GSI: A Proxemics-Guided Generalized Safety Metric For Evaluating Safety in Social Navigation Context

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Abstract— **Human safety is critical in applications involving close human-robot interactions (HRI) and is a key aspect of physical compatibility between humans and robots. Less attention has been paid to assessing safety in social navigation settings where mobile robots and humans share the space. The paper introduces a new proxemics-guided generalized safety index (GSI) that instantaneously assesses human safety. It is particularly useful for evaluating mobile robots as they operate in social environments populated by multiple humans. The framework integrates several key metrics, such as each human's relative distance, speed, and orientation. We extensively validate GSI's capability of producing appropriate and fine-grained safety measures in real-world experimental scenarios and demonstrate its superior efficacy against extant safety models.**

I. Introduction

The study of human-robot interaction (HRI) and collaboration has gained importance as more humans and robots share workspaces and engage in proximal encounters [1], [2], [3]. A substantial body of literature focuses on human safety in industrial settings [4], [5], with established safety criteria and guidelines for collaborative robots [6], [7], [8] including industrial robot safety standards such as ISO 10218 and ISO/TS 15066 [4], [9]. Researchers have also introduced real-time safety assessments for large manipulators in human-robot collaborations [10], [11], [7]. While appropriate for close proximity and contact interactions, such as in manufacturing, these safety standards and measures cannot be readily transferred to mobile robots, which typically operate in large, unbounded workspaces, where the mobility of humans and robots significantly impacts human safety. Furthermore, existing methods in the literature tend to underestimate safety in multi-human environments. As such, there is a need for scalable measures of safety that can be obtained from different points of view (proprioceptive/exteroceptive) and for different utilities, such as safety assessments and motion control.

In this paper, we derive a novel safety measure termed the *Generalized Safety Index (GSI)* designed for mobile robot applications that combines the impact of distance, velocity, and the angular range (direction) between the robot and nearby humans. GSI is a proxemics-guided fine-grained safety assessment model, bounded between 0 and 1, where 0 represents an unsafe condition and 1 indicates full safety. Unlike existing safety scales that primarily focus on short-distance collaborations between a *single* human and a manipulator, GSI extends to multi-human HRI settings by prioritizing the safety of those at greater risk than averaging across multiple humans. Notable, GSI is designed solely for safety evaluation rather than active robot control, ensuring an accurate assessment of human safety without dictating motion responses. Together, GSI is amenable to being used in large, crowded environments, making it a versatile tool for safety analysis. These contributions are pivotal to motivating and stimulating further innovations in the evaluation and improvement of human safety around mobile robots.

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II. Related Work

Several models assess safety in HRI [12], but few address safety for mobile robots in dynamic, human-shared environments [13]. One key concept in understanding human comfort in such spaces is **proxemics**, introduced by Hall [14], which defines four interpersonal spatial zones—intimate (0–0.46m), personal (0.46–1.2m), social (1.2–3.7m), and public (¿3.7m). These zones have been widely applied in HRI to model safe interaction distances [15], [16]. Numerous findings involving human subject studies [17], [18], [19] have corroborated that humans perceive an interaction with an approaching robot as safe if it can stop in the personal zone and unsafe if it is (or about) to breach the intimate zone. Motivated by these findings, an appropriate safety measure should provide a granular value of safety level based on whether the robot can stop within the public zone (safe) and never breach any human's intimate zone (unsafe).

Kulic and Croft [10] defined a Danger Index (DI) based on a product formulation of human-robot distance and velocity for safe trajectory planning in robot arms. Lacevic et al. [20] developed the Kinetostatic Danger Field (KDF) for real-time danger assessment and control adjustments. Lippi et al. [11] extended the KDF to a human-safety assessment (HSA) for multi-robot collaboration, adjusting paths based on human proximity. Palmieri et al. [7] presented a human safety field (HSF) control architecture to improve safety in shared workspaces by adjusting manipulator trajectories. However, these models are intended for single-human collaboration with industrial manipulators and often fail in dynamic, unbounded spaces in the context of social navigation, as the safety models themselves are unbounded, requiring careful design for cut-off thresholds. KDF, HSA, and HSF may allow extensions to multiple humans but were not explicitly tested in their respective studies. For instance, in HSF [7], the authors mention the possibility of averaging the scale to aggregate the safety of multiple humans. Also, in KDF and HSA, the authors average the influence of multi-robots (multi-point safety considerations) in the safety measure.

