

# Journal of Advanced Research Design



Journal homepage: https://akademiabaru.com/submit/index.php/ard ISSN: 2289-7984

# Innovative Safety Measures for Human-Robot Interaction in Dynamic Environment Using RRT and IR Sensing

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#### **ARTICLE INFO**

#### Article history:

Received 2 February 2025 Received in revised form 22 June 2025 Accepted 10 September 2025 Available online 18 September 2025

#### **ABSTRACT**

This study addresses the critical challenge by developing reliable safety protocols for robots in domestic environments, introducing an advanced safety algorithm leveraging dynamic path planning and real-time obstacle avoidance strategies. Motivated by the gap in research focusing on domestic HRI as opposed to industrial contexts, this study utilizes a 7-degree of freedom (DOF) Kinova Gen3 arm robot model in simulated settings. The methodology is evaluated against ISO/TS 15066:2016 protocols, demonstrating its efficacy and adaptability in real-world scenarios. The open-source 3D robotics simulator Gazebo is employed to run the simulations, incorporating safety protocols to control the robot's arm velocity and trajectory, minimizing the risk of collision and auto-correcting the trajectory in the presence of obstacles. An IR distance sensor is embedded in the virtual robot to measure distance data, including range and field of view. In the simulation, a human is defined as a 'virtual obstacle,' and the robot uses the IR distance sensor to measure the distance to the human through infrared light. The Open Motion Planning Library (OMPL) uses the Rapidly Exploring Random Tree (RRT) algorithm for motion planning, selecting random configurations while respecting the robot's kinematic constraints. The robot interprets sensor readings to determine the distance to nearby humans and adjusts its speed accordingly. The robot stops moving to avoid collision when the distance falls below a determined threshold. The simulation results provide valuable insights into the features necessary to adapt this HRI system to real-life domestic environments, evaluating the safety region for HRI within a range from -0.1m to 0.1m. The significance of this study lies in its focus on domestic environments, an area that has been relatively underexplored compared to industrial settings. By addressing the complexities and unpredictability of home environments, this research aims to enhance the integration of robots into everyday domestic settings, promoting safer and more effective human-robot interactions. The findings underscore the importance of dynamic safety measures and real-time adaptability, contributing to the advancement of safer HRI protocols in domestic environments.

#### Keywords:

Safety algorithm; RRT\*; Collision avoidance

# 1. Introduction

The proliferation of robots in domestic settings introduces complex challenges in safety and interaction dynamics. Unlike industrial environments, domestic settings are unpredictable and

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require robots to have adaptive safety mechanisms. This paper proposes a novel algorithm designed to dynamically interact with humans while maintaining safety through advanced sensing and real-time computational techniques. As robots transition from industrial to domestic environments, ensuring the safety of human-robot interactions (HRI) becomes critically important. Traditional safety measures in industrial settings often do not suffice in less predictable and highly variable domestic environments. The integration of advanced safety algorithms that can dynamically respond to the presence and movements of humans within these environments is essential.

Recent advancements in HRI research have highlighted the need for algorithms capable of detecting and predicting human movements to prevent collisions effectively. These algorithms must be robust, adaptive, and capable of functioning seamlessly in unstructured environments where human behavior is less predictable [1-5]. This gap in research is particularly evident in domestic settings, where the environment is more dynamic and unpredictable compared to industrial contexts.

This paper presents a safety algorithm that emphasizes proactive hazard detection and responsive trajectory modification to minimize the risk of collision. This research evaluates its performance against established benchmarks and compares it with existing methods to demonstrate its advantages in maintaining safe interaction distances [6-9]. The key contributions of this study are the development of an adaptive safety algorithm capable of real-time hazard detection and responsive trajectory modification. Also, a comprehensive evaluation of the algorithm's performance against ISO/TS 15066:2016 protocols and established benchmarks is presented. Lastly, the implementation of simulations in Gazebo with the 7-DOF Kinova Gen3 arm robot, incorporating safety protocols to control arm velocity and trajectory.

