Human-in-the-Loop Object-Goal Navigation in Household Settings

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***Abstract*—Household robots increasingly operate in environments shared with humans who move unpredictably, manipulate objects, and expect efficient yet socially acceptable robot behavior. Existing object-goal navigation systems typically optimize for task success and collision avoidance but rarely account for human comfort, disturbance, and legibility. We present a human-in-the-loop object-goal navigation framework in the Habitat 3.0/PARTNR simulation environment that allows a mobile robot to reach specified object categories while adapting its path around an actively working human. Our method incorporates human-state estimation via segmentation and depth, maintains a Gaussian belief over human location, predicts a human motion corridor, and modifies robot control actions to avoid intrusion into personal space. We then evaluate our method by conducting experiments using a scripted planner with varying proxemic safety thresholds. Our results demonstrate that our approach reduces social intrusion counts in personal zones compared to baseline. This work provides an early step toward socially aware object-goal navigation while being aware of human distance comfort in dynamic household environments.**

***Index Terms*—Human–robot interaction, Object-goal navigation, Social navigation, Household robotics**

I. Introduction

Household environments are dynamic, shared spaces in which humans move freely, perform multi-step tasks, and frequently interact with objects. For a robot operating in such settings, reaching a target object is only one part of the challenge. The robot must do so without causing obstruction, discomfort, or inefficient human–robot coexistence. Simply avoiding collisions is not sufficient, as socially acceptable behavior also requires respecting personal and working space, moving predictably, and avoiding interference with ongoing human activities.

Existing navigation systems largely optimize for geometric safety, focusing on collision avoidance without accounting for human comfort, legibility, or task context. As a result, a naïve object-goal navigation policy may unintentionally block human pathways, cut across a human's trajectory, or hover near objects required for the human's task. Such behaviors can lead to unnecessary disruption, slow task completion, and reduce trust—issues emphasized in prior studies of legible motion [1], proxemics [2], and socially competent navigation [3].

Motivated by these challenges, our goal is to enable robots to perform object-goal navigation in household environments while adapting their motion to ongoing human activities, ensuring safe, comfortable, and minimally disruptive behavior. Achieving this requires the robot to: (1) minimize disturbance by avoiding overly intrusive behaviors, (2) adjust its path to give the human priority and avoid interfering with human–object interactions, and (3) maintain efficient travel time and goal accuracy.

To address these objectives, we develop a human-in-the-loop navigation framework that integrates segmentation-based human detection, Gaussian belief tracking to handle occlusions, predictive motion-corridor estimation, and constrained control adjustment that modulates the baseline navigation action. We evaluate this approach through simulation in both human-only and human-with-robot scenarios, analyzing spatial intrusion, disturbance behaviors, and task-level impact to quantify how robot motion affects human performance in shared household environments.

II. Related Work

A. Human Disturbance and Social Navigation

Human-aware navigation has been widely studied in the HRI community, particularly through the lenses of proxemics, legibility, and social compliance. Rios-Martinez et al. [2] survey navigation approaches grounded in proxemics theory, emphasizing that robots must avoid violating personal space even when not physically colliding with humans. Dragan and Srinivasa [1] highlight the importance of legible motion—trajectories that clearly communicate a robot's intent to nearby observers. More recent multi-agent navigation work has explored socially competent trajectory generation, such as social momentum models that help robots behave predictably in multi-agent settings [3]. These frameworks motivate our focus on disturbance-minimizing behavior rather than pure collision avoidance.

B. Object-Goal Navigation

Object-goal navigation (ObjectNav) requires a robot to locate an instance of an object category in a realistic environment. Semantic exploration strategies have demonstrated strong improvements in navigation efficiency and success rates [4]. Curiosity-driven auxiliary objectives also enable more efficient exploration in unseen environments [5]. Habitat 3.0 [6] and the PARTNR benchmark [7] further support multi-agent interaction and natural language task specifications,

