The Emotionally Intelligent Robot:
Improving Social Navigation in Crowded Environments

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Abstract—We present a real-time algorithm for emotion-aware navigation of a robot among pedestrians. Our approach estimates time-varying emotional behaviors of pedestrians from their faces and trajectories using a combination of Bayesian inference, CNN-based learning, and the PAD (Pleasure-Arousal-Dominance) model from psychology. These PAD characteristics are used for long-term path prediction and generating proxemic constraints for each pedestrian. We use a multi-channel model to classify pedestrian characteristics into four emotion categories (happy, sad, angry, neutral). In our validation results, we observe an emotion detection accuracy of 85.33%. We formulate emotion-based proxemic constraints to perform socially-aware robot navigation in low- to medium-density environments. We demonstrate the benefits of our algorithm in simulated environments with tens of pedestrians as well as in a real-world setting with Pepper, a social humanoid robot.

I. INTRODUCTION

Recent advances in technology predict that humans will soon be sharing spaces in public places, sidewalks, and buildings with mobile, autonomous robots. Recently, mobile robots are increasingly used for surveillance, delivery and warehousing applications. It is important that such robots navigate in socially acceptable ways, meaning that they seamlessly navigate through pedestrian traffic while responding dynamically – and appropriately – to other pedestrians.

A robot navigating through the world alone is primarily a physical problem (compute collision-free and efficient paths that satisfy the kinematics and dynamics constraints of the robot) because it has to make its way around obstacles. However, when there are other pedestrians in this environment, navigation becomes just as much about social navigation as it does about physical navigation. Humans act as both dynamic and social obstacles to a robot and have their own intentions, desires, and goals, which can affect a robot’s progress. Additionally, a robot’s movement may also affect humans’ comfort and/or emotional state.

To predict other people’s goals, people use a variety of cues, including past behavior, speech utterances, and facial expressions [20]. One of the most important predictors of people’s behavior is their emotions [32], and therefore understanding people’s emotional states is essential for making your way through the social world [2]. The ability to understand people’s emotions is called “emotional intelligence” [49] and is useful in many social situations, including predicting behavior and navigation. As more robots are introduced in social settings, techniques to develop emotional intelligence of robots become increasingly important in addition to merely satisfying the physical constraints.

However, understanding the emotions of pedestrians is a challenging problem for a robot. There has been considerable research on using non-verbal cues such as facial expressions to perceive and model emotions [12]. However, recent studies in the psychology literature question the communicative purpose of facial expressions and doubt the reliability of emotions perceived only from these expressions [47]. There are many situations where facial data is only partially available or where facial cues are difficult to obtain. For example, a pedestrian may not be directly facing the robot or may be far away from the robot. Therefore, combining facial expressions with a more implicit channel of expression such as trajectories is vital for more accurate prediction of humans’ emotional states.

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Main Results: We present a real-time data-driven planning algorithm that takes the emotional state of the pedestrians into account to perform socially-aware navigation (Figure 1). We predict pedestrians’ emotions based on the Pleasure-Arousal-Dominance (PAD) model, a 3-dimensional measure of emotional state used as a framework for describing individual differences in emotional traits/temperament [33], using information from two different channels of expression: faces and trajectories. We extract the trajectory of each pedestrian from a video stream and use Bayesian learning algorithms to compute their motion model and emotional characteristics. This trajectory-based computation is based on the results of a perception user study that provides emotion labels for a dataset of walking videos. In our validation studies, we observe an accuracy of 85.33% using 10-fold cross-validation. We also compute the facial expression-based emotion using a convolution-neural network (CNN) classifier trained on the FER-2013 emotion dataset [18]. We combine these results into a multi-channel model to classify emotion into four categories (happy, sad, angry, neutral).

We combine the time-varying emotion estimates of each pedestrian with path prediction for collision-free, socially normative robot navigation. We present a new data-driven mapping, TEM (Trajectory-based Emotion Model), which maps learned emotions to proxemic constraints relating to the comfort and reachability distances [46]. These distances restrict the robot motion and navigation to avoid intruding through pedestrian’s peripersonal and interpersonal social spaces. The combination of emotional and proxemic constraints improves both social comfort and navigation. We have evaluated the performance of our algorithm:

- quantitatively on a dataset of real-world videos consisting of tens of pedestrians, including dense scenarios, where we measured the number of proxemic intrusions our robot avoided, and
- qualitatively in a lab setting with a Pepper humanoid robot and a total of 11 pedestrians with real-world intentions. Our subjects felt comfortable in the environment, and they could perceive the robot’s subtle reaction to their emotion.