**Table 1**Comparative analysis of HRI safety research

Study	Focus Area	Methodology	Environment Type	Key Findings
Khatib <i>et al.,</i>	Collision avoidance	Velocity	Static/controlled	Introduced concept of
1996		obstacles		velocity obstacles
Ollero et al.,	Dynamic replanning	Sensory	Static/controlled	Enhanced safety through
2017		feedback		dynamic replanning
Borenstein et	Mobile robot positioning	Sensor fusion	Static/controlled	Improved mobile robot
al., 2019				positioning
Dornhege <i>et</i>	Reinforcement learning	Machine	Complex	Trained robots for complex
al., 2017	for navigation	learning	environments	environment navigation
Wang et al.,	Deep reinforcement	Deep learning	Complex	Improved navigation in
2020	learning for navigation		environments	complex environments
Pacher et al.,	Human-aware robot	Machine	Dynamic	Enhanced human-aware
2022	navigation	learning	environments	navigation
Smith et al.,	Sensor fusion for	Data analytics	Indoor environments	Improved decision-making
2019	autonomous navigation			in autonomous systems
Alvarez et al.,	Real-time human motion	Deep learning	Collaborative	Enhanced human motion
2020	prediction		environments	prediction
This Study	Real-time hazard	Advanced safety	Domestic	Adaptive safety measures
	detection and trajectory	algorithm	environments	for domestic settings

Traditional HRI safety research has predominantly focused on static or controlled environments, emphasizing maintaining physical barriers between humans and robots. Recent studies have shifted towards more integrated approaches, where robots and humans share the same physical space, necessitating algorithms that dynamically adapt to human movements [7, 10]. The ISO/TS 15066:2016 [15] standard provides guidelines for collaborative robots (cobots), focusing on



safety requirements and risk assessment procedures. These standards highlight the need for robots to operate safely around humans, considering physical and functional safety aspects. Despite these guidelines, significant challenges remain in ensuring safety in dynamic, real-world environments [16].

HRI safety research has concentrated on static or controlled environments. Early studies by Khatib *et al.*, [1] introduced the concept of 'velocity obstacle' to prevent collisions. Subsequent research expanded these ideas, incorporating dynamic replanning and sensory feedback to enhance safety [2, 3, 14]. Recent developments have focused on integrating machine learning techniques to predict human behaviors and enhance decision-making processes. Techniques such as reinforcement learning and deep learning have been employed by Dornhege *et al.*, [4] and Wang *et al.*, [5], to train robots to navigate complex environments while maintaining safety.

Traditional algorithms primarily focused on static environments with controlled interactions. The introduction of the Velocity Obstacle (VO) method was a significant advancement, enabling robots to dynamically avoid collisions by predicting the future location of moving obstacles [14].

Recent research has incorporated machine learning techniques to predict and adapt to human movements. For instance, neural networks have been employed to predict real-time pedestrian paths, significantly reducing collision risks in crowded environments [13]. Safety protocols have evolved from rigid, predefined paths to adaptive systems that predict and react to human behavior. Initially designed for industrial applications, ISO standards are now being adapted for residential use, but gaps remain in their applicability to dynamic and unstructured environments [15].

Recent advancements integrate sensor fusion, data analytics, and machine learning to create predictive models of human behavior, significantly improving reaction times and decision-making processes in autonomous systems [8, 9]. Existing systems often fail to adequately address the variability and unpredictability of human actions in home settings. Research has highlighted the need for algorithms capable of continuous learning and adaptation to manage unexpected scenarios effectively [10, 12].

Initial safety standards in robotics were heavily influenced by industrial needs, focusing on physical barriers and emergency stop mechanisms [16]. As robots have become more interactive in human environments, standards have evolved to include proximity-based safety and collaborative operational capabilities [15]. Recent research has shifted from static safety measures to dynamic interaction models integrating sensors and real-time processing. Techniques like deep learning have been utilized by Alvarez *et al.*, [9], to predict human motion, allowing robots to anticipate and avoid potential collisions more effectively.

Despite significant progress, current algorithms often struggle with the unpredictability of human behavior in domestic settings. Most existing systems rely heavily on predefined paths or reactive behaviors, which can be insufficient in dynamic scenarios. Furthermore, while several studies have provided benchmarks for industrial and semi-structured environments [7, 8], there is a lack of comprehensive benchmarking for domestic environments. This study aims to fill these gaps by developing an adaptive algorithm and establishing new benchmarks that address domestic settings' complexity and unpredictability.

