Emotion-Aware and Entitativity-Optimized Socially Invisible Robot Navigation with Acceptable Interactions

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***Abstract*— This paper introduces an integrative, real-time algorithm that harnesses the principles of both entitativity-based navigation and emotion-aware strategies to guide robots seamlessly in social environments. Building upon the psychological tenets of entitativity and the Pleasure-Arousal-Dominance (PAD) model, our approach predicts human emotional states and adjusts robot behaviors to ensure socially invisible interactions. By synchronizing the estimation of group-like perceptions with emotion detection like facial cues and trajectories, we aim to achieve efficient navigation while minimizing negative emotional reactions. Our method is validated in simulated environments, demonstrating its potential to ensure that multi-robot systems not only move inconspicuously but also respect human emotional spaces.**

I. INTRODUCTION

Navigating among humans is both a physical and social challenge. As robots aim to avoid physical collisions, they must also acknowledge humans as dynamic entities with emotions and intentions. Recognizing and respecting these emotions is critical for socially normative robot navigation. On the other hand, as multi-robot systems become prevalent, their collective movement might evoke feelings of unease or threat among pedestrians due to high entitativity, emphasizing the need for strategies that can mitigate these perceptions.

The proliferation of robots in our daily environments has opened new challenges in ensuring they move harmoniously and unobtrusively among humans. Previous works have separately highlighted the importance of minimizing robot group-like perceptions [1] and the necessity of being cognizant of human emotions for socially acceptable navigation [2]. In this paper, we bridge these paradigms to pioneer an approach that simultaneously minimizes the robot's social visibility while being emotionally intelligent.

By amalgamating insights from entitativity research with emotion detection techniques, our method proposes a holistic framework for robot navigation that prioritizes human comfort and emotional well-being. This fusion seeks to ensure that robots, whether moving individually or in groups, remain sensitive to the emotional states of humans, adjust their trajectories accordingly, and avoid patterns that might seem threatening or unnerving.

Building upon the robust computational techniques and user studies from prior works, our methodology offers a novel perspective on robot-human interaction, ensuring that our mechanical counterparts not only move efficiently but also remain emotionally attuned and socially inconspicuous. Figure 1 shows an overview of our approach.

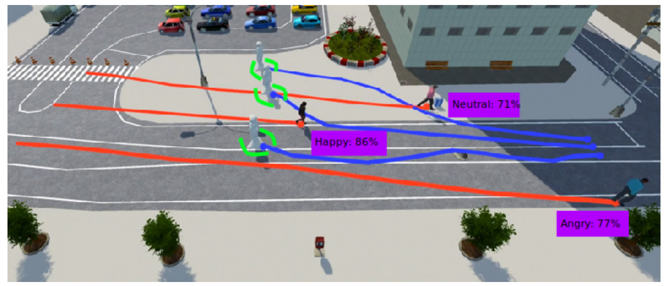

Fig. 1: *In this multi-robot system approach, humans are marked with red trajectories & robots are marked with blue. Our novel algorithm predicts human emotional states (marked in purple) and adjusts the robot's behavior (in green arcs) taking into account various levels of physical and social constraints.*

II. RELATED WORK

Humans inherently perceive social interactions as a critical aspect of their experience. This involves complex brain interactions to navigate the social landscape. Delving into how humans perceive groups reveals unique patterns.

A. The Psychological Perspectives on Group Dynamics & Emotions

The group context plays a pivotal role in shaping human behavior, with certain social dynamics leading to adverse outcomes, particularly in group perceptions [3]. Extensive research indicates humans often exhibit increased negativity towards groups than individuals [4], experiencing emotions such as hostility, fear [5], and threat. These emotional reactions, especially when directed at both humans and robots [[6], can have profound implications. Additionally, the burgeoning field of computer vision and AI has made strides in emotion recognition from facial expressions, predominantly using neural networks and datasets like FER [7]. Liu et al. [8] introduced a novel training model, the Boosted Deep Belief Network (BDBN), while EmotioNet catered to a vast spectrum of facial expressions. Furthermore, pedestrian trajectories, including variations in speed and direction, provide invaluable insights into their emotional states and anticipated actions [9] This aspect remains relatively untapped, with limited studies focusing on extracting emotions from movement patterns.

