Socially Invisible Navigation for Intelligent Vehicles

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***Abstract*— We present a real-time, data-driven algorithm to enhance the *social-invisibility* of autonomous vehicles within crowds. Our approach is based on prior psychological research, which reveals that people notice and–importantly–react negatively to groups of social actors when they have high *entitativity*, moving in a tight group with similar appearances and trajectories. In order to evaluate that behavior, we performed a user study to develop navigational algorithms that minimize entitativity. This study establishes mapping between emotional reactions and multi-robot trajectories and appearances, and further generalizes the finding across various environmental conditions. We demonstrate the applicability of our entitativity modeling for trajectory computation for active surveillance and dynamic intervention in simulated robot-human interaction scenarios. Our approach empirically shows that various levels of entitative robots can be used to both avoid and influence pedestrians while not eliciting strong emotional reactions, giving multi-robot systems socially-invisibility.**

I. Introduction

As robots have become more common in social environments, people's expectations of their social skills have increased. People often want robots to be more socially visible–more salient social agents within group contexts [17]. This social visibility includes being more capable of drawing the attention of humans and evoking powerful emotions [21]. Cases of social visibility include tasks in which robots must work collaboratively with humans. However, not all contexts require socially visible robots. There are situations in which robots are not used to collaborate with people but instead used to monitor them. In these cases, it may be better for robots to be socially invisible.

Social invisibility refers to the ability of agents to escape the attention of other people. For example, psychological research reveals that African Americans often go unnoticed in social environments[10], especially reactions related to threat. Evolution has attuned the human brain to respond rapidly to threatening stimuli, thus the less a person–or a robot–induces negative emotion, the less likely it is to be noticed within a social milieu. The social invisibility conferred by not inducing emotion is especially important in surveillance contexts in which robots are expected to move seamlessly among people without being noticed. Noticing surveillance robots not only makes people hide their behavior, but the negative emotions that prompt detection may also induce reactance [8], which may lead to people to lash out and harm the robots or even other people [11] Research reveals a number of ways of decreasing negative emotional reactions towards social agents [9], but one element may be especially important for multi-robot systems: entitativity [12], "groupiness") is tied to three main elements, uniformity of appearance, common movement, and proximity to one another. The more agents look and move the same, and the closer agents are to each other, the more entitative a group seems, which is why a marching military platoon seems more grouplike than people milling around a shopping mall.

The threatening nature of groups means that the more entitative (or grouplike) a collection of agents seem, the greater the emotional reaction they induce and the greater their social visibility. As maximizing the social invisibility of collections of agents requires minimizing perceptions of threat, it is important for multi-robot systems to minimize their entitativity. In other words, if multi-robots systems are to move through groups without eliciting negative reactions [16], they must seem more like individuals and less like a cohesive and coordinated group.

Main Results: We present a novel, real-time planning algorithm that seeks to optimize entitativity within pedestrian environments in order to increase socially-invisible navigation (by minimizing negative emotional reactions). First, we conduct a user study to empirically tie trajectories of multi-robot systems to emotional reactions, revealing that–as predicted–more entitative robots are seen as more unnerving. Second, we generalize these results across a number of different environmental conditions (like lighting). Third, we extract the trajectory of each pedestrian from the video and use Bayesian learning algorithms to compute their motion model. Using entitativity features of groups of robots and the pedestrians, we perform long-term path prediction for the pedestrians. To determine these entitativity features we establish a data-driven entitativity mapping (EDM) between the group robot motion and entitativity measure from an elaborate web-based perception user study that compares the participants' emotional reactions towards simulated videos of multiple robots. Specifically, highly entitative collections of robots are reported as unnerving and uncomfortable. The results of our mapping are well supported by psychology literature on entitativity [33]. Our approach is an extension of the approach presented in [5]. We refer the readers to read [5] for the technical details.

We highlight the benefits of our data-driven metric for use of multiple robots for crowd surveillance and active interference. We attempt to provide maximally efficient navigation and result in maximum social invisibility. In order to pursue different sets of scenarios and applications, we highlight the

