Exploring the Performance of a Sensor-Fusion-based Navigation System for Human Following Companion Robots

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***Abstract*— One of the biggest challenges in implementing assistive companion robots is the ability to navigate around obstacles while being visually tethered to a human subject. This is further complicated when advanced hardware and computation-heavy algorithms such as Light Detection and Ranging (LiDAR) modules or Simultaneous Localization and Mapping (SLAM) are not readily available. This research aims to prove the validity of a robot navigation model that relies on multi-sensor fusion of a depth camera, proximity sensors array and an active IR Marker tracking system, all of which consist of commercial off the shelf (COTS) components. Common indoor robot navigation solutions rely on prior environmental mapping to be able to plot routes beyond obstacles in the immediate vicinity. This model differentiates itself by considering the general direction of the target person and the mid-range depth landscape in addition to the immediate vicinity of the robot. To examine its performance, a set of three scenarios were created to emulate the testing conditions of several similar robot navigation studies presented by existing literature. The simulation results show that the implemented navigation system can maintain a consistent distance from the target while traversing a route that is shorter and less impeded by obstructions compared to the benchmark studies.**

***Index Terms*— human-robot interaction, human-following, indoor navigation, sensor fusion, vision-based**

I. Introduction

Robotics have become one of the most prolific avenues of assistive technologies in recent years, especially for augmenting therapeutic sessions [1]–[4] and as part of behavioral intervention for children with Autism Spectrum Disorder (ASD) [5]–[7]. Companion robots such as MATILDA [8] and the IROMEC [9] were developed to accompany and follow their users in indoor environments. This presents significant implementation difficulties considering that reliable localization systems such as GPS do not work in indoor areas. As such, there are a variety of research work for solutions to indoor navigation and human-following, which include a combination of utilizing Light Detection and Ranging (LiDAR)[10], [11], Radio Frequency Identification (RFID) [12], [13], wireless networks [14], vision-based systems [13], [15], [16] and embedded environments[17], [18].

The integration of these technologies can incur high costs in the development of any companion robot. This is due to factors such as logistics (embedding sensor networks throughout the home), computational resources (required for Simultaneous Localization and Mapping), and availability of advanced hardware such as LiDAR [19]. One study aimed to develop a companion robot that can accomplish its mission of being both a telepresence avatar as well as a human-following activity monitor by relying on a combination of commercial off-the-shelf (COTS) sensors and components. The Companion Avatar for the Mitigation of Injuries (CARMI) [20] was designed for autonomous following and monitoring the activity of a child with ASD. This is done using a Kinect device and the Kinect SDK which is equipped with a neural-network that can be trained to identify gestures that lead to injuries such as punches, jumps and falls [21]. However, the device only has a 60°field of view and can only reliably track a person's body at a distance between 2-3m [22]. Therefore, CARMI must consistently center its sensors nest (located in its rotating head) on the correct target Child (in case of multiple persons in view) and move itself so that the Child is within the 2-3m range while avoiding obstacles during the approach. A navigation system was proposed and implemented for utilizing the onboard sensory resources that CARMI possesses.

The navigation model, inspired by the Potential Field Method [23] and Wandering Standpoint Algorithm [24], transforms data from a depth camera, an array of proximity sensors and an InfraRed (IR) Active Marker Tracking system [25] for considering the close and mid-range visual landscape as well as the relative direction of the target before deciding the best motion path for the robot. This pathfinding method does not rely on prior mapping or external sensory information, effectively enabling the implementation of standalone autonomous indoor human-following. The navigation system was built and integrated into CARMI using Microsoft Robotics

Developer Studio (MRDS) 4, which is equipped with a Visual Simulation Environment (VSE). VSE was used extensively for both unit and functional testing. The design and development process are explored in the next section.

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The successful construction and functional testing of the CARMI navigation system greenlighted further extensive testing of its routing performance. This research paper documents three simulation scenarios from similar robot navigation studies which are recreated in VSE for performance comparison with CARMI. The aim of this research is to prove that the CARMI navigation system can determine a route that is both shorter and less obstructed than that of the other benchmark robot candidates. The scenario design, subsequent simulation and results are also documented in the following sections.

II. NAVIGATION SYSTEM CONCEPT AND DESIGN

The CARMI robot has two modes of operation: telepresence avatar and autonomous companion. At any time during its operation, a Carer operator may wirelessly connect to the robot and converse with the Child via video call using CARMI as the avatar. Otherwise, CARMI engages its autonomous companion mode where the Kinect's gesture tracking system is activated to monitor the Child's activities. Any matches to its database of injurious gestures will trigger the posting of a notification to the carer. The CARMI system interactions with both the Child and the carer is visualized in the CASE diagram shown in Fig. 1. Only the Carer has direct interface access to the CARMI system, while the Child's own actions and presence constitute the sum of its interactions with the robot. Thus, CARMI acts as a passive companion that has no physical contact with the Child. This model also assumes that CARMI is used to monitor one Child exclusively, so the presence of other children must be subtracted from the system's tracking operation.