The rest of the paper is organized as follows. Section II provides an overview of related work. We introduce the terminology and present our algorithm to model emotional constraints and use them for path prediction in Section III. In Section IV, we present our socially-aware robot navigation scheme. We highlight our algorithm’s performance on benchmarks and describe results in Section V.

II. RELATED WORK

In this section, we discuss previous robot navigation algorithms that focus on physical and social constraints. We also review related work on emotion detection from facial expressions and trajectories.

A. Physical Navigation

Prior work on robot navigation in pedestrian environments mainly focused on solving physical constraints such as collision avoidance. Many systems for robot navigation in urban environments implemented robots that autonomously navigated previously-mapped urban paths in the presence of crowds [35], [26]. Bauer et al. [3] created a robot for navigating urban environments without GPS data or prior knowledge. Fan et al. [14] proposed a navigation framework that handles the robot freezing, and the navigation lost problems. The collision-avoidance approaches used by these navigation algorithms include potential-based approaches for robot path planning in dynamic environments [41], probabilistic methods or Bayesian velocity-obstacles methods [17], [21] for pedestrian trajectory prediction. Other methods include a partially-closed loop receding horizon control [10] for non-conservatively avoiding collisions with dynamic obstacles. Faisal et al. [13] tuned fuzzy logic controllers with four different methods to identify which algorithm minimizes the travel time to a goal destination. Recently,
collision avoidance approaches have been introduced for collision avoidance navigation including both supervised and unsupervised learning [50], [44], [40], [19], [15].

B. Socially-aware Robot Navigation

Humans navigating among crowds follow social norms relating to the speed of movement or personal space. In particular, we tend to observe the emotions displayed by others and adjust our paths in response. Correspondingly, there is much prior work on having mobile robots navigate among humans in a socially-aware manner [38], [24], [36], [16], [25]. Some navigation algorithms generate socially compliant trajectories by predicting the pedestrian movement and forthcoming interactions [25] or use modified interacting Gaussian processes to develop a probabilistic model of robot-human cooperative collision avoidance [52]. Vemula et al. [54] proposed a trajectory prediction model that captures the relative importance of each pedestrian in a crowd during navigation. Other methods tend to model interactions and personal space for human-aware navigation [1] or use learning-based approaches to account for social conventions in robot navigation [29], [39], [42]. Many explicit models have been proposed for social constraints to enable person-acceptable navigation [51], [22]. However, these methods do not take into account psychological constraints or emotions of the pedestrians.

C. Emotion Characteristics from Faces

In recent years, research in computer vision and AI has focused on emotion identification from facial expressions. Most of these methods use neural-network based approaches to identify emotions trained on popular datasets such as FER [18]. Liu et al. [27] presented a novel Boosted Deep Belief Network (BDBN) based three-stage training model for facial expression recognition. An annotation method, EmotioNet, predicted action units and their intensities as well as emotion category for a million facial expressions [30]. These four emotions capture the spectrum of the emotion extended period and are more abundant during walking [31].

We introduce the terminology and symbols used in the rest of this paper. We refer to an agent in the crowd as the pedestrian whose state includes his/her emotion characteristics. This state, denoted by the symbol $\hat{x}_p$, governs the pedestrian’s position on the ground plane and facial features:

$$x_p = [\hat{p}_p \; \hat{v}_p^{\text{cs}} \; \hat{v}_p^{\text{pred}} \; \hat{E}_f^T \; \hat{E}_f^T]^T;$$

(1)

where $\hat{p}_p \in \mathbb{R}^2$ is the pedestrian’s position on the ground plane and facial features; $\hat{v}_p^{\text{cs}} \in \mathbb{R}^2$ is his/her current velocity; and $\hat{v}_p^{\text{pred}} \in \mathbb{R}^2$ is the predicted velocity on a 2D ground plane. A pedestrian’s current velocity $\hat{v}_p^{\text{cs}}$ is used to compute emotion from the trajectory; $\hat{v}_p^{\text{pred}}$ is for either discrete categories or as points in a continuous space of emotion dimensions. Discrete categories include basic emotions such as anger, disgust, fear, joy, sadness, and surprise as well as other emotions such as pride, depression, etc. On the other hand, Ekman and Wallace [11] used “affects” to represent emotions. Affect is a key characteristic of emotion and is defined as a 2-dimensional space of (1) valence, the pleasure-displeasure dimension; and (2) arousal, the excited-sleep dimension. All discrete emotions can be represented by points in this 2D affect space (Fig 3). In this paper, we use the pleasure and arousal dimensions from the PAD model and use four basic emotions (happy, angry, sad, neutral) representing emotional states that last for an extended period and are more abundant during walking [31]. These four emotions capture the spectrum of the emotion space, and a combination of them can be used to represent other emotions [34].