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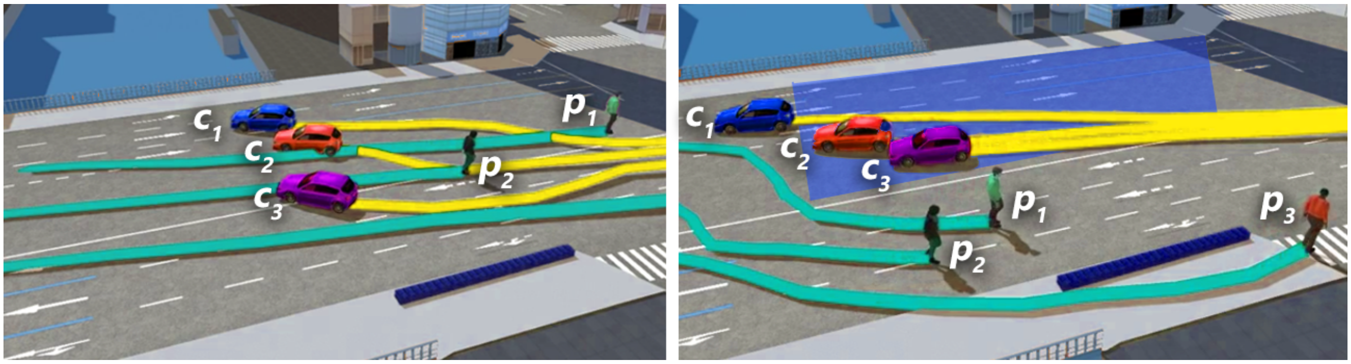

Fig. 1: *Multi-robot navigation systems (vehicles (c_x) marked by yellow trajectories) navigate amongst crowds. Our novel navigation algorithm takes into account various levels of physical and social constraints and use them for: (a) Active Navigation in the presence of pedestrians (**teal** trajectories) while moving through them with no collisions; (b) Dynamic intervention where the robots try to influence the crowd behavior and movements and make the pedestrians avoid the area marked by a **dark blue** overlay.*

performance of our work in multiple surveillance scenarios based on the level of increasing social interaction between the robots and the humans.

Our approach has the following benefits:

1. Entitativity Computation: Our algorithm accurately predicts emotional reactions (entitativity) of pedestrians towards robots in groups.

2. Robust computation: Our algorithm is robust and can account for noise in pedestrian trajectories, extracted from videos.

3. Fast and Accurate: Our algorithm involves no pre-computation and evaluates the entitativity behaviors at interactive rates.

The rest of the paper is organized as follows. In Section 2, we review the related work in the field of psychology and behavior modeling. In Section 3, we give a background on quantifying entitativity and introduce our notation. In Section 4, we present our interactive algorithm, which computes the perceived group entitativity from trajectories extracted from video. In Section 5, we describe our user study on the perception of multiple simulated robots with varying degrees of entitativity.

II. Related Work

Human beings are inherently social creatures, making interacting with and perceiving others an important part of the human experience. Complex interactions within brain regions work harmoniously to navigate the social landscape [36]. Interesting patterns emerge when attempting to understand how humans view groups of people.

A. Psychological Perspectives on Group Dynamics

A long-standing tenet of social psychology is that people's behaviors hinge upon their group context. Importantly, the impact of social dynamics is highly influenced by group contexts [39]–often for the worse. Decades of psychological research reveals that people interact more negatively with groups than with individuals [33], expressing more hostility towards and feeling more threatened by a group than an individual [16].

B. Human-Aware Robot Navigation

Many approaches have been applied towards the navigation of socially-aware robots [30], [25], [29], [19], [26], [24], [7], [41], [32]. This type of navigation can be generated by predicting the movements of pedestrians and their interactions with robots [26]. Some algorithms use probabilistic models in which robots and human agents cooperate to avoid collisions [40]. Other techniques apply learning models which have proven useful in adapting paths to social conventions [27], [31], [34], [14]. Yet other methods model personal space in order to provide human-awareness [1]. This is one of many explicit models for social constraints [38], [23], [13]. While these works are substantial, they do not consider psychological constraints or pedestrian personalities.

C. Behavior Modeling of Pedestrians

There is considerable literature in psychology, robotics, and autonomous driving on modeling the behavior of pedestrians. Many rule-based methods have been proposed to model complex behaviors based on motor, perceptual, behavioral, and cognitive components [37], [15]. There is extensive literature focused on modeling emergent behaviors [35]. Other techniques have been proposed to model heterogeneous crowd behaviors based on personality traits [6], [2], [22], [3].