The human-following and obstacle avoidance navigation system is constantly in effect throughout both modes, effectively ensuring that CARMI consistently maintains the Child within the Kinect device's optimal tracking zone as well as the video call interface. During the initial process of the robot's system design, the navigation model is integrated with the gesture tracking and telepresence subsystems. This can be observed in the behavior model derived from the interactions modelling process (Fig. 2). Here, each action is distilled into system functions that can be further translated into individual activity diagrams for software development. During this stage, it had been decided that the telepresence and gesture tracking subsystems be abstracted from the state machine as parallel operations. Both were to be developed as detached software components that operate separately from the navigation system for continued operation in case of failure in any of them.

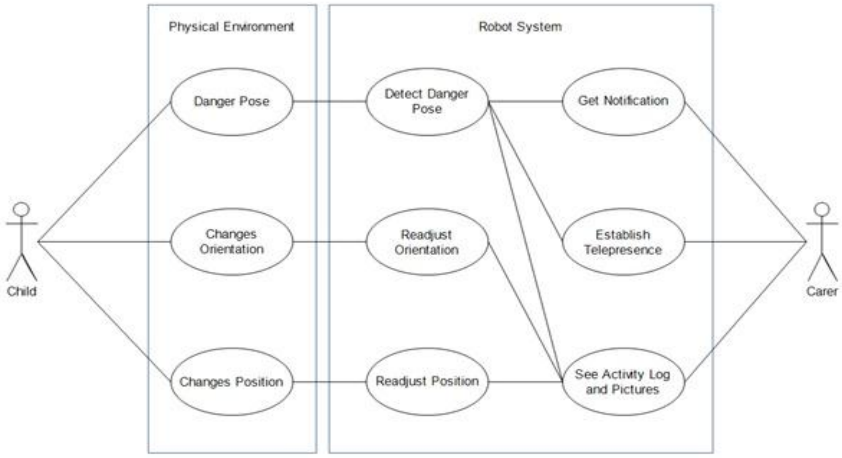

Figure 1. CARMI general interaction model.

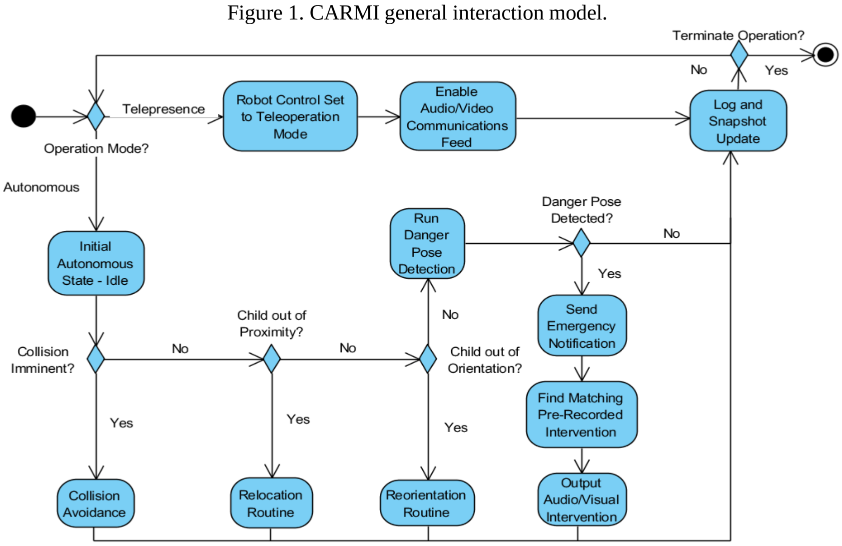

Figure 2. CARMI behavior block diagram.

The navigation model consists of two phases: Subject-Locking and Pathfinding. Subject-Lock utilizes the active IR marker tracking system as a redundancy check against bodies detected by the Kinect SDK. Through a process of linear offset and scaling factor calibration, the view-spaces from both sensor packages help eliminate false detections and miscellaneous persons so only the intended Primary Target is being tracked [26]. Once the subject is locked-on, the Pathfinding phase is initiated, gauging the target distance and deciding whether the robot's position require changing. If an obstruction is encountered during the move, the system evaluates the short-range proximity (through the input from the perimeter sensors array), mid-range landscape (from the raw depth camera feed) and the general direction of the Child (by referencing the view-space position of the Primary Target from the Subject-Locking phase) to determine whether to begin maneuvering around the obstacle from the left or right side.

