A Lasting Impact: Using Second-Order Dynamics to Customize the Continuous Emotional Expression of a Social Robot

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ABSTRACT

Robots are increasingly being developed as assistants for household, education, therapy, and care settings. Such robots need social skills to interact warmly and effectively with their users, as well as adaptive behavior to maintain user interest. While complex emotion models exist for chat bots and virtual agents, autonomous physical robots often lack a dynamic internal affective state, instead displaying brief, fixed emotion routines to promote or discourage specific user actions. We address this need by creating a mathematical emotion model that can easily be implemented in a social robot to enable it to react intelligently to external stimuli. The robot's affective state is modeled as a second-order dynamic system analogous to a mass connected to ground by a parallel spring and damper. The present position of this imaginary mass shows the robot's valence, which we visualize as the height of its displayed smile (positive) or frown (negative). Associating positive and negative stimuli with appropriately oriented and sized force pulses applied to the mass enables the robot to respond to social touch and other inputs with a valence that evolves over a longer timescale, capturing essential features of approach-avoidance theory. By adjusting the parameters of this emotion model, one can modify three main aspects of the robot's personality, which we term disposition, stoicism, and calmness.

KEYWORDS

social robots, robot emotions, internal emotional state, long-term mood, affective model, social touch

ACM Reference Format:
Rachael Bevill Burns and Katherine J. Kuchenbecker. 2023. A Lasting Impact: Using Second-Order Dynamics to Customize the Continuous Emotional Expression of a Social Robot. In *Proceedings of HRI '23: ACM/IEEE International Conference on Human-Robot Interaction (HRI '23).* ACM, New York, NY, USA, 5 pages. https://doi.org/10.1145/1122445.xxxxx

1 INTRODUCTION

Robots may soon join our daily interactions as home assistants, companions, educational tutors [10], and therapy aids [20]. While meeting a new robot is often exciting, its novelty can wear off quickly [14]. It is important for such robots to maintain user interest over a sustained period of time in order to maximize the benefits of their use, such as completing an educational game series [22] or a physical therapy regimen.

One effective way to promote long-term human-robot interaction (HRI) is to create robot behaviors that mirror aspects of human-human interaction [3]. In particular, robots can convey emotions during social interaction to increase their perceived naturalness (i.e., how similar the robot's behaviors are to what the user expects), attentiveness (i.e., how much the robot detects its environment), and engagement (i.e., how it reacts to the detected input) [5]. In many user studies, the robot is controlled by a human operator to provide fast and appropriate emotional responses [12]. However, teleoperation is not a sustainable method of interaction for autonomous robots. In other research approaches, either the robot's affective state (i.e., its simulation of emotion) is a fixed routine, regardless of user interaction, or the robot's affective state is instantly changed by user action, usually to reward certain user behaviors [11]. These approaches neither demonstrate situational awareness from the robot nor adapt with the user, and therefore they may not promote long-term interaction. While complex emotion models do exist, they have been only partially implemented in robots [25] or have solely been implemented with virtual chat agents [24]. There is a clear need for a *robust and customizable method that enables a robot to produce dynamic emotion responses that are believable and adapt with the interaction.* Furthermore, the limited computational resources available onboard mobile robots favor simple solutions.

We address this need by introducing a mathematical model for the emotions of a robot undergoing short-duration external stimuli such as physical contact, which could be pleasant, neutral, or aversive. We represent the robot's internal affective state over time as the present position of a mechanical second-order dynamic system, i.e., a mass connected to ground through a spring and damper in parallel. Modifying the parameters of this model enables us to customize specific attributes of the robot's personality so that it can emotionally respond to the same series of stimuli in substantially different ways. This approach produces a robot that can react to external stimuli over long periods of time, producing a smooth emotional response that is more realistic and dynamic than previous hard-coded representations.

In the remainder of this paper, we highlight related work in Section 2, we explain the mathematical model of our emotion response system in Section 3, and we discuss its future potential in the fields of robot personalization and adaptivity in Section 4.