III. Social Interaction

In this section, we present our interactive algorithm for performing socially-invisible robot navigation in crowds. Our approach can be combined with almost any real-time pedestrian tracker that works on dense crowd videos. Figure

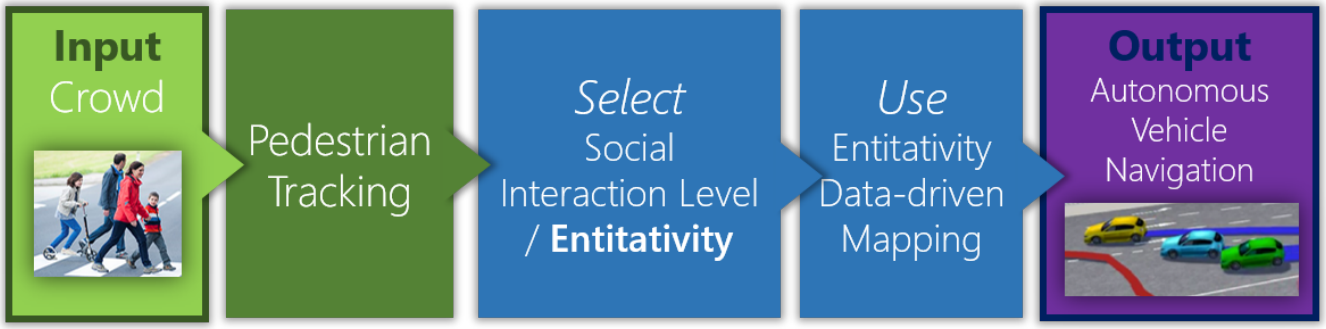

Fig. 2: *Our method takes a live or streaming crowd video as an input. We extract the initial set of pedestrian trajectories using an online pedestrian tracker. Based on the level of social invisibility we want to achieve, we compute motion model parameters of the robot group using a data-driven entitativity mapping (which we compute based on a user-study(Section IV)).*

2 gives an overview of our approach. Our method takes a live or streaming crowd video as an input. We extract the initial set of pedestrian trajectories using an online pedestrian tracker. Based on the level of social invisibility we want to achieve, we find motion model parameters of the robot group using a data-driven entitativity mapping (which we compute based on a user-study(Section IV)).

A. Entitativity

Entitativity is the perception of a group comprised of individuals as a single entity. People sort others into entities like they group together objects in the world, specifically by assessing common fate, similarity, and proximity [12]. When individuals are connected by these properties, we are more likely to perceive them as a single entity. Larger groups are more likely to be perceived as entities, but only when there is similarity among the groups individual members [28].

Entitativity is the extent to which a group resembles a single entity versus of collection of individuals; in other words, it is the groups "groupiness" or "tightness" [12], [20]. Overall, entitativity is driven by the perception of three main elements:

1. Uniformity of appearance: Highly entitative groups have members that look the same.

2. Common movement: Highly entitative groups have members that move similarly.

3. Proximity: Highly entitative groups have members that are very close to each other.

B. Notation and Terminology

The motion model is the local navigation rule or scheme that each agent uses to avoid collisions with other agents or obstacles and has a group strategy. The parameters of the motion model is denoted $\mathbf{P} \in \mathbb{R}^6$. We based our model on the RVO velocity-based motion model [42]. In this model, the motion of each agent is governed by these five individual pedestrian characteristics: *Neighbor Dist, Maximum Neighbors, Planning Horizon, (Radius) Personal Space, and Preferred Speed* and one group characteristic: *Group Cohesion*. We combine RVO with a group navigation scheme in Section 4.2. In our approach, we mainly analyze four parameters ($\mathbf{GP} \in \mathbb{R}^4$): *Neighbor Dist, (Radius) Personal Space, Group Cohesion, and Preferred Speed.*

Trajectories extracted from real-world scenarios are likely to have incomplete tracks and noise [18]. Therefore, the state of each agent is computed using a Bayesian inference technique in order to compensate for such errors.

Entitativity Metric: Prior research in psychology takes into account properties such as uniformity, common movement, and proximity, and models the perception of *entitativity* using the following 4-D feature vector:

$$\mathbf{E} = \begin{pmatrix} Friendliness \\ Creepiness \\ Comfort \\ Unnerving \end{pmatrix} \quad (1)$$

Friendliness, Creepiness, Comfort and *Unnerving (ability to unnerve)* are the emotional impressions made by the group on observers. Using Cronbach's α (a test of statistical reliability) in pilot studies we observed that the parameters were highly related with $\alpha = 0.794$, suggesting that they were justifiable adjectives for socially-invisible navigation.

IV. Data-Driven Entitativity Model

We performed a user study to understand the perception of multiple pedestrians and vehicles with varying degrees of entitativity. For the details of the user study, we refer the readers to read [5].