These models often use summative or product-based formulations and do not scale well to unstructured, multi-human environments. Averaging risk across multiple humans, as suggested in HSF and KDF, can dilute critical safety violations—e.g., one person in danger may be overshadowed by others in safe zones—leading to misleading assessments. To be effective in social navigation, safety models must move beyond simplistic averaging and explicitly account for proxemics and individual human risk contributions.

III. Evaluating Proximics-Guided Human Safety

Let a mobile robot r with pose, $p_r = \langle \boldsymbol{x}_r, \theta_r \rangle$ where $\boldsymbol{x}_r = (x_r, y_r, z_r)$, be positioned in conjunction with multiple humans, $\{h_i | i = 1 \dots N_h\}$ where N_h is the number of detected humans. Let a human h_i be detected at a position $\boldsymbol{x}_{h_i} = (x_i, y_i, z_i)$ in a common frame of reference. The frame may be centered on the robot or global based on an external observer. We assume that the robot's motion constraints (e.g., maximum speed V_{max} and maximum deceleration A_{max}) are known, the robot has an RGB-D vision system to estimate the relative distance and velocities between every detected human and the robot, and the robot runs algorithms to detect and localize multiple humans [21] within the sensor's field of view. The problem facing GSI is to determine the current level of physical safety of all detected humans h_i around the robot r in its direction of travel θ_r.

A. Generalized Safety Index

In our framework, three key components are integrated to assess the safety of every detected human: distance, relative velocity, and the bearing of the human from the robot. These measures are generally deemed sufficient for assessing safety within the interaction space [8].

For each human h_i at position $\boldsymbol{x}_{h_i}$ in a common reference frame, let $d_{h_i,r}$ denote the distance from the robot, $d_{h_i,r} = \|\boldsymbol{x}_{h_i} - \boldsymbol{x}_r\|_2$. The relative velocity between them is the first-order derivative of the distance, $v_{h_i,r} = -\dot{d}_{h_i,r}$, which is a positive value when the distance between human and robot decreases and a negative value otherwise. Denote the relative bearing of the human h_i w.r.t. the robot as $\theta_{h_i,r} = \measuredangle(\boldsymbol{x}_{h_i} - \boldsymbol{x}_r) - \theta_r$. To clarify, this bearing is the angle (measured counterclockwise from the positive x-axis) between the segment joining the robot to the human and the robot's current orientation θ_r.

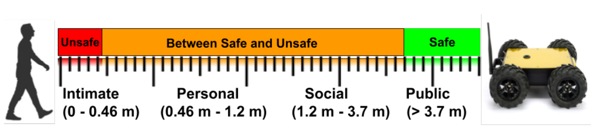


Fig. 1: GSI aligns its safety scale with the well-established proxemics ranges in HRI spaces. GSI takes a value of 1, indicating safe (green) in the public space, (0 - 1] (amber) in the personal and social spaces, and 0 (red) in the intimate space.

To arrive at a proxemics-guided safety scale, we rely on the well-known concepts of intimate, personal, social, and public spaces of human-robot interactions [14], which are illustrated in Fig. 1. Generally, a human's intimate space was empirically determined to be a sphere of radius 0.46m centered on the human, her personal and social spaces are the spherical shells whose radius lies in (0.46m - 1.2m] and (1.2-3.7m] ranges respectively, and the region beyond 3.7m is considered a public space. Our approach is to assess human safety based on where and whether the mobile robot intrudes into these spaces (i.e., the stopping zone). Towards this, we define a generalized safety index of a human h_i as

$$\widehat{GSI}_{h_i}(d_{h_i,r}, v_{h_i,r}; \rho) = \left[\frac{d_{h_i,r} - \left(\mathrm{s}(v_{h_i,r}) \frac{v_{h_i,r}^2}{2A_{max}} + D_{min} \right)}{D_{max} - D_{min}} \right]^{\rho} \tag{1}$$

Here, A_{max} is a constant representing the maximum (de-)acceleration of the robotic platform; D_{max} is the distance beyond which the human's safety is assured – we may let $D_{max} = 3.7m$ (public space), and a mobile robot should not come closer than D_{min} – we may let $D_{min} = 0.46m$ (intimate space), or 0 if, for example, the robot needs to transport the human. The term $\frac{v_{h_i,r}^2}{2A_{max}}$ in (1) indicates the distance required for the robot to stop at its current relative speed $v_{h_i,r}$, given a maximum deceleration rate of A_{max}. $\mathrm{s}(v_{h_i,r})$ is the sign function that informs whether the human is approaching or moving away from the robot. The sign function is positive when the distance between the human and the robot decreases over time and negative otherwise.

