense of familiarity and comfort fosters more natural and engaging human-robot interactions. This aligns with previous research demonstrating the positive impact of warmth and competence on user perceptions of service robots [18]. Furthermore, the phenomenon of motor contagion, as explored by Bisio et al. [19] and Breazeal et al. [20], suggests that motions with a biological profile can facilitate a deeper connection between humans and robots, leading to more spontaneous and pleasant interactions.

Overall, the incorporation of biological motion profiles into the movements and gestures of social robots holds promise for enhancing gestural communication, mitigating discomfort, and fostering more natural, engaging interactions.

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