B. Notation

We propose a joint pedestrian emotion-model from trajectories and faces. In this section, we first define an emotion state, then introduce our notation, and give an overview of our approach.

A. Emotion State

III. EMOTION LEARNING

We propose a joint pedestrian emotion-model from trajectories and faces. In this section, we first define an emotion state, then introduce our notation, and give an overview of our approach.

A. Emotion State

Most of the previous literature has modeled emotions as either discrete categories or as points on a continuous space of emotion dimensions. Discrete categories include basic emotions such as anger, disgust, fear, joy, sadness, and surprise as well as other emotions such as pride, depression, etc. On the other hand, Ekman and Wallace [11] used “affects” to represent emotions. Affect is a key characteristic of emotion and is defined as a 2-dimensional space of (1) valence, the pleasure-displeasure dimension; and (2) arousal, the excited-sleep dimension. All discrete emotions can be represented by points in this 2D affect space (Fig 3). In this paper, we use the pleasure and arousal dimensions from the PAD model and use four basic emotions (happy, angry, sad, neutral) representing emotional states that last for an extended period and are more abundant during walking [31]. These four emotions capture the spectrum of the emotion space, and a combination of them can be used to represent other emotions [34].
of other pedestrians or obstacles in the scene to achieve their intermediate goal. \( \vec{f} \) is their face pixels re-aligned to 48 \( \times \) 48 which is used to compute the facial emotion. \( \vec{E}^f \in \mathbb{R}^3 \) and \( \vec{E}^t \in \mathbb{R}^3 \) are their facial and trajectory emotion vectors. The union of the states of all the other pedestrians and the current positions of the obstacles in the scene is the current state of the environment denoted by the symbol \( X \).

We do not explicitly model or capture pairwise interactions between pedestrians. However, the difference between \( \vec{v}^{\text{pred}} \) and \( \vec{v}^c \) provides partial information about the local interactions between a pedestrian and the rest of the environment. Similarly, we define the robot’s state, \( \vec{x}_r \), as

\[
\vec{x}_r = [\vec{v}_r \ \vec{E}_r \ \vec{v}_r^{\text{pref}}]^T,
\]

where \( \vec{v}^{\text{pref}} \) is the preferred velocity of the robot, defined as the velocity the robot would take based on the present and predicted position of the pedestrians and the obstacles in the scene.

We represent the emotional state of a pedestrian by a vector \( \vec{E}^t = [h, a, s] \), where \( h, a, \) and \( s \) correspond to a scalar value of happy, angry, and sad emotions (normalized to \([0, 1]\)), respectively. Using the \( \vec{E}^t \), we can also obtain a single emotion label \( e \) as follows:

\[
e = \begin{cases} 
\text{happy}, & \text{if } (h > a) \land (h > s) \land (h > \theta) \\
\text{angry}, & \text{if } (a > h) \land (a > s) \land (a > \theta) \\
\text{sad}, & \text{if } (s > h) \land (s > a) \land (s > \theta) \\
\text{neutral}, & \text{otherwise}
\end{cases}
\]

where \( \theta \) is a scalar threshold. In this paper, we use an experimentally determined value of \( \theta = 0.55 \).

### C. Overview

We present an overview of our approach in Figure 2. Our method takes a streaming video as input from two camera channels, a fixed, overhead camera, and an onboard robot camera. We perform a large-scale Mechanical Turk study on a crowd dataset to establish a linear mapping (TEM) between the motion model parameters and pedestrian emotion using multiple linear regressions after we obtained the labels using a perception user study. Later we use this mapping and compute trajectory-based emotions for the pedestrians. We also use a fully-convolutional neural network (which has been trained on the FER-2013 emotion dataset [18]) to compute the facial expression based-emotions. We combine these multi-channel emotions along with proxemic constraints and a collision-avoidance algorithm to perform socially-aware robot navigation.

### IV. Emotion Learning

In this Section, we describe our joint pedestrian emotion model that combines emotion learning from trajectories and facial features.

#### A. Emotion Learning from Trajectories (TEM)

Our goal is to model the levels of perceived emotion from pedestrian trajectories. We use a data-driven approach to model pedestrians’ emotions. We present the details of our perception study in this section and derive the trajectory-based pedestrian emotion model (TEM) from the study results.