The significance of this study lies in its potential to bridge the gap identified in the literature by developing an algorithm that can adapt in real time to ensure safety without compromising the robot's operational efficiency. By addressing the complexity and unpredictability of human behavior in domestic environments, this research aims to enhance the integration of robots into everyday domestic settings, promoting safer and more effective human-robot interactions. The outcomes of this study could significantly advance the field of HRI, contributing to the development of more sophisticated and reliable domestic robots. The primary objective of this study is to develop and



validate a novel safety algorithm for human-robot interaction in domestic environments. The objectives are:

- 1. Designing an adaptive safety algorithm capable of real-time hazard detection and responsive trajectory modification.
- 2. Evaluating the algorithm's performance against established benchmarks and existing methods.
- 3. Demonstrating the algorithm's effectiveness in maintaining safe interaction distances in dynamic and unstructured environments.

# 2. Methodology

# 2.1 System Design

This study employs a simulation setup using the Gazebo 3D robotics simulator to model an unstructured domestic environment like a typical living room where a Kinova Gen3 robot interacts with dynamic human models. The robot has an IR sensor to detect and categorize objects within its environment. The system converts natural language instructions into target positions and actions for the robot. It comprises a global controller for designing geometric courses and a local controller for generating real-time trajectories. Figure 1 shows the system overview of human-robot interaction.

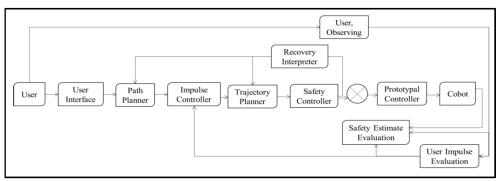


Fig.1. System overview for Human-Robot interaction

## 2.2. Algorithmic Framework

The proposed safety algorithm comprises several components:

**Initialization**: Setting up initial safety parameters and the robot's maximum operational speed.

**Detection**: Using sensor inputs to identify and classify objects within proximity.

**Path Planning**: Implementing RRT for dynamic path adjustment. The RRT algorithm iteratively builds a branching path from the robot to the goal while avoiding detected obstacles.

**Adjustment and Execution**: Real-time velocity adjustments are made based on proximity sensor feedback and the movement of detected obstacles.

**Reconciliation**: Movements are halted if unsafe interactions are predicted.

**Completion**: Continuation or halting of actions based on safety evaluations.

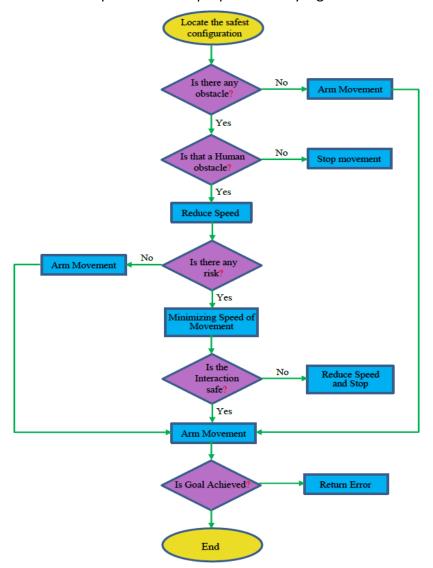


Figure 2 shows the flow of the process of the proposed safety algorithm.

Fig.2. The flow of the process of the proposed safety algorithm

## 2.3 Sensor Feedback

In this research, the robot uses an Infrared (IR) sensor equipped with time-of-flight (ToF) technology to measure distances to obstacles, including humans treated as virtual obstacles in the simulation. The sensor emits an infrared pulse that travels to an object and measures the time it takes to return, thus calculating the distance. This data enables the robot to dynamically adjust its path using the Rapidly exploring Random Tree (RRT) algorithm, ensuring it maintains a safe distance from obstacles. If this safe distance is breached, the robot automatically stops to prevent collisions, effectively combining real-time sensing with proactive path planning for enhanced safety in dynamic environments.