Given the entitativity features obtained using the psychology study for each variation of the motion model parameters, we can fit a generalized linear model to the entitativity features and the model parameters. We refer to this model as the *Data-Driven Entitativity Model*. For each video pair i in the gait dataset, we have a vector of parameter values and a vector of entitativity features $\mathbf{E}_i$. Given these parameters and features, we compute the entitativity mapping of the form:

$$\begin{pmatrix} Friendliness \\ Creepiness \\ Comfort \\ Unnerving \end{pmatrix} = \mathbf{G_{mat}} * \begin{pmatrix} \frac{1}{14}(Neighbor\ Dist - 5) \\ \frac{1}{3.4}(Radius - 0.7) \\ \frac{1}{2}(Pref.\ Speed - 1.5) \\ \frac{1}{1.8}(Group\ Cohesion - 0.5) \end{pmatrix} \tag{2}$$

We fit the matrix $\mathbf{G_{mat}}$ using generalized linear regression with each of the entitativity features as the responses and the parameter values as the predictors using the normal distribution:

$$\mathbf{G_{mat}} = \begin{pmatrix} -1.7862 & -1.0614 & -2.1983 & -1.7122 \\ 1.1224 & 1.1441 & 1.7672 & -0.2634 \\ -1.0500 & -1.2176 & -2.1466 & -0.9220 \\ 1.1948 & 1.7000 & 0.9224 & 0.3622 \end{pmatrix}. \tag{3}$$

We can make many inferences from the values of $\mathbf{G_{mat}}$. The negative values in the first and third rows indicate that as the values of motion model parameters increase, the friendliness of the group decreases. That is, fast approaching and cohesive groups appear to be less friendly. This validates the psychological findings in previous literature. One interesting thing to note is that creepiness increases when group cohesion decreases. When agents/pedestrians walk in a less cohesive group, they appear more creepy but they may appear less unnerving.

We can use our data-driven entitativity model to predict perceived entitativity of any group for any new input video. Given the motion parameter values $\mathbf{GP}$ for the group, the perceived entitativity or group emotion $\mathbf{GE}$ can be obtained as:

$$\mathbf{GE} = \mathbf{G_{mat}} * \mathbf{GP} \tag{4}$$

A. Socially-Invisible Vehicle Navigation

To provide socially-invisible navigation, we use the entitativity level of robots. We control the entitativity level depending on the requirements of the social-invisibility. We represent the social-invisibility as a scalar $s \in [0, 1]$ with $s = 0$ representing very low social-invisibility and $s = 1$ representing highly socially-invisible robots. Depending on the applications and situations, the social-invisibility can be varied.

We relate the desired social-invisibility (s) to entitativity features $\mathbf{GE}$ as follows:

$$s = 1 - \frac{\|\mathbf{GE} - \mathbf{GE}_{min}\|}{\|\mathbf{GE}_{max} - \mathbf{GE}_{min}\|} \tag{5}$$

where $\mathbf{GE}_{max}$ and $\mathbf{GE}_{min}$ are the maximum and minimum entitativity values obtained from the psychology study.

According to Equation 5, there are multiple entitativity features $\mathbf{GE}$ for the desired social-invisibility s. This provides flexibility to choose which features of entitativity we wish to adjust and we can set the desired entitativity $\mathbf{GE}_{des}$ that provides the desired social-invisibility level. Since $\mathbf{G_{mat}}$ is invertible, we can compute the motion model parameters $\mathbf{GP}_{des}$ that achieve the desired entitativity:

$$\mathbf{GP}_{des} = \mathbf{G_{mat}}^{-1} * \mathbf{E}_{des} \tag{6}$$

These motion model parameters $\mathbf{GP}_{des}$ are the key to enabling socially-invisible collision-free robot navigation through a crowd of pedestrians. Our navigation method is based on Generalized Velocity Obstacles (GVO) [43], which uses a combination of local and global methods. The global metric is based on a roadmap of the environment. The local method computes a new velocity for each robot and takes these distances into account. Moreover, we also take into account the dynamic constraints of the robot in this formulation - for example, mechanical constraints that prevent the robot from rotating on the spot.

V. Applications

We present some driving applications of our work that are based on use of multiple autonomous car navigation systems. In these scenarios, our method optimizes multi-robot systems so that they can interact with such crowds seamlessly based on physical constraints (e.g. collision avoidance, robot dynamics) and social invisibility. We simulate our algorithm with two sets of navigation scenarios based on the level of increasing social interaction between the robots and the humans:

1) Active Navigation: This form of navigation includes autonomous robots that share a physical space with pedestrians. While performing navigation and analysis, these robots will need to plan and navigate in a collision-free manner in real-time amongst crowds. In this case, the robots need to predict the behavior and trajectory of each pedestrian. For example, marathon races tend to have large populations, with a crowd whose location is constantly changing. In these scenarios, it is necessary to have a navigation system that can detect shifting focal points and adjust accordingly.

