Distinguishing Robot Personality from Motion

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ABSTRACT

The central research question of this work is can robot motion effectively communicate distinct robot personalities? In this study, we implemented three distinct robot motion personalities inspired by a subset of the seven dwarfs: Happy, Sleepy, and Grumpy. We implemented autonomous motion generation systems that mapped each personality to path shape, timing, and seeking/avoidance of the participant features. A user study demonstrated that our 24 participants could distinguish these personalities. Robot motion style predicted robot personality features such as politeness, friendliness, and intelligence, which, for the most part, matched logically to the intended dwarf personality designs. These results indicate that robot motion style is sufficient to indicate a robot's personality during its interactive behaviors with people.

KEYWORDS

Human-Robot Interaction, Robot Movement, Robot Personality

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1 INTRODUCTION

Personality is integral to creating engaging, believable and likable interactions in human-human behavior [6]. And prior research in robotics indicates robot personality can influence interaction partner engagement and trust. However, simple robots have limited communication channels to convey such personalities. While prior work has shown that simple robots can communicate via motion, this work seeks to understand if motion alone is sufficient to communicate personality.

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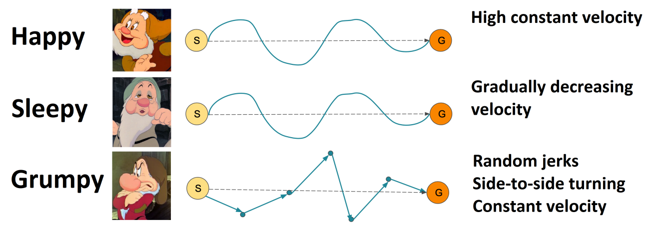

Figure 1: Trajectory examples for Happy, Sleepy, and Grumpy, whose expressive motion features including Space and Time Efforts and seeking/avoidance the participant.

To assess the potential of this approach we select the metaphor of the Seven Dwarfs from Snow White, implementing three motion 'personalities,' based on Happy, Sleepy, and Grumpy. In the original fairytale, each dwarf has a personality mapping to his name. We extend prior work on robot motion leveraging the Laban Effort System Space and Time Efforts [5], introducing a new *interest-in-people* variable, in which a robot seeks out or avoids people. We map our three personas onto this novel time-space-interest personality space, and run a study in which participants interact with each robot for several minutes at a time. The happy robot seeks them out with smooth motions at moderate speed. The sleepy robot is likely to seek people out but with a delay and slow accelerations. Finally, the grumpy robot avoids people, with erratic path motions, and a wide distribution of velocities.

We implemented our method on a Neato robot, and performed user study (*N=24*) where the robot (Neato) follows the human, while portraying different (*3*) personalities. Our user-study results show that simple variations of path shape and path execution can influence human perceptions of a robot's behavior in case of three chosen states: happy, grumpy and sleepy.

2 PERSONALITY IMPLEMENTATION

While various past works have investigated robot motion behaviors [1, 4, 8], this paper explicitly explores how to convey personality by motion behaviors alone.

2.1 Happy, Sleepy, and Grumpy

The motions designs are summarized in Fig. 1. They were designed via an informal improv session in which research team members

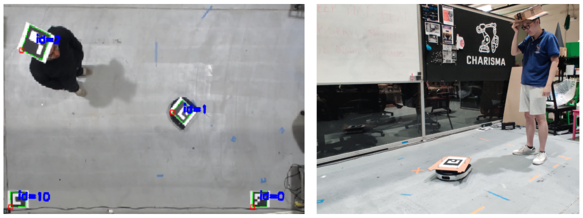

Figure 2: Experimental Setup included overhead tracking of the participant, robot and corners of the interaction area (left), and improvisational interactions between the participant and robot in each of the three personas (right).

watched videos of the drawfs, then acted out their motions. From this exercise and prior work, we conceptualized path shape (prior), velocity profile (prior), and relative motion (new). **Happy** is characterized by its sinusoidal path shape and high constant velocity, seeking out people. **Sleepy** has the same path shape as Happy but it differs in its inconsistent velocity, gradually decreasing from the starting speed, and inconsistently seeking out people. **Grumpy** is characterized by its jagged path shape, jerky velocity, and avoidance of people.