For software development, the model is translated into a state machine diagram as shown in **Figure 3**. Both phases of the model are expressed as separate state machine loops. The Subject-Locking loop switches between 'Subject-Locked' and 'Scanning' states, depending on whether the Child is acquired by the tracking system or not. Once acquired, the Pathfinding loop activates, revolving between 'Idle' and 'Approach' states to adjust CARMI's distance from the Child so that the Kinect device acquires the target within the optimal detection zone. If CARMI encounters an obstruction during the 'Approach' state, then the 'Pathfinding' state will take precedence, making the path decision before performing avoidance maneuvers.

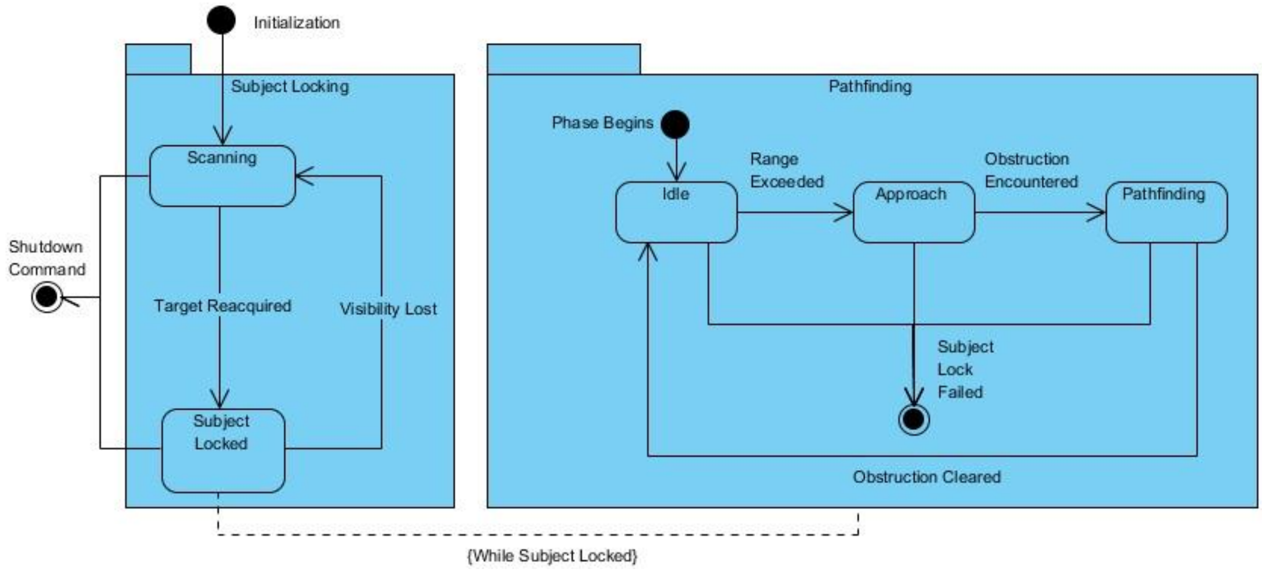

Figure 3. Navigation system parallel state machines.

The navigation system was implemented using Microsoft Robotics Developer Studio (MRDS) 4 which provided a service-based robot control runtime and a Visual Simulation Environment (VSE) for running virtual testing scenarios. Several functional test scenarios were created based on the type of obstacles CARMI is expected to encounter in a typical living room setting, which were run for an average amount of 5 data sets. Fig. 4 shows the scenario results for both single uniform and non-uniform obstacles between the robot, decoys and Child entities. Uniform obstacles represent objects that present identical route qualities regardless whether CARMI maneuvers around it from the left or right side. Fig. 4(a) showed all 5 test runs where CARMI chose to navigate from the left side because the system also considered the proximity of the rightmost decoy (which was nearer to the robot than the other Child entities). Non-uniform obstacles represent most furniture types such as sofas and tables which may exceed the field of view of the navigation system. Fig. 4(b) indicated a 20% chance that CARMI will opt for the longer route despite the indeterminate distance it may take to reach the obstacle's left-most edge. That does mean that the probability of CARMI picking the shorter edge is 80%.