B. Behavior Modeling of Pedestrians

Modeling pedestrian behavior remains a central theme in psychology, robotics, and autonomous driving research [10].

Several methods aim to capture the heterogeneous nature of crowd behaviors, especially those based on personality traits [11]. The intersection of behavior modeling with the robot's ability to navigate socially and emotionally presents a promising frontier for future advancements.

C. Robot Navigation: Physical and Social Awareness

Historically, robot navigation in pedestrian settings was heavily centered on physical constraints, including collision avoidance [12]. Systems have emerged that enable robots to autonomously navigate urban environments, with some even eliminating the need for GPS data, as evidenced by Buss et al. [13]. Fan et al. [14] addressed specific challenges in robot navigation, such as freezing. Collision-avoidance techniques have evolved, ranging from potential-based methods [15], and probabilistic approaches [16], to loop-receding horizon controls. Faisal et al. [17] notably optimized travel time using fuzzy logic controllers.

Building on these foundations, there has been a surge in socially aware robot navigation research [18]. Many solutions, such as those predicting pedestrian movements and interactions with robots [19] and [20], derive from models accounting for social dynamics. Crucially, there's been a concerted effort to make robots more in tune with social norms [21] and [22], taking cues from how humans adapt their paths based on perceived emotions and societal conventions. Emphasizing the significance of personal space and social constraints has also been a focus in this research [23] and [24].

Our study stands at the crossroads of these developments, pioneering the integration of facial expressions, trajectory data, and established navigation techniques for a more nuanced, socially-aware robot navigation system.

III. OVERVIEW AND METHODOLOGY

Much of our methodology is heavily inspired by the work of Bera et al. [2]. This paper serves as an extension to their work.

A. Emotion Learning

1) Emotion State: Building upon the psychological tenets of the Pleasure-Arousal-Dominance (PAD) model, our integrative, real-time algorithm categorizes emotions into three dimensions: Pleasure, Arousal, and Dominance. This study primarily focuses on the pleasure and arousal dimensions, thereby classifying into four fundamental emotional states: happy, angry, sad, and neutral.

To achieve a cohesive understanding of the robot's surroundings, we utilize parameters primarily sourced from the robot's front-facing sensor. These parameters about the pedestrians and the robot itself are then monitored and represented:

- Pedestrian state, $\boldsymbol{x}_p$, merges emotion attributes, positional data, facial features, and velocity. This representation not only captures the physical location and motion of the pedestrian but also their emotional state.

$$\boldsymbol{x}_p = [\boldsymbol{p}_p, \boldsymbol{v}_p^c, \boldsymbol{f}, \boldsymbol{v}_p^{pred}, \boldsymbol{E}^f, \boldsymbol{E}^t]^T$$

  where $\mathbf{p}_p$ is pedestrian's position, $\mathbf{v}_p^c$ is the current velocity of the pedestrian, $\mathbf{f}$ is the facial feature vector derived from the CNN, $\mathbf{v}_p^{pred}$ is the predicted velocity or direction of the pedestrian, $\mathbf{E}^f$ is the emotion vector derived from facial features, and $\mathbf{E}^t$ is the emotion vector derived from trajectories. While the typical walking pattern of pedestrians is largely straight with average speeds of 1.2 to 1.4 meters per second, deviations from this pattern, such as abrupt changes in direction or speed, can hint at emotional states such as distress or urgency. However, this method is supplementary and primarily used in conjunction with facial emotion detection to enhance the accuracy of the model.
- Robot's state, $\boldsymbol{x}_r$, comprises its position and its velocity data. This information is critical for determining the robot's navigation decisions.