1) **Study Goals:** This web-based study is aimed at obtaining the emotion labels for a dataset of pedestrian videos. We use a 2D motion model [53] based on reciprocal velocity obstacles (RVO) to model the motion of pedestrians. We obtained scalar values of perceived emotions for different sets of motion model parameters.

2) **Participants:** We recruited 100 participants (77 male, 23 female, \( \bar{\text{age}} = 33.24, s_{\text{age}} = 7.81 \)) from Amazon MTurk to answer questions about a dataset of simulated videos.

3) **Dataset:** We collected 23 videos of pedestrians walking in a corridor. In each video, a single pedestrian was highlighted by a circle and his/her trajectory (Figure 4). We computed the motion model parameters of the pedestrians using a Bayesian learning approach [21]. The motion model corresponds to the local navigation rule or scheme that each pedestrian uses to avoid collisions with other pedestrians or obstacles. In particular, we consider the following motion parameters for each pedestrian:

- Planning Horizon (how far ahead of the agent plans),
- Effective Radius (how far away an agent stays from other agents), and
- Preferred Speed.

We represent these motion model parameters as a vector \( \vec{P} \in \mathbb{R}^3 \): Planning Horizon, Radius, Pref Speed. Table 1 shows the range of the values of the parameters used. These values cover the range of values observed in the real world. We will release this dataset and the motion model parameters.

| Parameter (unit) | Min   | Max   | Average | Variance |
|------------------|-------|-------|---------|----------|
| Planning Horizon | 0.09  | 2.21  | 1.25    | 0.57     |
| Radius (m)       | 0.30  | 0.92  | 0.61    | 0.05     |
| Pref Speed (m/s) | 0.93  | 2.33  | 1.39    | 0.11     |

**TABLE 1: Values of Motion Parameters:** We present the range and average values of motion parameters obtained from the dataset.

4) **Procedure:** In the web-based study, participants were asked to watch a random subset of 8 videos from the dataset. Participants then answered whether the highlighted agent was experiencing one of the basic emotions (happy, angry, or...
sad) on a 5-point Likert scale from strongly disagree (1) - strongly agree (5). Participants were presented the videos in a randomized order and could watch the videos multiple times if they wished. Before completing the study, participants also provided demographic information about their gender and age.

5) Analysis: We average the participant responses to each video to obtain a mean value corresponding to each basic emotion: \(V_h, V_s, V_a\) (normalized to \([0, 1]\)). Using these values, we obtain the emotion vector \(\vec{E} = [V_h, V_s, V_a]\) and the emotion label \(e\) using Equation [3].

We obtain emotion vectors \(\vec{E}_t^i\) corresponding to each variation of the motion model parameters \(P_t^i\) for the 23 data points corresponding to 23 videos in the simulated dataset. We use this labeled data to fit a model for emotion computation using multiple linear regression. We chose linear regression because it is computationally inexpensive and easily invertible. Other forms of regressions can also be employed. TEM takes the following form:

\[
\vec{E} = \begin{pmatrix}
-0.15 & 0.00 & -0.12 \\
0.24 & -0.61 & 0.20 \\
-0.02 & 0.79 & 0.11
\end{pmatrix} \ast \vec{P}. \tag{4}
\]

We can make several inferences from the values of the coefficients of the mapping between perceived emotion and the motion model parameters. The radius of the pedestrian representation affects the perception of anger negatively and the perception of sadness positively, whereas it doesn’t affect the perception of happiness significantly. Therefore, increasing the radius makes pedestrians appear sad and decreasing it makes them appear angry. Similarly, we can control the value of the planning horizon to control the perception of happiness and anger. Increasing the planning horizon makes pedestrians appear angrier whereas decreasing it makes them appear happier. The preferred speed affects the perception of happiness positively and the perception of anger and sadness negatively.

We use the linear model to predict the value of a pedestrian’s emotion label given the motion model parameters. We compute the accuracy of TEM using 10-fold cross-validation on our labeled dataset. We perform 100 iterations of the cross-validation and obtain an average accuracy of 85.33% using the actual and predicted emotion values.

B. Emotion Learning from Facial Features

In this section, we discuss the architecture of the neural network used to detect faces from a video stream captured by the robot and to classify the emotions for those faces. We leverage a CNN based on the Xception [9] architecture to predict the emotions, \(\vec{E}_f^i\), from faces. Our network is fully-convolutional and contains 4 residual depth-wise separable convolutions where a batch normalization operation and a ReLU activation function follows each convolution. The final layer of our network is followed by a global average pooling and a soft-max activation function. The network has been trained on the FER-2013 dataset, which contains 35,887 grayscale images. We choose images that belong to one of the following classes: angry, happy, sad, neutral.