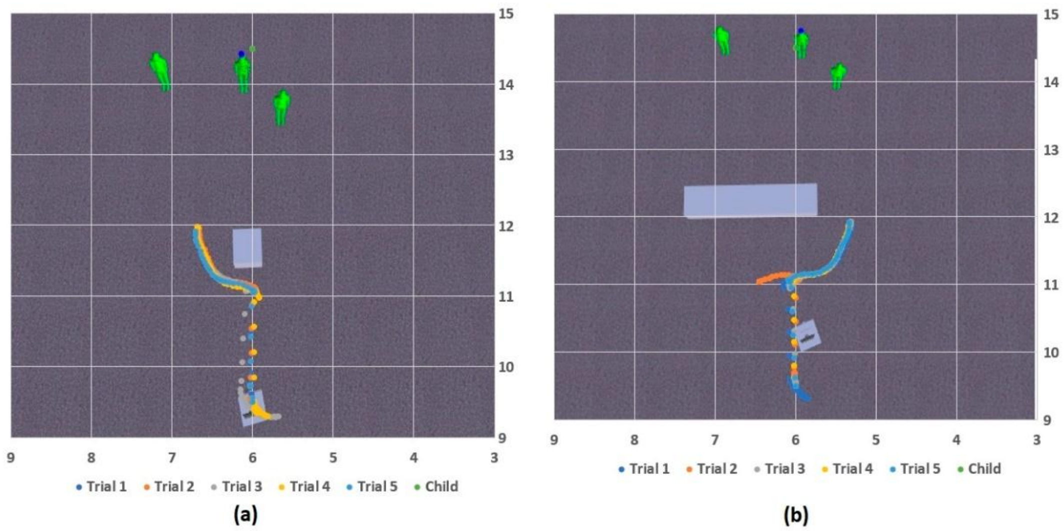

Figure 4. Functional testing results for single (a) uniform obstacle and (b) non-uniform obstacle.

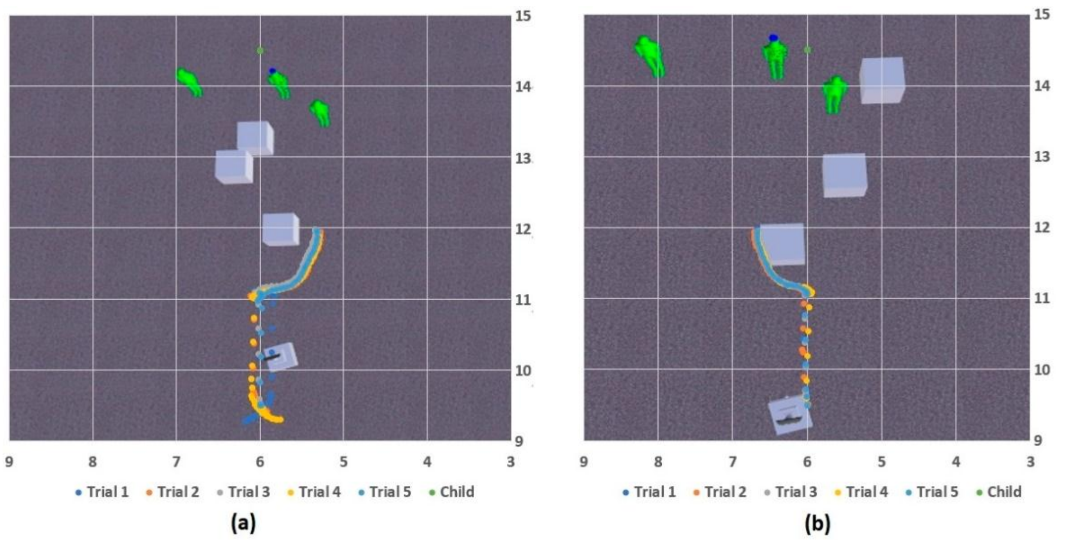

Figure 5. Functional testing results for single uniform obstruction variations, with (a) leftward-scatter and (b) rightward scatter.