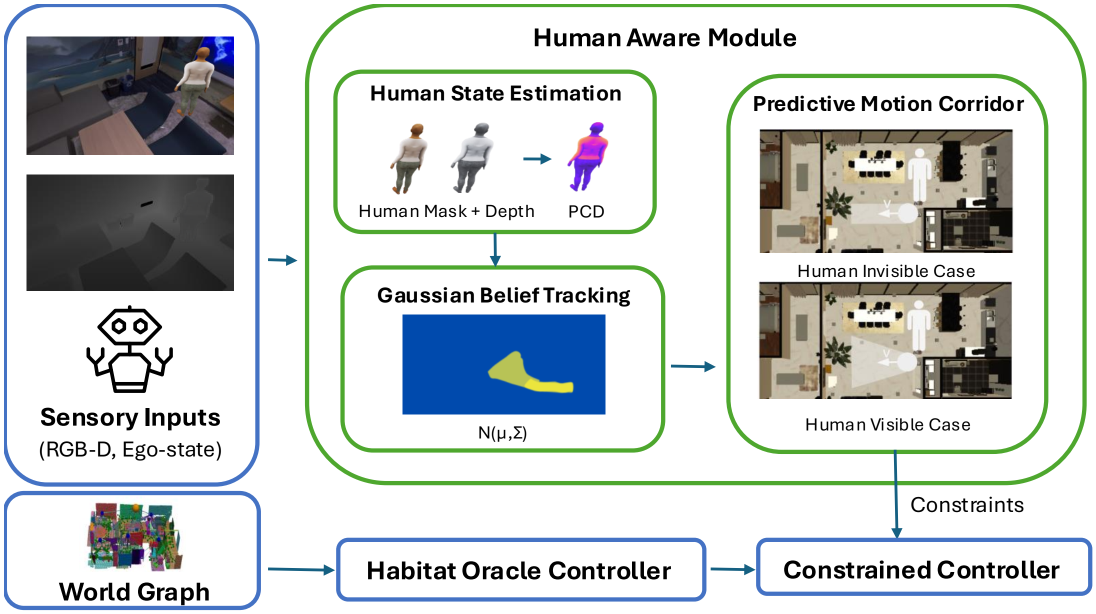

Fig. 1. Overview of Method Pipeline

enabling studies of household activities involving both humans and robots. Our work builds on this infrastructure by introducing human-aware constraints on top of standard ObjectNav planning.

III. Method

We introduce a training-free human-aware navigation module that augments the default PARTNR Oracle navigation skill. Our method consists of four components: (1) human state estimation from segmentation and depth, (2) Gaussian belief tracking over human location, (3) short-horizon prediction of human motion, and (4) a constrained control procedure that modifies the Oracle navigation command only when necessary to avoid interfering with human movement. Throughout, x_t^R denotes the robot base position at time t, and Δt is the simulator time step.

A. Human State Estimation via Sensor Inputs

At each timestep, the agent receives a depth image D_t and a human segmentation mask S_t:

$$O_t = \{D_t, S_t, \ldots\}.$$

We extract the set of pixels labeled as human:

$$\mathcal{V}_t = \{(u, v) \mid S_t(u, v) = \text{human}\}.$$

If $|\mathcal{V}_t| \geq n_{\min}$, the human is considered visible. Depth values at these pixels are back-projected into 3D using the calibrated camera intrinsics and extrinsics, producing a point cloud $\{p_i\}_{i=1}^N$ in world coordinates. We project each p_i onto the ground plane and take the mean as the estimated human position:

$$z_t^H = \frac{1}{N}\sum_{i=1}^{N} \text{Proj}_{xz}(p_i).$$

If a previous estimate exists, we compute a velocity estimate

$$\hat{v}_t^H = \frac{z_t^H - z_{t-1}^H}{\Delta t}.$$

B. Belief Over Human Position

We maintain a Gaussian belief over the human's ground-plane location:

$$b_t(z) = \mathcal{N}(\mu_t, \Sigma_t).$$

When the human is visible, we perform an observation update:

$$\mu_t = z_t^H, \qquad \Sigma_t = \Sigma_{\text{obs}},$$

where Σ_{obs} is the sample covariance of the observed human point cloud on the ground plane. When the human is not visible, we propagate the belief forward using a constant-velocity model with process noise Q:

$$\mu_{t+1} = \mu_t + \Delta t\, \hat{v}_t^H, \qquad \Sigma_{t+1} = \Sigma_t + Q.$$

If the uncertainty becomes too large, $\text{trace}(\Sigma_t) > \Sigma_{\max}$, or the human has not been observed for a long horizon, the belief is discarded.

C. Predictive Human Motion Corridor

Given the current belief, we predict the human's likely motion over a short horizon K:

$$\hat{\mu}_{t+k} = \mu_t + k\Delta t\, \hat{v}_t^H.$$

For each future step, we form an uncertainty-informed radius:

$$r_{t+k} = r_0 + \alpha\sqrt{\lambda_{\max}(\Sigma_{t+k})},$$

where Σ_{t+k} is the propagated covariance and $\lambda_{\max}(\cdot)$ denotes its largest eigenvalue. The *predicted human motion corridor* is the union of K disks:

$$\mathcal{C}_t^H = \bigcup_{k=1}^{K} \mathcal{B}(\hat{\mu}_{t+k}, r_{t+k}).$$

If $\mathrm{trace}(\Sigma_t) > \Sigma_{\max}$, the corridor is deemed unreliable and ignored.