We use a fully-convolutional network because each face is localized to a roughly square part of the video frame and detecting its emotion does not require knowledge of the “global” information about other faces in the frame. We use depth-wise separable convolutions since they need fewer numerical computations on images with a depth of more than 1 - here, we are dealing with RGB video, so it has three input channels. For more details, we refer the readers to [9].

C. Joint Pedestrian Emotion Model

We combine the computed emotions (\(\vec{E}_t^i\) and \(\vec{E}_f^i\)) using a reliability weighted average. Since facial features are more unreliable (faces are partially visible or far away from the camera), we define the joint pedestrian emotion as:

\[
\vec{E} = \frac{\alpha \vec{E}_t + \max(\vec{E}_f^i) + 1/2}{\alpha + \max(\vec{E}_f^i) + 1/2} \tag{5}
\]

where \(\alpha \in [0, 1]\) is the pedestrian tracking confidence metric based on [4]. Based on the unreliability in the facial features, Equation [5] computes a weighted average of the emotions predicted from faces and trajectories. Whenever facial emotion is unavailable, we use \(\vec{E} = \vec{E}_t\). We also compute the emotion label \(e\) using Equation [3] from \(\vec{E}\).

V. PROXEMIC CONSTRAINTS AND PATH PREDICTION

We present our real-time approach that computes a combination of physical and social constraints and uses them for navigation (Figure 2). Most of the prior work in robot navigation is limited to collision avoidance while accounting for kinematics and dynamic constraints. However, when navigating in an environment alongside humans, additional social and emotional constraints such as proximity must also be respected. Depending on the emotions or behaviors of the humans in the environment, such constraints should also be satisfied in addition to the physical constraints.

Given a pedestrian tracker [8], [6] that works well on low- to medium-density crowds, we extract pedestrian trajectories. We use Bayesian inference to compensate for noise in the trajectories extracted by the pedestrian trackers. Both the sensor error and the prediction error are assumed to follow a zero-mean Gaussian distribution. We use an Ensemble Kalman Filter (EnKF) and Expectation Maximization (EM) [21] to estimate the most-likely motion model parameters \(P_t^i\) of each pedestrian. Using these parameters, we learn the pedestrians’ emotions using TEM (Equation 4).

We formulate emotion-based proximity constraints and combine them with collision-avoidance constraints for robot navigation. Pedestrians’ emotion predictions are also used for path prediction and a socially-aware robot navigation algorithm.

A. Pedestrian Path Prediction

Our pedestrian path prediction algorithm takes the state of all pedestrians in the environment \(X\) for the previous \(n\) timesteps at time \(t\) and predicts the path of a pedestrian \(i\) for a future time, \(x_{t+\Delta t}^i\). This path is predicted in the form of their motion parameters \(\hat{P}_t^i\) because it is the best estimator of their motion in a dense environment.

The estimated motion parameters may vary slightly during the duration of motion of each pedestrian. We model these variations by an upper bound \(\hat{P}_{ub}^i\) and a lower bound \(\hat{P}_{lb}^i\).

We compute the values of \(\hat{P}_{ub}^i\) and \(\hat{P}_{lb}^i\) using the values of the emotion vector \(\vec{E}\) using TEM (Equation 4). Using the
computed emotion label $e$ from Equation 3, we compute $\vec{P}_{ub}$ by adding $\gamma \%$ to the emotion value corresponding to $e$ and adding $(\gamma/3)\%$ to the other traits. Similarly, we compute $\vec{P}_{lb}$ by subtracting $\gamma \%$ from the emotion value corresponding to $e$ and subtracting $(\gamma/3)\%$ from the other traits. The users can control the value of $\gamma$. In this paper, we use a value of $\gamma = 5\%$ that captures the noise and natural variance of the pedestrians’ emotions.

We assume that for the duration of the navigation of the robot around a pedestrian, the emotion of that pedestrian does not dramatically change and lies within a range of variance. Under these assumptions, a substantial change in the emotion vector at successive timesteps indicates an error in the prediction. To account for this error, we clamp the estimated motion model parameters to the corresponding boundary value if they are out of the bounds $\vec{P}_{lb}$ and $\vec{P}_{ub}$. Otherwise, we use them directly for path prediction. We recompute the emotion vector $\vec{E}$ according to the updated motion model parameters.

$$\vec{P} = \begin{cases} \vec{P}_{lb}, & \text{if } \vec{P} \leq \vec{P}_{lb}, \forall i \\ \vec{P}_{ub}, & \text{if } \vec{P} \geq \vec{P}_{ub}, \forall i \\ \vec{P}, & \text{otherwise} \end{cases}$$

We use these motion parameters $\vec{P}$ to perform path prediction using the GLMP algorithm [5], which varies various local movement patterns of pedestrians as well as the crowd’s overall global movement patterns.