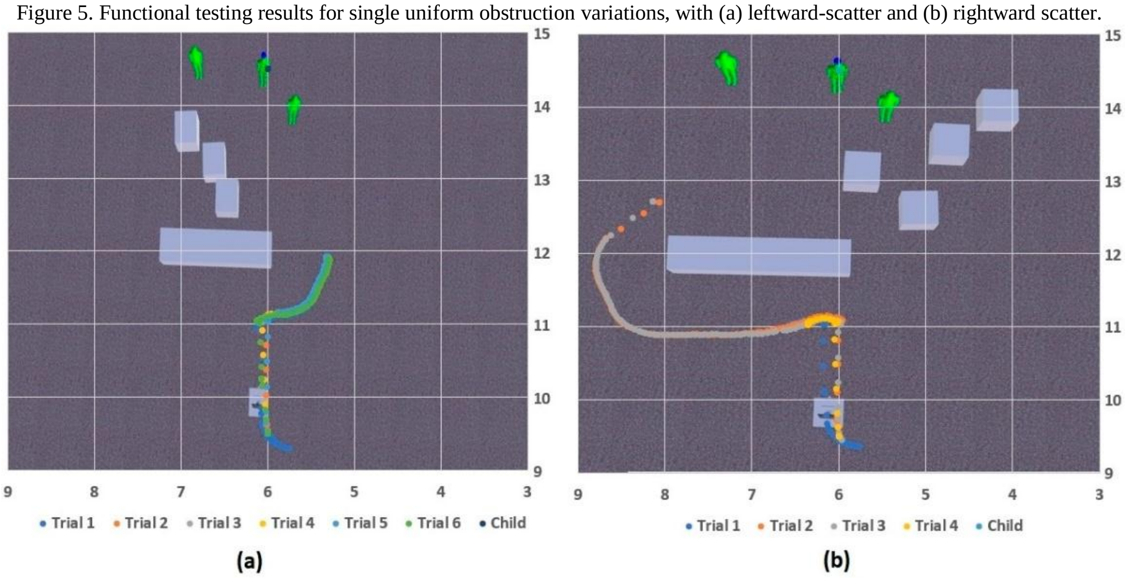

Figure 6. Functional testing results for single non-uniform obstruction variations, with (a) leftward-scatter and (b) rightward scatter.

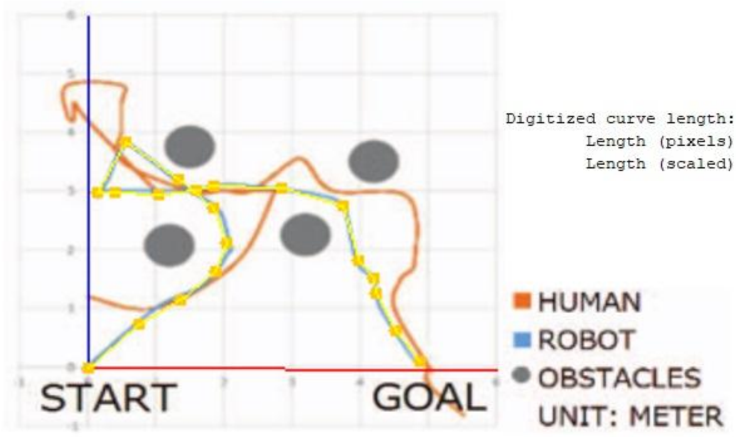

Figure 7. Testing scenario 1 for human-following robot in a crowded area [27].

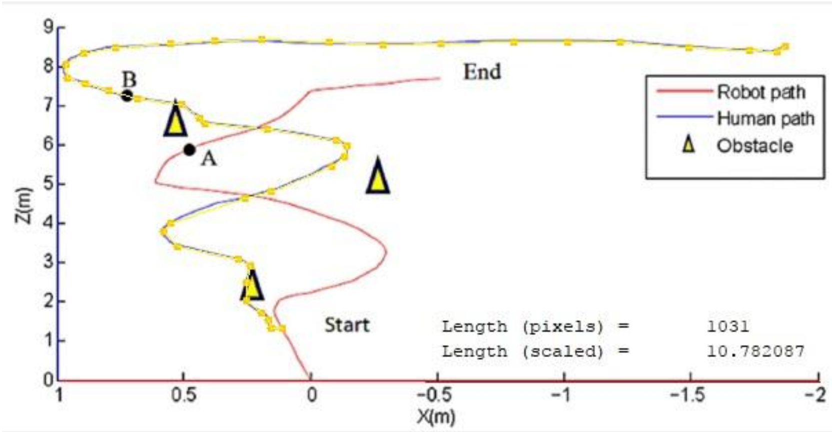

Figure 8. Testing scenario for multimodal human-following robot [28].

The subsequent scenarios expand upon both uniform and non-uniform obstacle with leftwards and rightwards scattered objects (Fig. 5 and Fig. 6). These sets are meant to examine the effects of adjusted weights for proximity array, mid-range depth map and target position on the path decision. As expected, CARMI successfully picked the opposite sides of the scattered objects, indicating that the navigation system's tendency to avoid paths that lead into further obstructions ahead.

These findings greenlighted the main purpose of this research, which was to create extended scenarios that mirror adjacent robot navigation studies and running them with the CARMI navigation system for performance comparisons. The highlighted studies and their selected scenarios are detailed in the following section.

III. Benchmark Studies and Scenario Design

The first benchmark study candidate is the development of a human-following robot that was capable of navigating through a crowded environment carried out in 2016 [27]. The robot was built using the RT MiddleWare framework and scans the environment with a laser rangefinder (LRF) and a depth camera. The Xtion depth camera requires the target to be within 80-120cm away for optimal tracking - a similar challenge to the Kinect. However, the its body tracking system only locks onto the torso feature of the target upon initial pairing and can be lost if the target moves out of sight while the robot is in motion.