HRI '23, March 13–16, 2023, Stockholm, Sweden

ACM ISBN 978-x-xxxx-xxxx-x/YY/MM.
https://doi.org/10.1145/1122445.xxxxx

2 RELATED WORK

2.1 Adaptation and emotion in social robots

Robots can use adaptive behavior to maintain user engagement and be perceived as intelligent social agents [22, 26]. Beyond adapting its behavior, a robot can also display emotions to make the user aware of its internal state, to reinforce a user's action, or even to guide the user to a goal behavior [3]. For example, the robot seal PARO coos pleasantly in response to gentle touches, and it cries when handled with a high level of force [1]. Emotional display directly improves user interaction: children reacted more expressively and positively toward a NAO with a teleoperated emotion model than with its non-emotive counterpart [27]. The autonomous Roboceptionist by Kirby et al. used emotions, moods, and long-term attitudes toward repeat visitors (identified by a swipe of their university ID cards) during chat-based interactions [13]. Users significantly changed their interactions with the robot based on its mood, hinting at the power of this capability for social robots.

Within the study of emotion usage for social robots, there has been a strong focus on human recognition of and responses to static robot emotions, rather than methods for building dynamic emotion systems that change over time [4, 25]. This focus on static emotions may be due to the fact that existing computational emotion models are complex, multi-faceted, and difficult to translate to a different robotic platform. There is a need to develop emotion systems that allow for the easy adjustment of personality parameters, demonstration of the internal affective state over increasingly long time scales, and usability across a variety of robotic systems.

2.2 Existing computational emotion models

Ojha et al. provide a thorough review of existing computational models of emotion from the last two decades [19]. However, several of these models have been implemented with virtual agents [23] rather than on physical robots, and they typically focus on providing lifelike visual responses to text- or chat-based input [2, 8], which are complex and highly cognitive. Some models utilize machine-learning approaches, such as a Gaussian mixture model [15] or a series of neural networks [6], to recognize and reproduce the user's emotional cues or otherwise adjust the robot's affective behavior.

The TAME Framework by Moshkina et al. [18] aimed to create an affect model for physical robots composed of traits (T), attitudes (A), moods (M), and emotions (E). Each of these four categories is affected by both internal and external factors over varying time scales, with fundamental traits remaining constant over time, attitudes changing very slowly, moods changing over the course of a day, and emotions changing quickly in reaction to immediate stimuli. Two proof-of-concept user studies with partial implementations of the framework showed preliminary success, with the traits and emotion components enabled in the dog-like robot AIBO [17] and a simple demonstration of mood and emotion enabled in the humanoid robot NAO [16]; however, the existing equations for the individual categories are complex, and no code is provided for replication or adaptation by other researchers. Thus, inspired by the TAME framework, we sought to create an efficient mathematical model in which emotional state is affected by internal and external factors across multiple time scales and that is easy to implement on real robots.

2.3 Approach-avoidance theory

To facilitate high-quality HRI, we aimed to develop a robot emotion model that is rooted in behaviors that can be observed in nature. Approach–avoidance theory is a well-validated theory in psychology which states that when an organism receives a positive stimulus (i.e., something which supports survival), it feels a positive emotion, which motivates approach behaviors, such as lifting arms and cooing for a baby. A negative stimulus (i.e., something which hinders survival) elicits a negative emotion and motivates the organism to avoid and withdraw [9].

Furthermore, approach-avoidance theory explains that intense emotional responses tend to be bi-phasic: if a very negative stimulus is presented and then removed, the emotional state not only returns to neutral, but also temporarily springs up to a positive state [7]. Conversely, the removal of a very positive stimulus can result in a negative mood. For example, a person might feel negative emotions while they are sick or injured. When they are healthy again, they not only no longer feel negative, but they also feel even more positive and more appreciative of their good health than they did before the illness began. This pattern suggests that a robot's emotional state should have this property of bouncing back beyond neutral after spending a longer duration of time either positive or negative.

By using an emotion model consistent with approach-avoidance theory, robots can produce naturalistic responses during social interactions, which is especially important for robots in heavily social roles such as a peer-like tutor, an empathetic caretaker, or an attentive animal companion.

3 MATHEMATICAL EMOTION MODEL

Dynamic systems describe how natural phenomena evolve over time, such as the flow of water through pipes or the population of a community. Since such dynamics can easily be computed over time, they are a natural choice for a robot emotion model.