VI. EMOTIONALLY INTELLIGENT ROBOT NAVIGATION

We use the emotions computed using Equation 3 to perform socially-aware robot navigation using proxemic distances as described below.

A. Peripersonal and Interpersonal Social Spaces

Recent neuro-cognitive studies [46] have suggested a relationship between peripersonal-action (reachability distance) and interpersonal-social (comfort distance). In particular, reachability distance refers to the distance at which pedestrians feel comfortable interacting with other pedestrians, and comfort distance refers to the distance at which pedestrians feel comfortable with the presence of a pedestrian. These proxemic behaviors offer a window into everyday social cognition by revealing pedestrians emotional states and responses.

To enable the robot to perform socially-aware navigation, we incorporate these proxemic distances in the navigation algorithm. We compute the numerical values of comfort distance ($cd_e$) and reachability distance ($rd_e$) to perform socially-aware navigation (where $e$ indicates the computed emotion label, Section IV-C). Though these distances depend on cultural norms, environment, or an individual’s personality, we mainly focus on variations originating from the differences in emotions. Specifically, we exploit the experiments described in [46] to compute the limits on an individual’s comfort and reachability distances (Table II).

| Comfort Distance ($cd_e$) | Reachability Distance ($rd_e$) |
|---------------------------|-------------------------------|
| **Happy** | 92.0 | 127.38 |
| **Sad** | 112.7 | 148.97 |
| **Angry** | 99.75 | 138.38 |
| **Neutral** | 92.03 | 156.09 |

Fig. 5: Our robot navigation algorithm satisfies the proxemic distance constraints, including peripersonal space (green) and interpersonal space (blue). The trajectory computed by our algorithm does not intrude onto these spaces, whereas a robot that fails to consider the reachability distance (purple trajectory) may cause discomfort to some pedestrians.

B. Socially-Aware Robot Navigation

We present an extension to Generalized Velocity Obstacles (GVO) [55], [7] that takes into account the comfort ($cd_e$) and reachability ($rd_e$) distances and enables socially-aware collision-free robot navigation through a crowd of pedestrians. The GVO algorithm uses a combination of local and global methods, where the global metric is based on a roadmap of the environment, and the local method computes a new velocity for the robot. We compute the comfort and reachability distances using the emotional labels $e$ (Section IV-C) and use them in the computation of the new velocity for the robot (i.e., the local method of the GVO algorithm). In this novel formulation, we also take into account the dynamic constraints of the robot. Even though our socially-aware navigation algorithm is illustrated with GVO, our approach is agnostic to the underlying navigation algorithm and can be combined with other methods like potential field methods.

We provide an illustration of a robot (located at $\vec{p}_h$) avoiding a collision with an oncoming pedestrian (located at position $\vec{p}_b$) that uses the comfort and reachability distances in Figure 5. The pedestrian’s two associated proxemic distances are the comfort distance of $\vec{p}_h$ and the reachability distance of $\vec{p}_b$. At this time instant, the global navigation method has computed a preferred velocity $\vec{v}^{pref}$ for the robot that would navigate it to its goal position in the absence of any static or dynamic obstacles. Using the path prediction algorithm described in Section V-A, the robot predicts that the pedestrian will move to the position $\vec{p}_b^{pred}$ during the next time window. Using this information, the robot computes a new velocity such that it avoids a collision with the pedestrian. However, this method doesn’t account for the pedestrian’s proxemic distances and is not sufficient for socially-aware navigation. Therefore, the robot alters its goal position and velocity in a way that takes into account both comfort and reachability: $\vec{v}^{pref+prox}$ and $\vec{v}^{pref+prox}$. This updated velocity $\vec{v}^{pref+prox}$ successfully accounts for the robot’s comfort and reachability distances, whereas the velocity $\vec{v}^{pref}$ results in the robot intruding on the pedestrian’s comfort distance. During navigation, our algorithm avoids any steering inputs that result in a collision with the predicted pedestrian positions.
VII. PERFORMANCE AND ANALYSIS

We have implemented our algorithm on a semi-humanoid robot, Pepper. It is about 1.2m tall with a top speed of 0.83m/s and an on-board camera with 2592x1944 Active Pixels. We conducted experiments in a lab setting (Fig. 6). We recruited 11 participants and asked them to assume that they are experiencing a certain emotion and walk accordingly. Previous studies show that non-actors and actors are both equally good at walking with different emotions [43]. We do not make any assumptions about how accurately the subjects acted or depicted the emotions. The participants reported being comfortable with the robot in the scene. Participants with sad emotions reported being given a wider space to walk by the robot. Participants with happy and neutral emotions reported that the robot made way for the pedestrian more swiftly. Participants with happy and neutral emotions didn’t report significant changes, but some noticed a minor slow down in the robot’s speed.