The hyperparameter $\rho > 0$ provides a way to fit GSI to various kernels based on the current application setting and the subjective human perception of safety. We may select different values of ρ in applications involving GSI-aided motion control, where higher $\rho > 1$ decay of safety can be appropriate in robots with slow reaction times or large mass (i.e., a larger than usual buffer from the human is preferred for more cautious human perceptions of safety or higher chances of a platform failure to stop in fast motion settings [22]. Previous work has utilized a similar parameter for industrial robots, where it is set to 2 [10]. On the other hand, lower values of $\rho < 1$ may be utilized if the human is comfortable around mobile robots [23], reducing the need for unnecessary interventions [10]. Finally, a balanced trend can be obtained with $\rho = 1$ providing a rational GSI [22], and therefore, we use this setting ($\rho = 1$) for assessing the current safety level. Fig. 2 illustrates the impact of ρ on the GSI model.

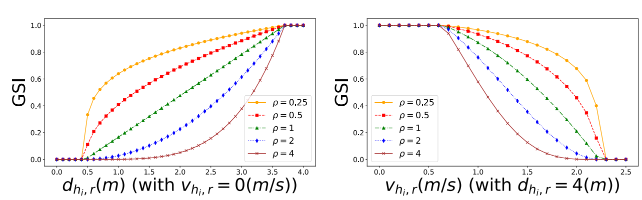


Fig. 2: GSI can be fitted to various applications, robot platform properties, and subjective safety perceptions of humans through parameter $\rho > 0$. For instance, $\rho = 1$ is set for assessing safety, $\rho > 1$ for more cautious robot control, and $\rho < 1$ for a more closer interaction with human who are already comfortable.

In essence, $\widehat{GSI}_{h_i}$ accounts for the robot's ability to stop before breaching the intimate zone of a human and we bound it between 0 and 1, so any value less than 0 will be set to 0 and any value greater than 1 is set to 1. A value $= 0$

represents an unsafe condition (i.e., the intimate space has or is about to be breached), while GSI $= 1$ asserts a fully safe condition (i.e., the robot is in the public zone). Any value between 0 and 1 measures the safety level, closer to 0 indicates less safety, and higher risk to the human at that point in time, whereas closer to 1 suggests that the human is likely to be safe at that time.

Eq. 1 is applicable for a static scenario or if we assume the robot and human are directly approaching each other, i.e. $\theta_{h_i,r} = 0°$. For a non-zero bearing of the human w.r.t. the robot, we extend Eq. 1 to scale the GSI with how close the robot gets to the human as it passes by it. More specifically, we obtain a directional GSI as given below,

$$GSI_{h_i}(d_{h_i,r}, v_{h_i,r}, \theta_{h_i,r}; \rho) = 1 - (1 - \widehat{GSI}_{h_i}) \cos\theta_{h_i,r}. \tag{2}$$

We illustrate the derivation of Eq. 2 using Fig. 3(a), which shows that $\cos\theta_{h_i,r}$ can be used to scale the complement of the GSI value that is obtained as if the robot is heading straight for the human. Notice that when $\theta_{h_i,r} = 0$, $\cos\theta_{h_i,r} = 1$ and $GSI_{h_i}(d_{h_i,r}, v_{h_i,r}, \theta_{h_i,r}; \rho)$ collapses to $\widehat{GSI}_{h_i}(d_{h_i,r}, v_{h_i,r}; \rho)$ as we may expect. And, if $\widehat{GSI}_{h_i}(\cdot)$ indicates not safe, then $GSI_h(\cdot)$ tempers down the non-safety by how close the robot is expected to pass by the human. Thus, GSI represents a dynamic measure of safety, integrating real-time motion input to assess the human's safety in the shared workspace given the robot's movement.