$$\boldsymbol{x}_r = [\boldsymbol{p}_r, \boldsymbol{v}_r^c, \boldsymbol{v}_r^{pref}]^T$$

  where $\boldsymbol{p}_r$ is the robot's position, $\boldsymbol{v}_r^c$ os the current velocity of the robot, and $\boldsymbol{v}_r^{pref}$ is the preferred or target velocity of the robot.
- Emotional labeling, represented by 'e', provides a preliminary classification of detected emotions and plays a pivotal role in understanding the pedestrian's state of mind. This labeling, 'e', is derived using a comparison among different emotional scores.

$$e = \left\{ \begin{array}{ll} \text{happy}, & \text{if } (h > a) \land (h > s) \land (h > \theta) \\ \text{angry}, & \text{if } (a > h) \land (a > s) \land (a > \theta) \\ \text{sad}, & \text{if } (s > h) \land (s > a) \land (s > \theta) \\ \text{neutral}, & \text{otherwise} \end{array} \right\}$$

  In the equation above, h, a, and s represent scores for happy (*high pleasure, high arousal*), angry (*low pleasure, high arousal*), and sad (*low pleasure, low arousal*) emotions, respectively. The thresholds and conditions for determining 'e' were derived from preliminary tests, where different emotional states were artificially induced and analyzed. The threshold value of θ = 0.55 was empirically determined through iterative testing to ensure that a detected emotion is pronounced enough to be taken into account.

2) Data Acquisition: For effective emotion detection, data is primarily sourced through:

- A dual camera setup, which offers a more comprehensive visual feed, capturing the nuances of facial expressions and trajectories better.
- Facial emotions are deduced from trajectories and facial features. The trajectory can reveal a lot about a pedestrian's state. For instance, erratic movement might indicate distress or urgency.

3) Emotion Learning Methodologies: The dual approach of deducing emotions from trajectories and facial features ensures a holistic understanding:

1) Path Trajectories: This is a novel approach where emotions are deduced based on how people move. Some emotions result in characteristic movement patterns.

- Variables such as Planning Horizon (how far ahead the pedestrian is planning), Effective Radius (personal space around the pedestrian), and Preferred Speed (usual walking speed) are influential.

2) From Facial Features: Direct emotion detection from facial expressions.
   - A CNN rooted in the Xception architecture provides state-of-the-art emotion detection. The depth-wise separable convolutions guarantee efficient and fast processing.
3) Joint Pedestrian Emotion Model: The formula for E, given by equation (1), is derived from a weighted average of trajectory-based emotion and facial-based emotion. The weights α and β were derived empirically from initial testing to ensure an optimal balance between the two methods.

$$\boldsymbol{E} = \frac{\alpha \boldsymbol{E}^t + \beta \left(\max(\boldsymbol{E}^f) + 1/2 \right) \boldsymbol{E}^f}{\alpha + \left\lfloor \max(\boldsymbol{E}^f) + 1/2 \right\rfloor} \tag{1}$$

The factor α is a weight parameter that can be adjusted based on the environment and the perceived accuracy of each method, while β is a weight parameter that adjusts the influence of the PAD model in the emotion vector. This equation ensures that the emotion vector $\boldsymbol{E}$ is a balanced mix of trajectory-based emotion $\boldsymbol{E}^t$ and facial-based emotion $\boldsymbol{E}^f$.

B. Entitativity and Social Navigation

1) Entitativity: Entitativity is a groundbreaking concept pivotal to our integrative, real-time algorithm. It focuses on the perception of groups as cohesive entities, a crucial factor in determining robot navigation strategies within groups of pedestrians. Leveraging this understanding, our approach emphasizes entitativity-based navigation to guide robots seamlessly in social environments.