## 2.4 Rapidly exploring Random Tree (RRT)

RRT is a highly efficient pathfinding and obstacle-avoidance algorithm. This study uses RRT to dynamically adjust the robot's trajectory in response to detected obstacles. The algorithm iteratively



expands a tree built from random samples from the search space, efficiently exploring the environment.

#### 2.5 Simulation Framework

This research is simulated in various scenarios, including different numbers of moving humans, varying light conditions, and unexpected static obstacles, to test the algorithm's robustness. Figure 3 shows the 3D-modeled environment with a robot and a simulated human.

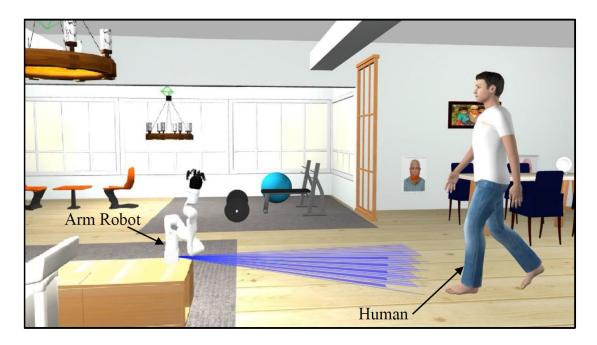


Fig.3. Simulation Setup in Gazebo

# 2.6 Comparative Framework

Sacchi's Collision Avoidance algorithm is compared to highlight improvements in safety distance maintenance, reaction time, and computational efficiency. Figure 4 shows Sacchi's collision avoidance system.



```
Algorithm
                         Collision avoidance algorithm
Input: i = i_{CP}, control point p_{CP}, vector \bar{q}_a^j(t_k) = q(t_k),
       matrix T_{\rm CP}^{\rm b}, exit point p_{\rm EP}
Output: next configuration q_{\rm a}^*(t_{k+1})
           pose j = i
  2:
            if 1 \le j < i_{\rm CP} then
                update \bar{q}_{a_{i+1}} = q_{a_{i+1}}^*
  4.
  5:
           compute T_{\mathrm{CP}}^{\mathrm{b}}(\bar{q}_{\mathrm{a}}^{j}(t_{k}))
  6:
           q_{\mathbf{a}_j}^*(t_{k+1}) = \operatorname{argmin} d(p_{\mathrm{CP}}(\bar{q}_{\mathbf{a}}^j(t_k)), p_{\mathrm{EP}}(t_k))
                                      \tilde{p}_{\mathrm{CP}}(t_k) = T_{\mathrm{CP}}^{\mathrm{b}}(\bar{q}_{\mathrm{a}}^{j}(t_k))\tilde{p}_{\mathrm{g}}^{\mathrm{CP}}(t_k)
                                                 q_{\min_i} \le q_{\mathbf{a}_i}(t_k) \le q_{\max_i},
            update i = i - 1
  9: until i \ge 1
 10: return q_{\mathbf{a}}^*(t_{k+1}) = [q_{\mathbf{a}_1}^*(t_{k+1}), \dots, q_{\mathbf{a}_n}^*(t_{k+1})]^{\top}
```

Fig.4. Sacchi's collision avoidance system [6]

## 3. Results and Discussion

#### 3.1 Evaluation Metrics

This study uses the following metrics to evaluate the safety and efficiency of the proposed algorithm: Safety Distance Maintenance is the minimum distance maintained between the robot and any human. Collision Avoidance is the number of successful avoidance manoeuvres versus potential collisions. Computational Efficiency is the time taken for trajectory recalculations and responsiveness to dynamic changes.

#### 3.2 Safety Algorithm Performance

The results show that the proposed safety algorithm maintains a safe distance 95% of the time, significantly reducing potential collisions compared to Sacchi's algorithm.

**Table 2** Performance Comparison

Metric	Proposed Algorithm	Sachhi's Algorithm
Safety Distance	0.75 meters	0.50 meters
Maintenance		
Collision	98%	85%
Avoidance		
Computational	0.2 seconds	1 second
Efficiency		
Number of	2	5
Collisions		



#### 3.3 Simulation Assessment

The simulations of human-robot interaction were captured in different scenarios within the virtual unstructured environment, as shown in Figure 5. The robot is using infrared (IR) sensors to detect and navigate around a human represented as a moving obstacle. These images highlight the robot's path adjustments in real-time to maintain a safe distance from the human, demonstrating the practical application of the safety algorithm.