GSI for settings shared with multiple humans Implications of robot motion on the safety of multiple humans (e.g., in crowded pedestrian areas [24]) are studied from motion planning and physiological social awareness perspectives [13], [25]. The presence of multiple humans in the shared workspace complicates the determination of safety as we now face an additional challenge: how to aggregate individual safety indications to determine the safety of the whole.

Previous work (HSF [7]) advocates averaging individual safety values in all humans. But, the disadvantage with it is it may *overestimate* the overall safety when the robot is safe for a majority of the humans in the group but unsafe for a few in the shared space. Therefore, we posit that the safety index for the whole should not only be directional but should also attribute higher importance to the safety of those humans for whom the robot presents significant safety implications in its intended direction. Toward this, let $\boldsymbol{d}_{h,r} = \langle d_{h_i,r} | i = 1, \ldots, N_h \rangle$ represent the vector of relative distances between the mobile robot and each human i in the shared space and analogously $\boldsymbol{v}_{h,r}$ and $\boldsymbol{\theta}_{h,r}$ represent the vector of relative velocities and angles, respectively. Rather than simply returning the minimum of the $GSI_h(\cdot)$ values, we utilize a smooth minimum LogSumExp (also known as the realsoftmin) of the individual values, to obtain the *collective GSI* for the group of N_h humans in the robot's shared space.

$$\begin{aligned} &GSI(\boldsymbol{d}_{h,r}, \boldsymbol{v}_{h,r}; \boldsymbol{\theta}_{h,r}; \rho, \tau) = \\ &-\tau \ln\left(\frac{1}{N_h}\sum_{i=1}^{N_h} e^{\frac{-GSI_{h_i}(d_{h_i,r}, v_{h_i,r}, \theta_{h_i,r}; \rho)}{\tau}}\right) \end{aligned} \tag{3}$$

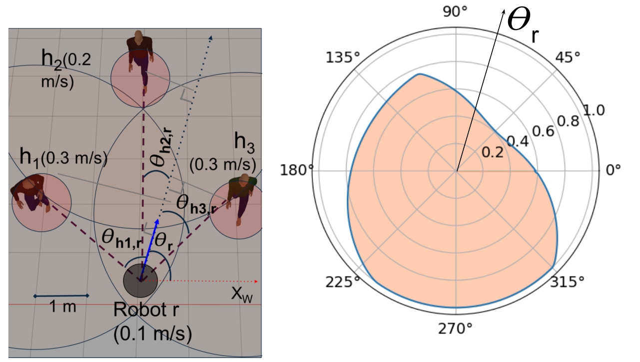


Fig. 3: An example setting with three humans in the vicinity of the mobile robot r. GSI yields a directional safety value for each human. In this example, $GSI_{h_1} = 0.7$ with $\theta_{h_1,r} = 290°$, $GSI_{h_2} = 0.9$ with $\theta_{h_2,r} = 345°$, and $GSI_{h_3} = 0.4$ with $\theta_{h_3,r} = 30°$, each of which is calculated using Eq. 2.

where $GSI_h(\cdot)$ is as defined previously in Eq. 2 for a single human in the vicinity, τ is a hyperparameter that controls the smoothness of the approximation of the minimum of the $GSI_h(\cdot)$ values. As τ reduces, GSI converges to the minimum $GSI_h(\cdot)$ across all humans i. We set $\tau = 0.01$ for obtaining close to the absolute minimum. The LogSumExp function heavily penalizes larger $GSI_h(\cdot)$, which makes it sensitive to the small $GSI_h(\cdot)$ values, thereby obtaining a safety index corresponding to the human that influences the most. GSI in Eq. 3 satisfies the core properties of safety measures [11], [20] such as a monotonic increase (decrease) with distance (velocity) and differentiability. These properties enable a differential safety scale that is useful in evaluating and integrating mobile robot algorithms. We summarize GSI for various scenarios in Table I and compare it with other scales for appropriateness.