Widely used in psychology and HRI, Russell's Circumplex of Affect describes emotions across a continuous scale in two dimensions [21]. The first dimension, valence, refers to the positive or negative feeling of the emotion, and the second, arousal, refers to its energy level. We currently focus on modeling the valence dimension of a robot's emotional state over time; it can take any value between -100 and 100. For visualization, we draw the valence as the height of the robot's mouth. At maximum positive valence the robot has a perfect concave-up semicircle for a smile, and the inverse is true for maximum negative valence.

3.1 Appropriate model order

Different natural phenomena can be best represented by dynamic systems of varying orders; we explore their suitability for HRI in Fig. 1. Simple reactions, where the robot's affective state is a single response instantly called by the user's action, can be represented as a zeroth-order system. The output (here, the robot's valence) is proportional to the input (the external stimulus); a mechanical analogue is a linear spring with no mass or damper, which deflects as soon as a positive or negative force is applied. However, as noted in approach-avoidance theory, adding or removing a stimulus does not cause only a single, instantaneous, hard-coded response – rather, it also causes the organism's internal state to be propelled toward a more-lasting mood. Therefore, a zeroth-order system is not the best way to represent natural emotions.

A first-order mechanical system has stiffness and damping, but it does not have mass. Therefore, it does not tend to oscillate. This

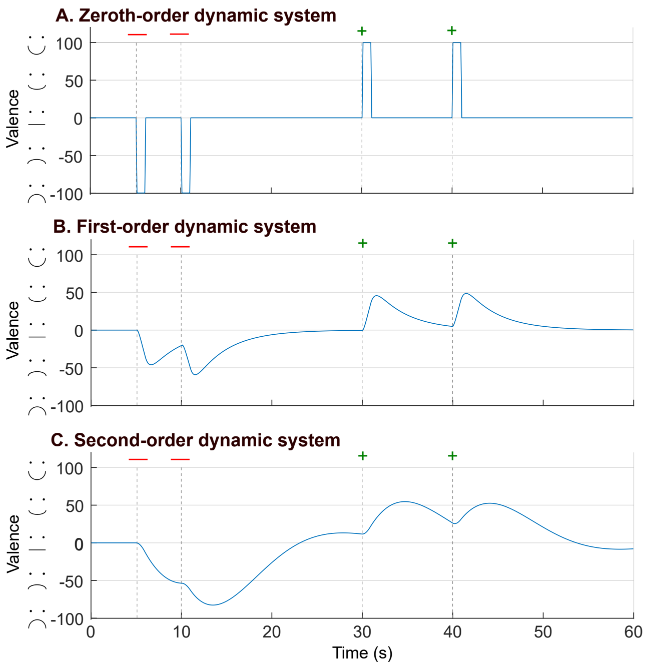

Figure 1: Modeling a robot's internal affective state using dynamic systems of increasing orders. The – and + symbols indicate negative and positive stimuli, respectively.

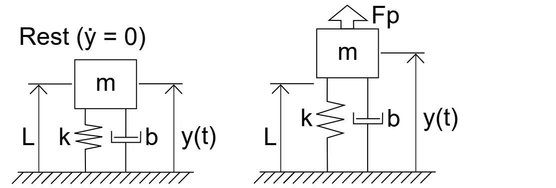

Figure 2: Our emotion model can be represented as a mass-spring-damper system. We illustrate its properties both at rest (left, $y(t) = L$) and when past force pulses have moved the mass away from its neutral position (right, $y(t) > L$).

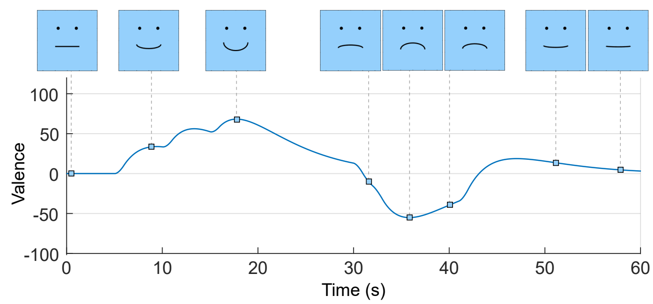

Figure 3: The height of the robot's smile or frown directly corresponds to the internal valence. Blue squares indicate the valence that corresponds with the picture above it.

order of system can represent richer emotions than a zeroth-order system because it maintains some memory of past experiences over time. As depicted in Fig. 1, we need a second-order system to have the oscillation feature described in approach-avoidance theory.