The navigational decisions are influenced by various parameters related to the crowd, robots, and their states. Systematic definitions of these terms ensure consistency in algorithm design:

- Emphasis is laid on defining terms like 'Crowd', 'Pedestrians', 'Robots', 'State', and 'Motion Model' which are central to understanding robot navigation. These terms cover aspects like the number of entities, their positions, velocities, and emotional states.
- Parameters such as "Neighbor Distance" (distance from a robot to the nearest pedestrian), "Radius" (defines the robot's personal space), "Group Cohesion" (degree to which pedestrians are moving together), and "Preferred Speed" (optimal speed the robot wants to achieve) are carefully elaborated upon.

2) Entitativity Metric: This metric quantifies the perceived entitativity of a group by observers. It incorporates emotional responses like 'Friendliness' (how friendly the group seems), 'Creepiness' (the degree to which the group seems unsettling), 'Comfort' (level of ease or discomfort the observer feels), and 'Unnerving' (the degree to which the group seems intimidating). This metric aids the robot in deciding whether to navigate through a group or around it.

3) Data-Driven Robot Entitativity (EDM): This novel approach is rooted in the perception of robots as provided below:

- Study Goals: The primary objective is to understand how humans perceive robots when they move in groups, factoring in different movement parameters like speed, proximity, and alignment.
- Experimental Design: Participants are shown videos of robots moving in various formations and patterns. Post viewing, participants assess robots based on their perceived entitativity attributes.
- Analysis: After collecting the data, an entitativity mapping is created, symbolized by the matrix G_{mat}. This mapping will aid in predicting human perception of robot entitativity based on movement parameters.

4) Socially-Invisible Navigation: Our algorithm's cornerstone is the concept of socially-invisible navigation, ensuring that robots move unobtrusively without causing social disturbances. Using principles of entitativity-based navigation combined with emotion-aware strategies, the robot adjusts its behavior in real-time. By predicting human emotional states using the PAD model, our approach tailors the robot's movement to maintain the desired invisibility level, promoting harmonious human-robot interactions in shared spaces.

- Robots adjust their actions to match the desired level of social invisibility. This ensures that the robot's movement is perceived as natural and doesn't draw undue attention.
- The desired level of social invisibility is symbolized by a scalar 's'. The entitativity matrix G_{mat} assists the robot in tuning its movement parameters to achieve this target level.

$$A(s) = \sum_{i=1}^{n} s_i \times g_{mat,i} + \gamma E \tag{2}$$

where s_i represents the robot's state in the shared space, γ is a coefficient that weighs the influence of the PAD-based emotional state in the robot's navigation.

By adjusting the coefficients β in (1) and γ in (2), our navigation algorithm, which is based on potential field methods for obstacle avoidance, can dynamically alter its behavior in real-time based on the context. This dynamic adaptation ensures that the robot maintains optimal social invisibility while navigating through various pedestrian densities.

The core of our socially invisible navigation is based on potential field methods, wherein pedestrians and robots are treated as obstacles with potential fields. The combined potential field dictates the robot's navigation decisions. The strength and influence of these potential fields are modulated based on the derived emotional states, ensuring that the robot respects both physical and emotional boundaries.

Conclusively, by fusing emotion detection and the principles of entitativity, this research delineates a powerful model for robot navigation. The overarching objective is for robots to be emotionally in sync and to maintain the desired invisibility level. This ensures a harmonious human-robot coexistence in shared spaces.

IV. RESULTS AND ANALYSIS

A. Participant Interaction Analysis

We had the participation of 8 individuals, instructing them to emulate and walk exhibiting specific emotions. It is worth noting that both non-actors and actors have been demonstrated to effectively represent various emotions through their walking patterns [25]. Independent of the accuracy of emotional representation by participants, observations were recorded. A significant majority reported a comfort level with the robot's presence. Intriguingly, participants portraying sadness felt that the robot allocated a wider berth for them to pass. Meanwhile, those exhibiting anger felt the robot yielded their path more promptly. Emotions such as happiness and neutrality led to less marked differences, although some participants identified a slight reduction in the robot's pace.