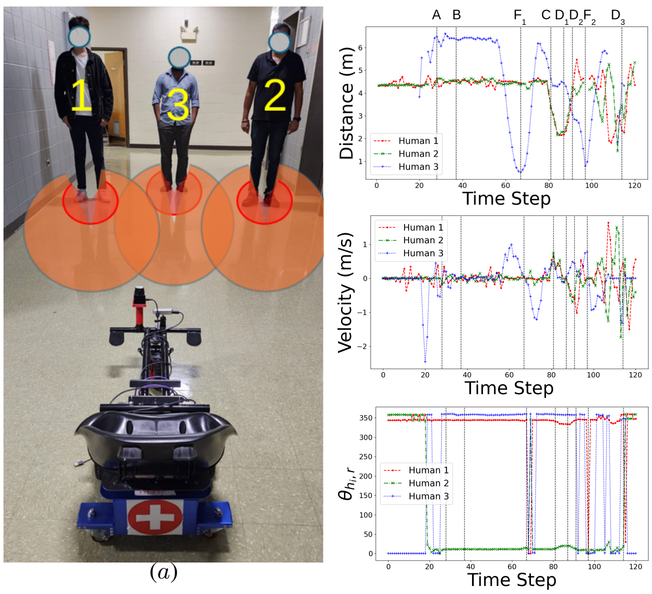
IV. Experimental Evaluation

We conducted physical robot experiments with a Ubiquity Magni platform customized for use in a medical evacuation application and equipped with an Intel RealSense D435i mounted in front, as we show in Fig. 4(a). We created a multi-human scenario with three humans in the robot's view simultaneously. While the robot was stationary, the humans followed various trajectories at regular walking speeds to simulate a pedestrian walkway. This included: 1) Human 3 alone walks toward the robot and then moves away. Other humans stay put; 2) Humans 1 and 2 walk toward the robot while Human 3 stays put; 3) Human 3 walks toward the robot while Humans 1 and 2 walk away; and 4) Random movement of all humans. We show the distances, velocities, and bearings of the three humans engaged in these behaviors in Fig. 4. Scenarios A – F presented in Table I manifest in these behaviors. These are marked in the three plots of Fig. 4(b). We note that the measures correctly track as humans move in the shared space, leading to the scenarios.

We compare the GSI safety scale (with $\rho = 1$ and $\tau = 0.01$ as it is a service robot) with the existing KDF [20], HSF [7], and HSA [11] considering the averaging approach for

TABLE I: A summarization of the appropriateness of different safety scales in various scenarios (combinations of distance $d_{h_i,r}$ and relative velocity $v_{h_i,r}$). The appropriate safety level is determined based on the stopping zone of the robot to the closest human (Fig. 1). SH - single human. MH - multi-human. A ✓or × indicates whether the scale may correctly inform the appropriate safety level per the proxemics framework. ↑ and ↓ denote the possibility of overestimating or underestimating the safety levels, respectively.

Scenario	**Distance**	**Relative Velocity**	**Stopping Zone**	**Appropriate Assessment**	**GSI** [Ours]		**DI** [10]		**KDF** [20]		**HSF** [7]		**HSA** [11]	
					SH	MH	SH	MH	SH	MH	SH	MH	SH	MH
A	$d_{h_i,r} \geqslant D_{max}$	$v_{h_i,r} \leqslant 0$	Public	Safe	✓	✓	✓	N/A	✓	✓	✓	✓	✓	✓
B	$d_{h_i,r} \geqslant (D_{max} + \frac{v_{h_i,r}^2}{2A_{max}})$	$v_{h_i,r} \geqslant 0$	Public	Safe	✓	✓	✓	N/A	✓	✓	✓	✓	✓	✓
C	$d_{h_i,r} \geqslant D_{max}$	$0 < v_{h_i,r}^2 < 2A_{max}(d_{h_i,r} - D_{min})$	Within Personal/Social	Between	✓	✓	× ↑	N/A	✓	✓	× ↑	× ↑	✓	✓
D	$D_{min} \leqslant d_{h_i,r} \leqslant D_{max}$	$v_{h_i,r} = 0$	Within Personal/Social	Between	✓	✓	× ↑	N/A	✓	× ↑	✓	✓	✓	✓
E	$d_{h_i,r} \geqslant D_{max}$	$v_{h_i,r}^2 \geqslant 2A_{max}(d_{h_i,r} - D_{min})$	Intimate	Unsafe	✓	✓	× ↑	N/A	✓	× ↑	× ↑	× ↑	× ↑	× ↑
F	$d_{h_i,r} \leqslant (D_{min} + \frac{v_{h_i,r}^2}{2A_{max}})$	$v_{h_i,r} \geqslant 0$	Intimate	Unsafe	✓	✓	✓	N/A	✓	✓	✓	✓	✓	✓
G	$D_{min} \leqslant d_{h_i,r} \leqslant D_{max}$	$v_{h_i,r}^2 \leqslant -2A_{max}(D_{max} - d_{h_i,r})$	Public	Safe	✓	✓	✓	N/A	× ↓	× ↓	× ↓	× ↓	× ↓	× ↓