Fig. 7 shows one of the test scenarios used to test the human-following and obstacle avoidance performance of the system. From the results path, it appears that the robot had taken a route that mirrors the human path to maintain the subject within the Xtion optimal zone of detection. Another feature to note is that the robot must stop moving to re-center itself whenever the target approaches the edge of its field of view. Though only graphical data was presented in the study, a plot digitizer software was used to approximate the length of the robot path which resulted to 18.644m.

The next benchmark candidate study developed a multimodal telepresence avatar robot that performs human-following using three Kinect depth cameras [28]. This system supports following, escorting and leading position modes by switching priority between the Kinect devices. Obstacle detection and avoidance were done by analyzing the raw depth map from the cameras and applying an algorithm that treats objects in the vicinity as repelling forces, like how this research's navigation model is inspired by the Potential Field Method (PFM). Fig. 8 shows the testing scenario for this robot, indicating that the follow-path does not mimic the human path because of the optimal detection zone limitation. Plot digitization reported that the robot travel path approximates to 10.78m.

The third benchmark research explores the possibility of relying on ultrasonic sensors array to navigate around an unknown environment with the help of a fuzzy controller [29]. The navigation algorithm can attempt depth map reconstruction of the immediate vicinity of the robot just by fusion of multiple ranging sensors. This research was aimed at developing a navigation system that can minimize travel time of an autonomous robot during exploration of unmapped environments instead of human following. However, the scenario used for testing it can be adopted as a simulation for the CARMI navigation system to examine its following behavior if the Child entity were to emulate the travel path in this study. The scenario is depicted in Figure 9, showing that the robot travel path is estimated at 23.2m.

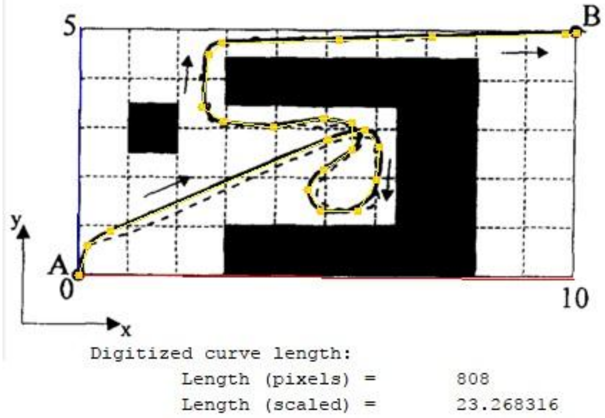

Figure 9. Testing scenario for Fuzzy Logic based autonomous exploration [29].

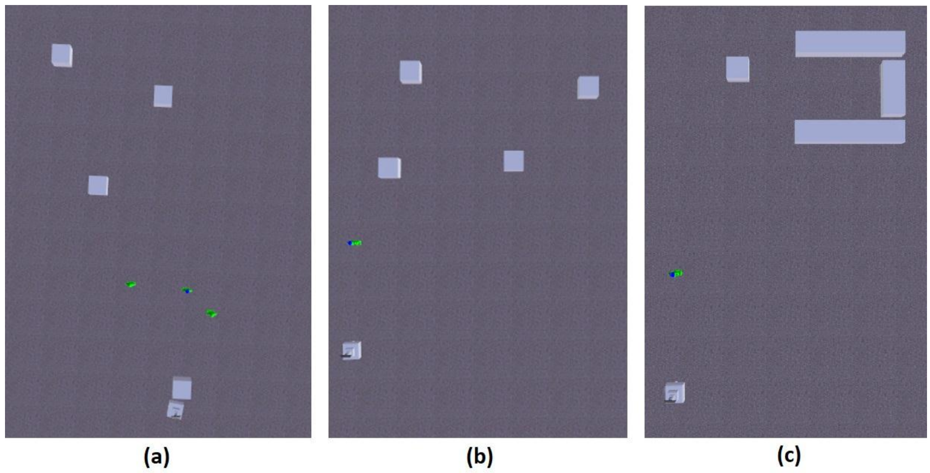

Figure 10. Set of three recreated benchmark simulation scenarios.

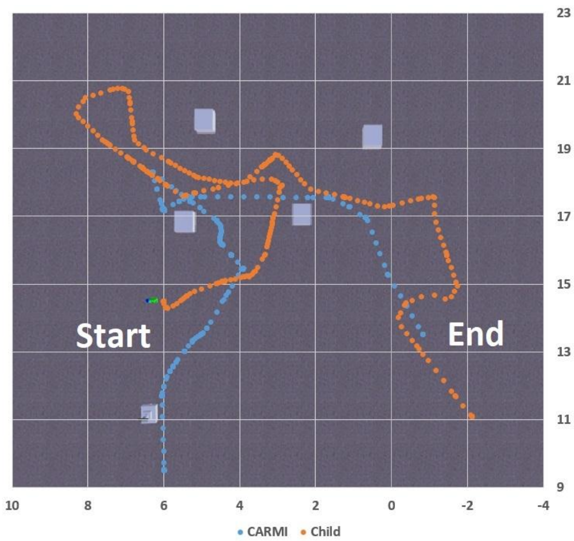

Figure 11. Scenario 1 benchmark simulation results.