3.2 Second-order dynamic system

The robot's valence is modeled as a linear second-order dynamic system with a point mass, a spring stiffness, a rest length for the spring, and damping (energy dissipation). The mass's position along the y-axis represents the robot's current affective state. External stimuli, such as visual user gestures, user dialogue, or touch contacts like petting or hitting, cause positive or negative force pulses that act on the mass and evoke an immediate emotional reaction from the robot. Furthermore, these pulses propel the mass along the y-axis and therefore also change the robot's mood over time. Importantly, these stimulus events influence the affective state toward a certain direction, but they do not teleport the robot instantly to a different affective state. This approach provides the robot with emotional memory, and its behavior is influenced by the entire recent history of interactions it has experienced.

A diagram of the mass-springer-damper system we use to represent the emotion model can be seen in Fig. 2. Using Newton's second law, the sum of the forces currently acting on the mass, m, can be related to the mass's instantaneous acceleration, $\ddot{y}$, as:

$$F_s + F_d + F_p = m\ddot{y}, \tag{1}$$

where F_s represents the force applied by the spring, F_d is the force applied by the damper, and F_p is the fixed-duration force pulse currently being generated by external stimuli, if any exist. To show linear stiffness and damping, this equation can be expanded out as:

$$-k(y - L) - b\dot{y} + F_p = m\ddot{y}, \tag{2}$$

where k is the spring constant, y is the position of the mass, L is the mass position where the spring exerts no force, b is the damping coefficient, and $\dot{y}$ is the mass's velocity. Finally, this equation can be rewritten in the form of a second-order differential equation as:

$$\ddot{y} + \frac{b}{m}\dot{y} + \frac{k}{m}(y - L) = \frac{F_p}{m}. \tag{3}$$

In the absence of force pulses, and assuming b, k, and m all have positive values, the mass will always return to the position L, pulled there by the spring, with oscillations calmed by the damping.

We provide a demonstration of our system in Fig. 3, where one can see the internal emotion level of the robot over time. In this example, a small illustration of a robot face changes in real time simultaneously as the graph is plotted; we show the robot's expression at eight timestamps. Though facial expression is convenient, a robot could use many other approaches to display its present valence level, such as ambient color, body posture, and sounds.

3.3 Customizing the robot's personality

We can adjust selected parameters to customize how the robot's emotional state changes in response to stimuli. First, we can calculate the natural frequency of this second-order system as $\omega_n = \sqrt{\frac{k}{m}}$. We can then determine whether the system is over-, under-, or critically damped by calculating its damping ratio as $\zeta = \frac{b}{2m\omega_n}$. A robot with an overdamped emotion model ($\zeta \gg 1$) may appear non-responsive, whereas one that is too underdamped ($0 \leq \zeta \ll 1$)

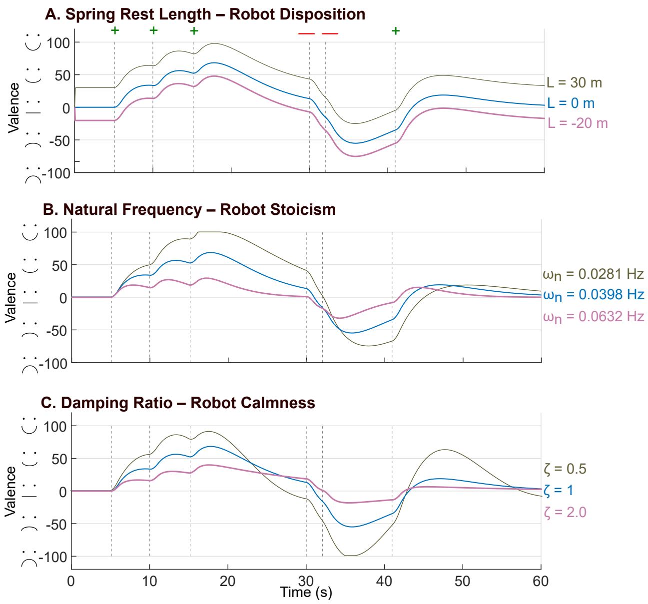

Figure 4: In each subplot, one parameter is changed to showcase how the robot's response to stimuli can be customized. All graphs use $m = 1$ kg, $F_p = 30$ N, and pulse duration $T = 1.0$ s. The middle blue trial is the same for all three subplots.

will experience large oscillations in its affective state and may appear erratic. As a small amount of oscillation is needed to mimic the bi-phasic response observed in approach-avoidance theory, we are most interested in damping ratios close to 1.