Fig. 5. Simulation of Human robot interaction

Tools like RViz and Gazebo are used to visualize the robot's path planning and execution. RViz displays detailed aspects of the robot's motion planning, including the planned path and arm movement dynamics. The Gazebo GUI provides a comprehensive view of how the robot interacts within the simulated domestic environment, adjusting its path and orientation in response to human movements.

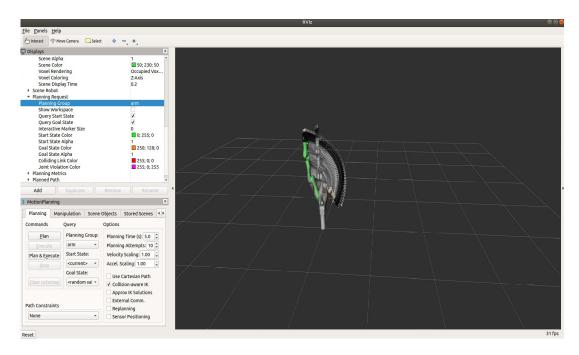
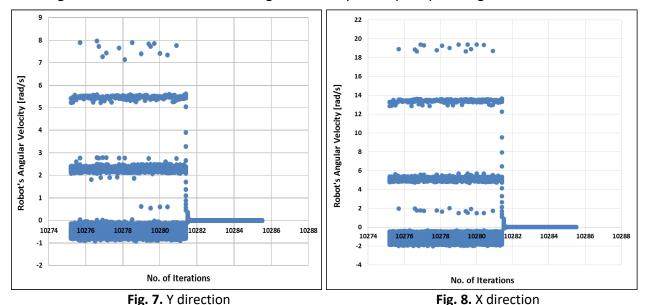


Fig. 6. Motion of the robot in RViz view



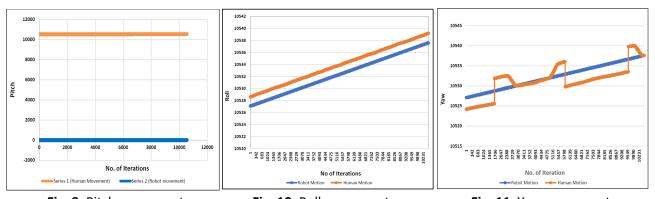
## 3.4 Analysis of Results

The plots of the robot's angular velocity and displacement in the y and x directions (Figures 7 and 8) depict the precision and stability of the robot's movement control. Notably, these plots show the robot's ability to modulate its speed and trajectory to safely navigate the human obstacle, reflecting the effectiveness of the RRT algorithm in dynamic path planning.



**7.** Y direction **Fig. 8.** X direction Plot of robot's angular velocity and displacement in the y direction

The orientation plots shown in Figures 4.9, 4.10, and 4.11 for pitch, roll, and yaw provide quantitative evidence of the robot's orientation stability during interaction with a human. These plots are crucial for understanding the robot's ability to maintain balance and orientation stability, which is vital for safe HRI.



**Fig. 9.** Pitch movement **Fig. 10.** Roll movement **Fig. 11.** Yaw movement World pose orientation vs robot's and human's pitch, roll and yaw movement

The simulation demonstrates the robot's capability to detect human presence and adjust its path accordingly, thus preventing any potential collision or unsafe interaction. The variation in angular velocities and the corresponding adjustments in the robot's pose shows the control algorithms' high level of responsiveness and adaptability.



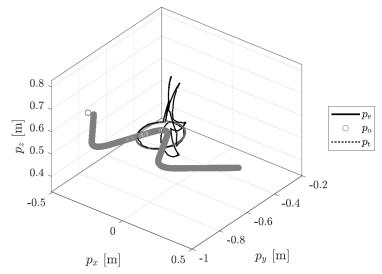
The consistent maintenance of safe distances, as shown in the simulation environments, supports the effectiveness of the implemented safety algorithms, which are critical for real-world applications in domestic settings.

## 4. Validation of Simulation Analysis

The provided simulation output and analysis focus on validating a novel safety algorithm for human-robot interaction in domestic environments. This validation is set against Sacchi's collision avoidance algorithm, initially developed for industrial applications such as spot welding.