In such scenarios, the robots need to be highly socially-invisible ($s = 0$). We achieve this by setting the entitativity features to the minimum $\mathbf{E} = \mathbf{E}_{min}$ (Equation 5).

2) Dynamic intervention: In certain scenarios, robots will not only share a physical space with people but also influence pedestrians to change or follow a certain path or behavior. Such interventions can either be overt, such as forcing people to change their paths using visual cues or pushing, or subtle (for example, nudging). This type of navigation can be used in any scenario with highly dense crowds, such as a festival or marathon. High crowd density in these events can lead to stampedes, which can be very deadly. In such a scenario, a robot can detect when density has reached dangerous levels and intervene, or "nudge" individuals until they are distributed more safely.

For dynamic intervention with pedestrians or robots, we manually vary the entitativity level depending on urgency or agent proximity to the restricted area. In these situations, we restrict the entitativity space by imposing a lower bound s_{min} on the social-invisibility (Equation 5):

$$s_{min} \leq 1 - \frac{\|\mathbf{E} - \mathbf{E}_{min}\|}{\|\mathbf{E}_{max} - \mathbf{E}_{min}\|}. \quad (7)$$

A. Performance Evaluation

We evaluate the performance of our socially-invisible navigation algorithm with GVO [43], which by itself does not take into account any social constraints. We compute the number of times a pedestrian intrudes on a designated restricted space, and thereby results in issues related to navigating through a group of pedestrians. We also measure the additional time that a robot with our algorithm takes to reach its goal position, without the pedestrians intruding a predesignated restricted area. Our results (Table I) demonstrate that in $< 30\%$ additional time, robots using our navigation algorithm can reach their goals while ensuring that the restricted space is not intruded. Table I also lists the time taken to compute new trajectories while maintaining social invisibility. We have implemented our system on a Windows 10 desktop PC with Intel Xeon E5-1620 v3 with 16 GB of memory.

Dataset	*Additional Time*	*Intrusions Avoided*	*Performance*
NPLC-1	14%	3	3.00E-04 ms
NDLS-2	13%	2	2.74E-04 ms
IITF-1	11%	3	0.72E-04 ms
NDLS-2	17%	4	0.98E-04 ms
NPLC-3	14%	3	1.27E-04 ms
NDLS-4	13%	2	3.31E-04 ms
IITF-2	11%	3	1.76E-03 ms

TABLE I: ***Navigation Performance for Dynamic Intervention:*** *A robot using our navigation algorithm can reach its goal position, while ensuring that any pedestrian does not intrude the restricted space with $<$ 15% overhead. We evaluated this performance in a simulated environment, though the pedestrian trajectories were extracted from the original dataset [4]. In all the videos we have manually annotated a specific area as the restricted space.*

VI. Conclusions, Limitations and Future Work

Drawing from work in social psychology, we develop a novel algorithm to minimize entitativity and thus maximize the social invisibility of multi-robot systems within pedestrian crowds. A user-study confirms that different entitativity profiles–as given by appearance, trajectory and spatial distance–are tied to different emotional reactions, with high entitativity groups evoking negative emotions in participants. We then use trajectory information from low-entitative groups to develop a real-time navigation algorithm that should enhance social invisibility for multi-robot systems.

Our approach has some limitations. Although we did generalize across a number of environmental contexts, we note that motion-based entitativity is not the only feature involved in social salience and other judgments. People use a rich set of cues when forming impressions and emotionally reacting to social agents, including perceptions of race, class, religion, and gender. As our algorithm only uses motion trajectories, it does not exhaustively capture all relevant social features. However, motion trajectories are an important low-level feature of entitativity and one that applies especially to robots, who may lack these higher-level social characteristics.

Future research should extend this algorithm to model the appearances of robots in multi-robot systems. Although many social cues may not be relevant to robots (e.g., race), the appearance of robots can be manipulated. Research suggests that robots that march will have higher entitativity and hence more social visibility. This may prove a challenge to manufacturers of autonomous vehicles, as mass production typically leads to identical appearances. Another key future direction involves examining the interaction of the perceiver's personality with the characteristics of multi-robot systems, as some people may be less likely to react negatively to entitative groups of robots, perhaps because they are less sensitive to general threat cues or, more specifically, have more experience with robots.

VII. Acknowledgements

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