2.2 Motion Control and Localization

We implemented these motions on a Neato Botvac robot as we wanted to use a simple and minimal robot to explore motion behaviors. This vacuum cleaning robot has an onboard LiDAR sensor and a bump sensor. To control the robot, we used a Raspberry Pi with ROS (Robot Operating System) running on it. Our experimental space setup (see Fig. 2) uses overhead cameras and ArUco markers [3] [7] to estimate the pose of the robot, human, and the boundaries of the arena. We implemented pursuit path planning, which is based on the assumption that it is easier for a robot to move in arcs compared to sharp turns[2].

3 USER STUDY

The within-subjects experiment consisted of three trials, with counterbalanced order across participants. Upon arrival, they were oriented to the space and boundaries. We instructed them to move around in the space while observing the robot's motions. Each trial lasted for 90 seconds, and the robot would use its current personality to set its motion generation style. Participants rated the robot politeness, friendliness, and intelligence after each trial using 5 point anchored scales (impolite/polite, unfriendly/friendly, and dumb/intelligent). After all trials were complete, there was an interview asking the participant to describe each robot, discuss its motion, and identify what kind of personality each robot seemed to have, individually and in contrast.

4 RESULTS

The final dataset included 24 participants. This section presents ANOVA results assessing the impact of motion personas on participant interpretations of robot personality.

Impolite/Polite: Robot personality significantly impacted politeness ratings (*$F(2,69)= 7.47$, $p = 0.00116^{**}$*). Grumpy was rated the least polite (mean= 2.38 out of five), with Happy (*mean = 3.38*) and

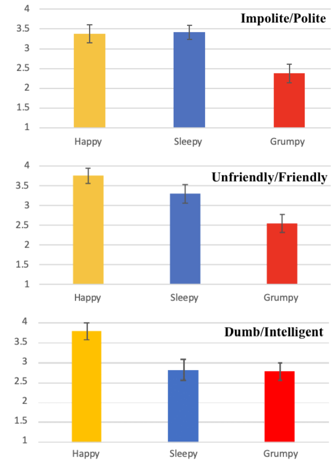

Figure 3: Participant Ratings of Motion Personas

Sleepy (*mean = 3.42*) just above neutral. These survey ratings act as partial manipulation checks, in that Grumpy was found to be least polite, which seems consistent with their dictionary definitions. Interestingly, however, Sleepy was rated most polite, perhaps because of its smooth acceleration and lower velocity.

Unfriendly/Friendly: Personality also significantly predicted friendliness ratings (*$F(2,69)= 7.57$, $p = 0.00107^{**}$*) ratings. As we hypothesized, the participants rated Happy (*mean = 3.75*) the highest, followed by Sleepy (*mean = 3.29*), and then Grumpy (*mean = 2.54*). This supports our hypothesis that Happy will generate positive feelings which will result in it being rated positively. Many of our participants commented on how Happy followed them much like a pet or a younger sibling would.

Dumb/Intelligent: Surprisingly, we found that motion personality significantly predicted intelligence (*$F(2,69)= 6.22$, $p = 0.00329^{**}$*) ratings. Happy (*mean = 3.79*) was rated the highest for intelligence followed by Sleepy (*mean = 2.83*) and Grumpy (*mean = 2.79*) which were rated about the same. We speculate that this may have something to do with the responsiveness and attentiveness of the robot in the happy condition.

5 CONCLUSION

This work implemented three distinct robot personalities – happy, sleepy, and grumpy – to evaluate whether people could distinguish robot personality from motion behaviors alone. We implemented autonomous motion generation systems for each, extending prior work in expressive motion with Laban Space and Time Efforts to the addition of an interest-in-people feature. Results from our within subjects experiment show that participants were able to distinguish the motion-based personas. Participants rated Grumpy as the least polite and least friendly, and Happy as most friendly and intelligent, consistent with their fairytale cognates. It also finds that motion style had an unexpected impact on people's intelligence ratings of the robot, which could potentially be used to decrease user trust in autonomous systems in cases where there is unreliable perception. We hope to extend this implementation to all seven dwarfs in the future, and assess the role of robot motion personality in the context of particular robot tasks.

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