Depending on how the parameters of the emotion algorithm are tuned, the robot can display different personalities and responses. To display the versatility of this approach to modeling robot emotions, we present a fictional scenario in which a user interacts with a robot over the course of one minute. Fig. 4 shows the robot's affective state in response to the described touch inputs. Each of the three subplots highlights how increasing and decreasing the value of a single parameter affects the robot's response. We provide a baseline parameter setting (the middle trial) that is identical across all three graphs. The user starts by stroking the robot three times (at 5 s, 10 s, and 15 s), which the robot perceives as positive touches. Then user then tries tickling the robot's feet (at 30 s and 32 s). The robot reacts negatively. Once the user realizes the robot didn't like this interaction, they attempt to console the robot by petting its head (at 41 s), to which the robot reacts positively.

We encourage the reader to carefully study Fig. 4 to see how the robot's reactions in this story change as each parameter is adjusted. For example, the value of the spring rest length L determines the default valence to which the robot will always return. We associate this parameter with the **robot disposition**; setting a positive L creates a positive robot, whereas a robot with a negative L will have a negative valence when left alone. As we keep the mass constant, changing the natural frequency ω_n adjusts the stiffness of the spring, which dictates how much the valence changes for the same input, as well as how quickly the system oscillates. We call this term **robot stoicism** – how strongly a robot resists reacting to external stimuli. A higher ω_n leads to a more stoic robot, whereas a robot with a lower ω_n reacts more and takes longer to return to its default L. Finally, the damping ratio ζ calms oscillations in the affective state of the robot and by extension controls **robot calmness**. An underdamped system produces a robot whose mood shifts dramatically and who appears to overreact, whereas an overdamped system produces a robot who appears calm and measured.

4 FUTURE WORK

We believe that this simple second-order model provides a powerful tool for simulating robot emotions and can be used to render a range of personalities for social robots. However, one can investigate even more concepts than what we have introduced here.

One could modify how external stimuli generate force pulses upon the system. For example, the sample touch stimuli we showed had the same magnitude for each of their force pulses. However, different stimuli could provide different magnitudes of force pulses. In the case of social touch, the force pulse generated could be a function of the type of social touch detected, the location on the body, and the amount of physical force applied by the user. Additionally, one could change the robot's internal reaction to external stimuli based on its current valence or the interaction context. For example, a robot that currently has a negative valence could react negatively to an ambiguous stimulus (e.g., tickling), while it could react positively to the same stimulus when at a positive level.

We used a dynamic smile to visualize the robot's valence, but other expression modalities could also be used. For example, we will conduct a study in which a NAO robot uses our emotion model in comparison to zeroth-order and first-order models to react to various social touches. Our NAO will embody its affective state using body posture and movement, and it will respond to touches using gestures (e.g., cheering movements or covering its face) and vocalizations. Participants will rate how lifelike, engaging, and appealing NAO appears in each condition.

Our model currently represents only the robot's valence; one could add a second axis with its own dynamics to represent the robot's arousal. Each stimulus could then influence both valence and arousal in positive, negative, or neutral ways, providing a potentially powerful platform for generating interesting social interactions over time. Furthermore, an operator could manually tune the robot's disposition, stoicism, and calmness over time to update the robot's behavior for personalized interaction. Alternatively, the model parameters could adapt automatically based on the user's interaction history. For example, a robot that consistently received positive stimuli could shift from a neutral default disposition to a positive one. Indeed, there are many avenues that can be explored by using this adaptable and accessible emotion model. Having a robot react to external stimuli in a customizable way has the potential to provide a plethora of new experiences for human-robot interaction.

ACKNOWLEDGMENTS

The authors thank the International Max Planck Research School for Intelligent Systems (IMPRS-IS) for supporting Rachael Burns, and they thank Mayumi Mohan for helping with the face animation.

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