D. Human-Aware Navigation as a Constrained Control Problem

The underlying PARTNR navigation skill provides a nominal velocity command:

$$u_t^0 = (v_t^0, \omega_t^0) = \pi_{\text{oracle}}(x_t^R, g^R).$$

We modify this command only when necessary to avoid the predicted human corridor. Let $d(x_t^R, \mathcal{C}_t^H)$ denote the signed distance from the robot to the corridor. The executed control is:

$$u_t^* = \begin{cases} u_t^0, & \text{if no reliable corridor is available,} \\ u_t^0, & \text{if } d(x_t^R, \mathcal{C}_t^H) > d_{\text{safe}}, \\ \text{SlowDown}(v_t^0) \oplus \text{SteerAway}(\omega_t^0), & \text{otherwise.} \end{cases}$$

where $\oplus$ denotes the combination of scaled linear velocity and adjusted angular velocity. The slowdown factor is proportional to how deeply the robot enters the safety margin, and the steering direction is determined by the gradient pointing away from the nearest predicted human position. If uncertainty becomes too large, the corridor is disabled and $u_t^* = u_t^0$, recovering the original Oracle navigation behavior.

This results in a fully training-free human-aware navigation policy that reacts smoothly when the human is visible, maintains a conservative prediction when the human temporarily leaves the field of view, and reverts to standard Oracle navigation when the belief becomes too uncertain.

IV. Experimental Evaluation

A. Experimental Setup

We evaluate our human-aware navigation framework in the Habitat 3.0 simulator using the PARTNR benchmark assets. Our experiments are conducted in a high-fidelity apartment scene populated with realistic furniture and a simulated human agent performing household activities, which can be seen at Fig. 2.

1) Task Definition: The objective is to evaluate the robot's ability to navigate to object goals concurrently with a human in the scene. We construct a dataset of **8 distinct episodes**. To test the generalization of the navigation policy rather than mapping memory, all episodes utilize the same static scene layout (a furnished living room) but vary the initialization:

- **Object Configuration:** Target objects are spawned in randomized valid locations within the living room for each episode.

Fig. 2. A top-down view of our apartment scene in Habitat 3.0 simulation

- **Human Activity:** The human agent executes different rearrangement tasks, resulting in variable trajectories and occupancy patterns.

The robot and human agents pursue **independent objectives**. The interaction is defined as non-collaborative and non-adversarial; the agents coexist in the shared space without explicit coordination or competition.

2) Baselines and Conditions: We compare three experimental conditions to assess the impact of robot navigation on human comfort and task efficiency:

1) **Human-Only (Reference):** The human agent performs tasks without any robot present. This establishes the upper bound for human task efficiency.
2) **Human + OracleNav (Baseline):** The human shares the space with a robot executing the default PARTNR object-goal navigation policy. This policy has access to the ground-truth map but lacks explicit human-aware constraints.
3) **Human + HumanAware (Ours):** The human shares the space with a robot controlled by our proposed method, which has Gaussian belief tracking and motion corridors.

B. Evaluation Metrics

Our evaluation focuses on two conflicting objectives: maximizing task efficiency and minimizing social intrusion.

1) Social Compliance (Proxemics): We quantify intrusiveness based on Hall's Proxemics Theory [2]. We define a set of distance thresholds $\mathcal{T} = \{0.2m, 0.4m, 0.7m, 1.2m\}$ representing the transition from the deep intimate zone (high danger/intrusion) to the outer boundary of the personal zone. For each threshold $\tau \in \mathcal{T}$, we compute:

- **Disturbance Count (N_{dist}^{τ}):** The total number of discrete events where the robot-human distance $d(h, r)$ falls in or below τ.