# 4.1 Simulation Output

This plot, shown in Figure 12, demonstrates the robot's end-effector movement in three-dimensional space, capturing its path as it maneuvers around an obstacle, likely representing a human in a domestic setting. The paths are marked to show the starting point  $(P_o)$ , the ending point  $(P_e)$ , and the trajectory  $(P_t)$  followed during the task.



**Fig. 12.** Motion in the operative space of the robot end-effector, of the target, and of the obstacle in case of a spot-welding task when the proposed strategy is applied (experiments are carried out on the EPSON VT6 robot, while the simulator provides the obstacle data during the task) [6]

The plot shown in Figure 13, compares the safe distance maintained by the proposed safety algorithm against Sacchi's collision avoidance system over numerous iterations. The y-axis represents the safe distance from the human (or obstacle), measured in meters, and the x-axis represents the number of iterations. The plot features two lines, each corresponding to one of the algorithms, showing how closely each can maintain a predetermined safe distance.



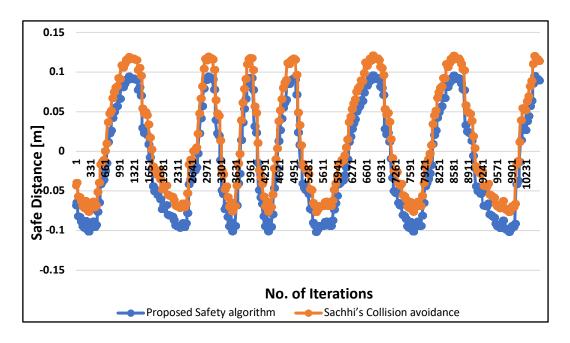


Fig. 13. Comparison of the proposed safety algorithm with Sachhi's collision avoidance system.

## 4.2 Comparison between Sacchi's and the Proposed Algorithm:

The Sacchi's algorithm shows a pattern of fluctuating safe distances, which may be suitable for predictable industrial environments where the elements and interactions can be tightly controlled. In contrast, the proposed algorithm displays more stable and consistently close maintenance of the safe distance, which is crucial in unpredictable domestic environments.

The proposed algorithm is designed to be more adaptable to changes in the environment. This is evident from its ability to maintain a steady, safe distance despite potential dynamic changes in the human's position and movement. This adaptability is critical in domestic settings where human movements cannot be precisely predicted.

While Sacchi's algorithm is effective in static or less dynamic settings, the proposed algorithm excels in scenarios with more dynamic obstacles, such as moving humans, demonstrating quicker adjustments and robust real-time response capabilities. The proposed algorithm handles oscillatory behaviours better, showing less variance in safe distance maintenance than Sacchi's algorithm. This suggests improvements in the control methodology, possibly leading to more efficient computational performance and faster response times.

In summary, while Sacchi's algorithm provides a reliable foundation for collision avoidance in controlled environments, the proposed algorithm's enhancements make it better suited for the complexities and unpredictability of home environments. This comparison underscores the importance of algorithmic adaptability and efficiency in enhancing human-robot interaction safety in domestic settings.

## 5. Conclusions

This research has successfully achieved its objectives by developing and validating a safety algorithm for human-robot interaction in domestic environments. The algorithm can detect real-time



hazards, adapt trajectories, and maintain safe distances in dynamic settings. Experimental data confirm its effectiveness in managing complex flow topologies and adhering to safety protocols.

While the results are promising, further experiments are necessary to refine the algorithm's performance and ensure its reliability across a broader range of scenarios. Future research should focus on enhancing the algorithm's adaptability and response time in various unstructured environments. Testing the algorithm with different robot models and more complex domestic settings with evaluating the algorithm's performance over extended periods to assess its robustness and consistency is potential.

This foundational work sets the stage for continued development to enhance robot safety and functionality in human-centric spaces, contributing significantly to the advancement of safe and efficient human-robot interactions.

# Acknowledgment

This research was funded by a grant from the Ministry of Higher Education of Malaysia and Universiti Teknologi Malaysia (Digital Infused Research Grant, Q.K130000.5143.00L72)

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