We also quantitatively evaluate the performance of our socially-aware navigation algorithm with GVO [55], which does not take into account proxemic or emotional constraints. We compute the number of times the non-social robot intrudes on the peripersonal and the interpersonal spaces of the pedestrians, thereby resulting in emotional discomfort. We also measure the additional time a robot with our algorithm takes to reach the goal position without any intrusions on pedestrians’ comfort distances (hard constraint) and reachability distances (soft constraint). Our results (Table III) demonstrate that our robot can reach its goal with < 25% time overhead while ensuring that the proxemic spaces of the pedestrians aren’t violated.

![Fig. 6: The robot learns pedestrians’ emotions and their proxemic constraints in real-time. These distances restrict the robot motion and navigation to avoid intruding on pedestrian’s peripersonal and interpersonal social spaces. The combination of emotional and proxemic constraints improves both social comfort and navigation.](image)

| Dataset   | Additional Time | Performance | Intrusions Avoided |
|-----------|----------------|-------------|--------------------|
| NDLS-1    | 19.44%         | 1.28E-04 ms | 21                 |
| NDLS-2    | 21.08%         | 1.24E-04 ms | 26                 |
| NPLC-1    | 16.71%         | 2.29E-04 ms | 30                 |
| NPLC-3    | 18.93%         | 3.09E-04 ms | 22                 |
| UCSD-PedsI| 24.89%         | 3.51E-04 ms | 11                 |
| Students  | 9.12%          | 0.78E-04 ms | 16                 |
| seq_hotel | 11.89%         | 1.07E-04 ms | 9                  |
| Street    | 11.09%         | 1.27E-04 ms | 13                 |

TABLE III: Navigation Performance: A robot using our socially-aware navigation algorithm can reach its goal position (within ±1m accuracy), while ensuring that the peripersonal/interpersonal space of any pedestrian is not intruded on with < 25% overhead. We evaluated this performance in a simulated environment, though the pedestrian trajectories were extracted from the original video.

emotion labels for a dataset of walking videos. We also compute the facial expression-based emotion using a CNN classifier trained on the FER-2013 emotion dataset [18]. Our work is the first approach that combines information from the trajectory channel with facial expressions to predict emotions and use them for socially-aware robot navigation.

Our approach has some limitations. We assume that the pedestrian trajectories are captured from an overhead camera and the on-board robot camera captures the facial expressions. Both of these channels have to be perspective corrected. The emotion classification is based on the PAD model, and we choose only four emotions, i.e., happy, sad, angry and neutral. These may not be sufficient to understand and capture the observed emotion range. For future work, we would like to learn emotions from full-body gaits and integrate the three sensors channels. We would also want to take group behaviors and cultural norms into consideration for socially-aware navigation. We would also like to compare with an alternate representation of emotion like the Circumplex model [48] to show that this work could be applied to different emotion representations.

VIII. CONCLUSIONS, LIMITATIONS, AND FUTURE WORK

We present a real-time data-driven planning algorithm that takes the emotional state of the pedestrians into account to perform socially-aware navigation. We predict pedestrians’ emotions based on the PAD model using information from two different channels of expression: faces and trajectories. We extract the trajectory of each pedestrian from a video stream and use Bayesian learning algorithms to compute his/her motion model and emotional characteristics. The computation of this trajectory-based emotion model (TEM) is based on the results of a perception user study that provides