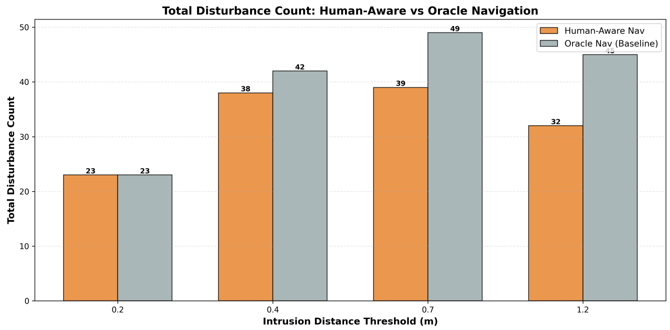

Fig. 3. Comparison of Total Disturbance Counts across four proxemic thresholds. The Human-Aware planner (Orange) consistently produces fewer intrusions than the Oracle baseline (Grey), with significant reductions of 20% and 29% in the 0.7m and 1.2m zones, respectively.

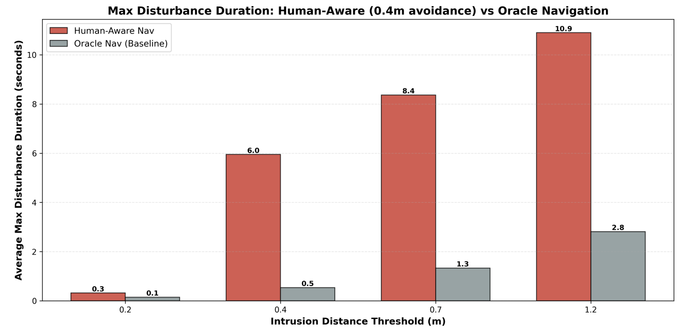

Fig. 4. Comparison of Maximum Disturbance Duration. The Human-Aware method (Orange) shows longer durations due to yielding behavior (stopping to wait), whereas the Oracle baseline (Grey) minimizes duration by aggressively traversing the human's space at high speed.

- **Max Disturbance Duration** (T^{τ}_{max})**:** The maximum continuous duration (in seconds) the robot remains within distance τ of the human.

2) Task Performance: To measure the impact of the robot on the global system efficiency:

- **Completion Rate:** The percentage of the amount of tasks that the human completes successfully from the instruction.
- **Completion Time:** The total time required to complete the episode. We analyze the variation in completion time (min, max, and average) to understand the consistency of the method.

The next section present our results by analyzing the trade-off between intrusion thresholds and performance. For the graphical analysis, we report the performance variability across the 8 episodes and take the average. For each method and threshold τ, we visualize the range of outcomes (minimum to maximum completion rates and times) alongside the average trend. This highlights not only the mean performance but also the worst-case scenarios.

V. Results

A. Social Compliance and Disturbance

We first evaluate the robot's ability to respect human personal space. Fig. 3 compares the total disturbance counts across four proxemic thresholds. The Human-Aware method demonstrates a clear reduction in intrusion frequency compared to the Oracle baseline, particularly in the larger social zones. At the *Mid-Personal* threshold (0.7m), our method reduces the total disturbance count by 20% ($49 \rightarrow 39$), and at the *Far-Personal* threshold (1.2m), disturbances are reduced by 29% ($45 \rightarrow 32$). This indicates that our predictive corridor effectively steers the robot away from the human's future path before an intrusion occurs.

We further analyze the nature of these interactions by examining the Max Disturbance Duration (Fig. 4). Interestingly, the Human-Aware method exhibits higher maximum durations within intrusion zones compared to the baseline. This counter-intuitive result highlights a fundamental difference in navigation behavior: the Oracle policy treats the human as a static obstacle and navigates around or through the space at high speed, minimizing duration but maximizing perceived aggression. In contrast, our Human-Aware policy controls the robot to slow down or stop to let the human pass. While this results in the robot remaining in proximity for longer periods, the robot's state is static or slow-moving, which is generally perceived as safer and more legible in HRI contexts.

B. Impact on Human Task Efficiency

We assess whether the presence of the robot negatively impacts the human's ability to complete their rearrangement tasks. We treat the Human-Only condition as the baseline for ideal workflow efficiency.

Our results indicate that the human maintains a consistent 87.5% task success rate across all conditions (Human-Only, Human + Oracle, and Human + Human-Aware). This suggests that our navigation constraints do not inadvertently block the human or force task abandonment. The human is able to complete their goals regardless of the navigation policy employed by the robot.

TABLE I
Average task completion time across different methods.

Method	Average Completion Time (s)
Human Only	33.2
Human-Aware (0.2m)	42.4
Oracle	39.6

However, social compliance does introduce a temporal cost. As shown in Table. I, the average human task completion time for the Human-Aware method (42.4s at 0.2m threshold) is approximately **7%** higher than the Oracle baseline (39.6s). This delay reflects the burden of interaction in a shared space: the Human-Aware robot remains in the environment longer due to stopping and re-routing, slightly prolonging the overall episode duration compared to the aggressive Oracle baseline.