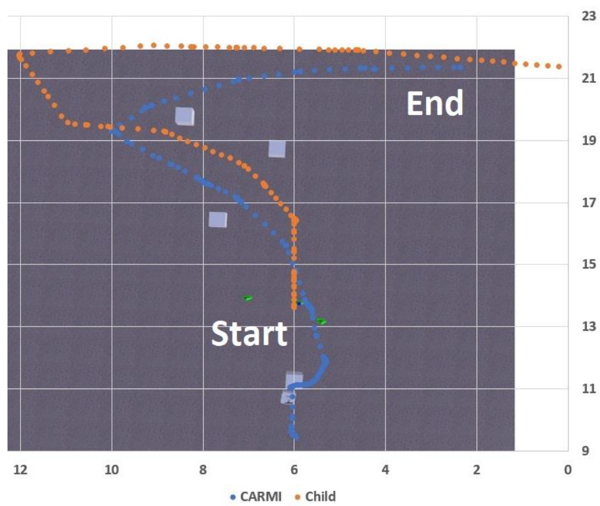

Figure 12. Scenario 2 benchmark simulation results.

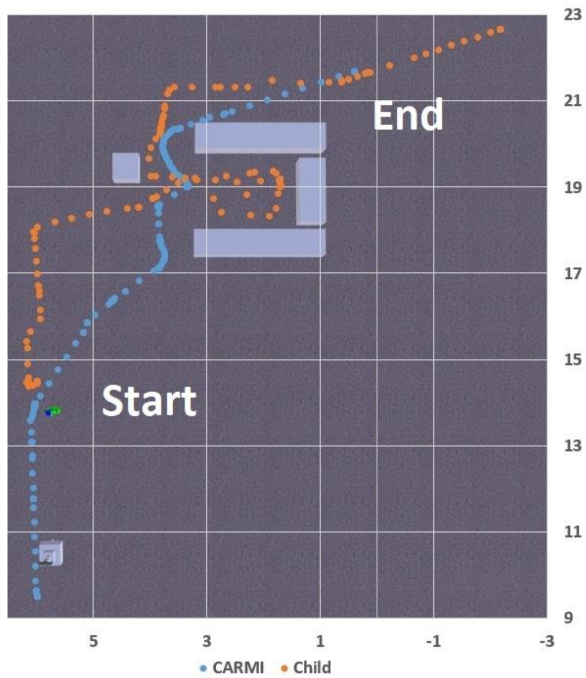

Figure 13. Scenario 3 benchmark simulation results

The test scenarios from all three selected studies had been recreated using the Visual Simulation Environment (VSE) (Fig. 10). These scenarios are used to examine how the CARMI navigation system behaves as well as to log its motion path for performance comparisons. Although the obstacle course can approximately be replicated, the motion path of the human subject had to be manually generated by a human controller. Thus, a better gauge for human-following performance would be to take the ratio between the robot and human travel paths. A companion robot navigation system can be considered efficient if its human-following function can be carried out with less total travel compared its target's. E.g. if a robot can maintain a target within escort distance at 70% of the human's total travel, then it is deemed efficient. Since the aim of this research is to present a navigation system that can achieve human-following around obstacles using the least impeded path, CARMI must be able to accomplish human-following with a lower ratio value than the original benchmark study's robot.

IV. Simulation Results and Discussion

The first scenario consists of four obstructions in a 6x6m open area. The Child entity was manually driven to emulate the path taken by the benchmark study's human target. The recorded paths for both Child and CARMI entities are depicted in Fig. 11. Graphical review between the benchmark and CARMI paths indicate that both robots appear to follow the same general route. This was to be expected as both systems were required to visually servo their position to maintain a specific distance from the target. However, significant differences can be garnered from examining the digitized plots, as listed in Table . The benchmark robot travelled 12.936m while escorting the target which moved 18.645m. The ratio of robot-to-human motion for the benchmark was 0.694, translating to the benchmark robot moving at 69.4% of its target's total movement. The CARMI navigation system managed to achieve a ratio of 0.537, which was much lesser than the benchmark competition. CARMI managed to maintain consistent tracking and following of the Child entity while minimizing its total travel by avoiding overshoots and optimizing path selections during obstacle avoidance.