B. Quantitative Evaluation

In our analysis, we juxtaposed the performance of our emotion-aware, socially invisible navigation algorithm against the GVO [26] algorithm, which traditionally disregards proxemic, emotional, or social constraints. Our evaluation focused on two primary metrics:

- **Intrusion Instances:** We assessed how frequently a robot without social awareness breached the peripersonal, interpersonal, and designated restricted spaces of pedestrians. Such intrusions are known to cause emotional discomfort and disrupt pedestrian group dynamics.
- **Navigation Efficiency:** We gauged the additional time our algorithm-equipped robot necessitated to reach its end point without impinging on the comfort distances (hard constraint) and reachability distances (soft constraint) of pedestrians. Remarkably, our results, as shown in Table I, revealed that our robot achieved its navigation objectives with less than 20% extra time, all the while respecting the proxemic boundaries of nearby pedestrians.

Additionally, Table I provides insight into the intrusions avoided and the performance of our navigation algorithm by documenting the time required for the robot to compute socially-invisible trajectories.

C. Active Surveillance Evaluation

The versatility of our algorithm was further evidenced when applied to active surveillance scenarios. In these contexts, pedestrian densities varied from low (1 robot/m^2) to medium (1-2 robots/m^2), escalating to high-density environments (more than 2 robots/m^2).

Dataset	Additional time	Intrusions Avoided	Performance
NDLS-1	17.14%	2.69E-04 ms	35
NDLS-2	19.23%	1.94E-04 ms	25
NPLC-1	14.57%	2.04E-04 ms	32
NPLC-3	16.75%	2.88E-04 ms	25
UCSD-Peds1	23.02%	3.13E-04 ms	10
Students	7.42%	0.59E-04 ms	17
seq_hotel	9.94%	0.84E-04 ms	11
Street	9.46%	1.02E-04 ms	12

TABLE I: *Using our algorithm, the robot can reach its goal within 1m accuracy, while ensuring that the interpersonal space of any pedestrian does not intrude with $<$ 20% overhead. The pedestrian trajectories were extracted from the video.*

V. CONCLUSION AND LIMITATIONS

In this paper, we present an integrative, real-time algorithm that stands at the intersection of entitativity-based navigation and emotion-aware strategies to guide robots in social environments. Building upon the psychological tenets of entitativity and the Pleasure-Arousal-Dominance (PAD) model, our approach predicts human emotional states and, in turn, fine-tunes robot behaviors to maintain socially invisible interactions. Such an algorithm not only ensures physical safety but also respects the intricate emotional dynamics of human beings in shared spaces.

Our work offers a fresh perspective towards robot navigation in social settings, with a dual emphasis on emotional awareness and minimizing perceptions of entitativity. By converging research on entitativity with cutting-edge emotion detection techniques, we introduce a paradigm where robots navigate seamlessly while ensuring human emotional comfort. The user studies we conducted to solidify the assertion that the combination of emotional cues and an understanding of entitativity can substantially bolster the social invisibility of robots amidst pedestrian crowds.

While our novel methodology brings forth a promising perspective on human-robot interaction, it is not without its limitations. Like many prior studies, our algorithm predominantly focuses on motion trajectories, sidelining a plethora of other social cues and judgments humans naturally lean on during interactions. Aspects such as appearance, race, class, religion, gender, and other socio-cultural judgments remain beyond the purview of our current framework. Moreover, despite our method harmoniously integrating the PAD model and entitativity principles, its strong reliance on facial cues and trajectories might falter in conditions where such data becomes less accessible or predictable.

For future endeavors, integrating robot appearances within our conceptual framework offers a promising direction. Empirical findings suggest that identical robots can induce heightened perceptions of entitativity. Exploring how manipulating robot appearances might mitigate such perceptions could be instrumental. A more personalized approach, taking into account the perceiver's personality and past experiences with robots, could refine robot navigation strategies tailored to individual human profiles.

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