C. Sensitivity to Safety Thresholds

Finally, we analyze how the strictness of the safety constraint affects system performance. Fig. 5 plots the completion

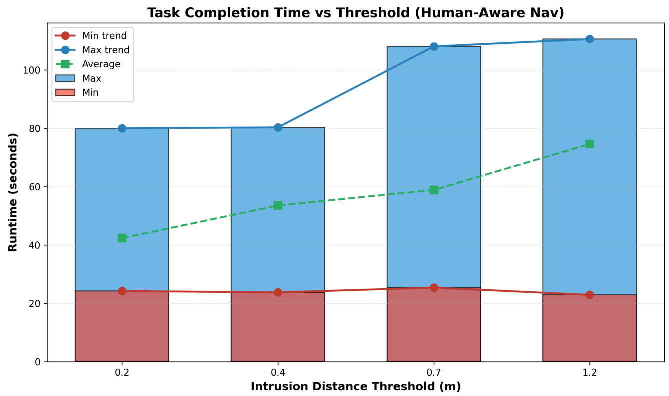

Fig. 5. Task Completion Time vs. Intrusion Distance Threshold. The Min bar plot is overlaying on top of the Max bar plot. As the safety constraint becomes stricter (larger threshold), the total episode time increases, confirming the trade-off between spatial efficiency and social caution.

time as a function of the intrusion distance threshold. We observe a positive correlation between the safety margin and task duration. As the threshold increases from 0.2m to 1.2m, the average completion time rises from 42s to roughly 75s. Stricter thresholds force the robot to take wider detours or wait at greater distances, confirming the trade-off between spatial efficiency and social caution.

VI. Discussion

Our experiments demonstrate that it is possible to integrate human-aware constraints into an object-goal navigation pipeline without retraining the underlying policy. However, the results highlight a distinct trade-off between social compliance and temporal efficiency.

While the Oracle baseline achieves lower completion times by treating the human as a static obstacle to be circumvented efficiently, it incurs high disturbance costs. In contrast, our Human-Aware navigation increases average task duration by approximately 7%. This aligns with findings by Dragan et al. [1], who demonstrate that legible and socially compliant motion inherently deviates from efficiency-optimal trajectories. Furthermore, our method avoids the ”Freezing Robot Problem” [8]; despite the conservative constraints, the system maintains task completion rates comparable to the baseline while successfully trading this marginal temporal cost for a 20–29% reduction in social intrusion count. We conclude that this 7% delay is an acceptable cost for gains in safety and the reduction of aggressive close-proximity maneuvers in household environments.

While our results demonstrate the efficacy of the proposed human-aware constraints, we acknowledge several limitations in the current study.

First, our evaluation is confined to the Habitat 3.0 simulation environment. While Habitat provides high-fidelity physics, real-world deployment introduces additional challenges such as sensor noise, estimation latency, and complex kinematics that are not fully captured in simulation. Future work will focus on bridging the sim-to-real gap by deploying our framework on a physical mobile manipulator.

Second, the current evaluation is conducted on a limited set of episodes ($N = 8$) within a single scene layout. To establish statistical significance and robustness, a more rigorous evaluation across diverse scene topologies and varying human activity types is necessary.

Finally, our method relies on explicit geometric constraints and heuristics. While this ensures interpretability and requires no training, it may lack the generalization capabilities of learning-based approaches. Future iterations of this work could explore integrating Vision-Language Models (VLMs) to provide semantically rich context for social navigation, or Deep Reinforcement Learning (DRL) to learn more fluid, context-aware avoidance policies.

VII. Conclusion

We introduced a human-in-the-loop object-goal navigation framework that incorporates human-state estimation, Gaussian belief tracking, predicted motion corridors, and constrained action adjustment. Our analysis of baseline navigation behavior demonstrates that disturbance and obstruction are common in shared household environments when human presence is not explicitly modeled.

By quantifying intrusion and its effects on human task performance, we establish the need for socially aware navigation methods. Future work will integrate our constrained control module with trained ObjectNav policies, expand evaluations to additional households, and ultimately validate the approach with real human participants.

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APPENDIX

TABLE II
PROPOSED PROJECT GRADING RUBRIC

Component	**Points (Total 150)**
Literature Review	30
Methodology	30
System Development and Simulation Setup	40
Evaluation Metric Definitions and Design	30
Report Writing	20