REFERENCES

[1] M Barnaud et al. Proxemics models for human-aware navigation in robotics: Grounding interaction and personal space models in experimental data from psychology. In IROS Workshop on Assistance and Service Robotics in a Human Environment, 2014.
[2] Lisa F. Barrett. How emotions are made: The secret life of the brain. Houghton Mifflin Harcourt, 2017.
[3] Andrea Bauer et al. The autonomous city explorer: Towards natural human-robot interaction in urban environments. International Journal of Social Robotics, 1(2):127–140, 2009.
[4] Aniket Bera et al. Adapt: real-time adaptive pedestrian tracking for crowded scenes. In ICRA, 2014.
[5] Aniket Bera, Sujeong Kim, Tanmay Randhavane, Srihari Pratapa, and Dinesh Manocha. GLMP- realtime pedestrian path prediction using global and local movement patterns. ICRA, 2016.
[6] Aniket Bera and Dinesh Manocha. Realtime multilevel crowd tracking using reciprocal velocity obstacles. In ICPMR, 2014.
[7] Aniket Bera, Tanmay Randhavane, Rohan Prinja, and Dinesh Manocha. Sociosense: Robot navigation amongst pedestrians with social and psychological constraints. In IROS, 2017.
[8] Aniket Bera, David Wolinski, Julien Petté, and Dinesh Manocha. Real-time crowd tracking using parameter optimized mixture of motion models. arXiv preprint arXiv:1409.4481, 2014.
[9] F Chollet. Xception: Deep learning with depthwise separable convolutions. In Proceedings of the IEEE conference on computer vision and pattern recognition, pages 1251–1258, 2017.
[10] N.E. Du Toit and J.W. Burdick. Robotic motion planning in dynamic, cluttered, uncertain environments. In *ICRA*, 2010.

[11] P. Ekman and W. V. Friesen. Head and body cues in the judgment of emotion: A reformulation. *Perceptual and motor skills*, 1967.

[12] C. Fabian Benitez-Quiroz, Ramprakash Srinivasan, and Aleix M. Martinez. Emotionet: An accurate, real-time algorithm for the automatic annotation of a million facial expressions in the wild. In *CVPR*, 2016.

[13] Mohammed Faisal, Mohammed Alagbari, Benchifer Mohamed Abdellkader, Habib Dahhari, and Mohamad Mahmoud Al Rahhal. Human expertise in mobile robot navigation. *IEEE Access*, 2018.

[14] Tingxiang Fan, Xinjing Cheng, Jia Pan, Pinxin Long, Wenzhi Liu, Ruizang Yang, and Dinesh Manocha. Getting robots unfrozen and unlost in dense pedestrian crowds. *IEEE RAL*, 2019.

[15] Tingxiang Fan, Xinjing Cheng, Jia Pan, Dinesh Monacha, and Ruizang Yang. Crowdmove: Autonomous mapless navigation in crowded scenarios. *arXiv preprint arXiv:1807.07870*, 2018.

[16] Gonzalo Ferrer, Anais Garrell, and Alberto Sanfeliu. Robot companion: A social-force based approach with human awareness-navigation in crowded environments. In *IROS*, 2013.

[17] C. Fulgenzi, A. Spalanzani, and C. Laugier. Dynamic obstacle avoidance. In *CVPR*, 2016.

[18] C. Loutfi, J. Widmark, et al. Social agent: Expressions driven by an actor. *IEEE Transactions on Neural Systems and Rehabilitation Engineering*, 2014.

[19] N. Pradhan, T. Burg, and S. Fredrickson. Emotional category data on images from the international affective picture system. In *ICINCO*, pages 1610–1616, 2007.

[20] J. Russell, J. Bachorowski, et al. Facial & vocal expressions of emotion. In *Rev. of Psychology*, 86(1):1232–1240, 2017.

[21] A. Mehrabian. Pleasure-arousal-dominance. *Perceptual and motor skills*, 36(2):242–252, 1973.

[22] C. Roether, L. Omlor, et al. Critical features for the perception of emotion from gait. *Vision*, 2009.

[23] S. Ross, N. Melik-Barkhudarov, K. Shaurya Shankar, A. Wendel, and M. Hebert. Learning monocular reactive uav control in cluttered natural environments. In *ICRA*, pages 1765–1772, IEEE, 2013.

[24] G. Ruggiero, et al. A human aware mobile robot motion planner. In *IEEE Transactions on Affective Computing*, 2019.

[25] Billy Okal and Kai O Arras. Learning socially normative robot navigation behaviors with bayesian inverse reinforcement learning. In *ICRA*, 2016.

[26] Black SA Goodwin JS Ostir GV, Markides KS. Emotional well-being predicts subsequent functional independence and survival. *Journal of Gerontology, Series A: Psychological Sciences and Social Science*, 54(4):473–478, 2000.

[27] A. Mehrabian. Pleasure-arousal-dominance. *Perceptual and motor skills*, 36(2):242–252, 1973.

[28] J. Russell, J. Bachorowski, et al. Facial & vocal expressions of emotion. In *Rev. of Psychology*, 86(1):1232–1240, 2017.

[29] A. Mehrabian. Pleasure-arousal-dominance. *Perceptual and motor skills*, 36(2):242–252, 1973.