(*a*) (*b*)

Fig. 4: (*a*) Setting for the physical robot experiment involving GSI on an Ubiquity Magni which is sharing space with three moving humans. (*b*) Validation of distances $\boldsymbol{d}_{h,r}$, relative velocities $\boldsymbol{v}_{h,r}$, and bearings $\boldsymbol{\theta}_{h,r}$ of the three humans.

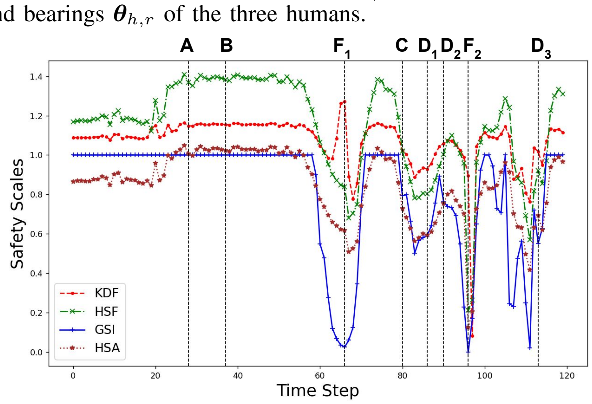


Fig. 5: Output of safety scales from the robot's viewpoint applicable to multiple humans in our experiments with three humans.

safety calculations in a multi-human environment per their designs. For comparison, we invert the KDF values as it is a danger scale (similar to DI) and normalize the HSF values by $Dmax$ as it relies solely on the distance factor.

Observe from Fig. 5 that KDF and HSF report safety values that are much higher than GSI. This is because of the averaging used by these scales that generally lift safety value when few but several humans are safe. For example, as Human 3 approaches the robot, where Humans 1 and 2 stay put, which corresponds to scenario F_1 depicting Human 3 breaching the intimate zone according to proxemics, KDF, HSF, and HSA reduce, but not as much as GSI. The latter's overall safety assessment emphasizes approaching humans over others, per proxemics.

Another stark distinction between the four safety assessments is in scenarios D_1 and F_2, when Humans 1 and 2 are walking away while Human 3 is approaching (D_1 depicting reaching personal/social zone) and when just Human 3 remains in the robot's viewable range and according to proxemics the robot is nearing the human's intimate space (F_2). While all assessments drop, the impact of Humans 1 and 2 walking back is much more on KDF and HSF, while GSI remains sensitive to the approaching human. On the other hand, the presence of a robot in close proximity to the human in F_2 causes all scales to report low safety values.

In scenario E (Table I), the relative velocity is significantly high (positive), and the robot cannot stop without breaching the human's intimate space, classifying the situation as unsafe. Conversely, in scenario G, if the robot is moving away from the human with high velocity (negative), the scenario is considered safe. Existing safety scales, such as KDF and HSA, which assign four times greater weight to distance than velocity, or HSF, which relies solely on distance, tend to misinterpret safety levels in such cases, leading to false assessments. Due to our robot platform's inability to generate high-velocity movements, these two scenarios are not observed in the data. Based on this detailed analysis, we note that GSI conforms to the proxemics framework, departing from the extant scales such as KDF, HSF, and HSA, even in contexts involving multiple humans. Indeed, KDF and HSF appear to consistently overestimate the overall safety of the situation, whereas GSI offers more specificity in assessing the appropriate safety of the robot operating in social settings.

V. Conclusion

We presented a new proxemics-guided safety assessment model (GSI) for mobile robots operating in a multi-human environment. This is integrated with an RGB-D camera-based safety assessment framework, which uses the GSI model to perform real-time safety assessments and allows multiple endpoint use. Physical robot experiments confirmed the validity of the model and its utility compared to other existing safety scales. The contributions in this work will help advance safety-aware algorithms and motion planners in human-rich mobile robot applications.

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