Scenario 2 poses similar navigation challenges as the previous setup, involving an arrangement of three objects in a 9x2m operation area. Both CARMI and Child entities are spawned and driven to emulate the benchmark study results' paths as closely as possible. The simulation paths for both are presented in Fig. 12. Comparing both the benchmark and the CARMI simulation results reveal clear differences in routing, with the CARMI diagram showing straight escort behavior. One possible reason for this outcome is the difference in robot design. CARMI consists of a rotating sensor nest mounted on the actuated body, enabling Subject-locking to occur while it is still moving. The benchmark robot uses a unibody rover that must stop each time it needs to re-center on the target. Each time this happens, the distance between both entities increase, resulting in a possible overshooting maneuver. Another potential source of the behavioral difference is the escort algorithm differences. Both benchmark robot and CARMI share the same Kinect tracking zone limitation during human-following, but the tracking solutions differ between the two. CARMI's path-decider service considers obstructions in the immediate proximity, mid-range Field of View (FOV) and the relative target position before deciding on a direction for maneuvers, thus eliminating overshooting motion. The path distance ratio between the benchmark and CARMI are 0.78 and 0.741 respectively (as shown in Table I). There is no significant difference between the ratios, as this may be attributed to the relatively compact test area of the scenario. Despite this, the CARMI simulation did perform slightly more efficiently compared to the benchmark robot.

TABLE I. BENCHMARK STUDIES AND SIMULATION RESULTS DATASETS ACCOMPANIED BY ROBOT-TO-HUMAN PATH RATIOS.

Scenario	Digitized Path	Benchmark Study	CARMI Simulation
1	Human	18.645	32.3
	Robot	12.936	17.33
	Travel Ratio	0.694	0.537
2	Human	10.872	23.473
	Robot	8.475	17.401
	Travel Ratio	0.780	0.741
3	Human	-	21.433
	Robot	23.268	11.410
	Travel Ratio	-	0.532

The third scenario was created by adopting the test setup for the benchmark exploration robot. Since this benchmark study is not related to human-following, the robot path was emulated as a virtual human target for CARMI to follow. The purpose for this scenario is to cater for possibility of using CARMI as an escort robot to follow an exploratory convoy (regardless of human or robot). In this case, the explorer (represented by the Child entity) roams the environment but CARMI aims to conserve system resources by minimizing motion during the escort activity. **Figure 13** shows the paths taken by both entities during simulation. It can be observed that CARMI idles while the Child roams within the square obstruction areas, before resuming escort at a specific distance. CARMI travelled a total of 11.41m while escorting the Child which roamed for 11.41m, translating to a ratio of 0.532. The navigation system resulted in a 46.8% conservation of robot motion compared to physically tethering it to an explorer.

V. CONCLUSION AND FUTURE WORK

The CARMI navigation model presented an effective method of indoor companion robot pathfinding by examining the close-range perimeter, mid-range depth landscape and relative position of the target human. This is accomplished through multi-sensor fusion from a proximity sensors array, depth camera and an IR active marker tracking system. Input from these sources are transformed into tendency arrays which are then used to decide whether the robot should maneuver around an obstacle from the left or right side so that the chosen route is both the shortest path as well as one that present the least amount of obstructions. This model was implemented in Microsoft Robotics Developer Studio (MRDS) 4 and tested using the Visual Simulation Environment (VSE). The system was tested by running simulations in crafted scenarios that are designed to induce the intended navigational behavior.

Upon successful testing, three robot navigation studies were selected to adopt their testing scenarios as benchmarks for performance comparisons. The three extended scenarios were constructed then used to run simulations with CARMI, in which the travel path for both robot and human entities were logged. Using a plot digitizer, the travel paths from the benchmark studies were also approximated and recorded. It was decided that the ratio of travel distance between the robot and human is used as the performance metric, as successful human-following accomplish by the robot with less travel than its target signifies efficiency. In all three scenarios, the CARMI navigation system was shown to have visible improvements over the benchmark robots. These improvements include significantly lower ratio of robot-human travel and taken directed paths with minimal overshooting. The third scenario was used as a case study where CARMI operated as an escort which follows an explorer entity. The results of the simulation showed that CARMI can minimize its movement while the followed subject is roaming, ensuring that system resources are wasted by directly imitating the subject's motion as done in basic human-following. Overall, the outcome of the extended simulation scenarios indicates that the navigation system's goal of dynamic indoor navigation without the reliance on mapping and external localization solutions is achievable.

The next step for this navigation system is to be ported onto the CARMI hardware for physical modelling and scenario testing using an actual living room testing area. In addition, the system can also be expanded to allow machine learning for real-time adjustment of the tendency array weights, shifting the priorities between close and mid-range landscapes for pathfinding decisions under changing environmental conditions. Lastly, additional benchmark scenarios should also be added as simulation exercises to help refine the current weight settings for increased adaptability.

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