

An Autonomous Navigation System Using the Passing Motion Planner Approach

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Article Info

Page Number: 243 – 257

Publication Issue:

Vol. 71 No. 3s (2022)

Abstract

This study proposes a genuine robot accommodating passing movement organizer to be utilized in swarms. The proposed technique figures out how to pass people on foot with smooth speed increase and deceleration by utilizing passing movement learning. A critical element of the proposed strategy is that it is prepared on a basic group reenactment with both dynamic and fixed people on foot. The mastered passing way of behaving can be utilized straightforwardly in an independent route. Assessments utilizing the group recreations demonstrate that the proposed technique beats the current ones as far as progress rate, appearance time, and staying away from the walkers. The proposed route structure is carried out on a versatile robot and exhibited its effective route between walkers in a science gallery.

Keywords: Passing movement plan, dynamic climate, versatile robot, profound support learning

Article History

Article Received: 22 April 2022

Revised: 10 May 2022

Accepted: 15 June 2022

Publication: 19 July 2022

1. Introduction

Versatile robots are expected to work in closeness to individuals, like in shopping centers or display corridors. To move proficiently, numerous portable robots use pre-created map data of the climate to work out a way, stay away from hindrances, and move to their objective.

As displayed in Figure 1, there are numerous walkers in a genuine climate, and a portable robot needs to distinguish and keep away from them with its ready sensors to securely run. Movement organizers typically utilize laid out defined approaches, for example, the powerful window approach (DWA) or flexible groups [1], [2], which accept that the ongoing place of the impediment is static. Be that as it may, as a general rule the impediments can be dynamic too. While utilizing these strategies, the robot expects that the walkers are fixed, subsequently, it might get excessively near them or even slam into them.

Speed deterrent (VO) [3] was proposed to think about powerful hindrances. VO is an organizer that produces evasion moves by choosing the robot speeds outside the crash cone, which comprises speeds that would bring about impact with obstructions moving at given

speeds soon. The creators of [4] proposed a complementary speed deterrent (RVO), which is an expansion of VO in a multi-specialist climate. In RVO, every specialist moves by considering the way of behaving of different specialists to accomplish a common crash evasion. Besides, the creators of [5] utilized a variation of RVO, specifically, the ideal equal crash evasion (ORCA) to favorably and effectively keep away from walkers. These social arrangements empower the robot to move productively even among dynamic walkers. In any case, while these arrangements are adequate in a fake climate where all specialists perform uniform developments, they are less ideal in reality since people on foot don't necessarily move true to form. Likewise, the movement model of the robot isn't thought of, in this way, the robot might speed up and turn quickly and is compelled to hazardously run.

There have been various examinations on techniques for movement arranging in powerful conditions. A few techniques have further developed execution by integrating walker movement models into the route [6-8]. In [9], a socially mindful repetitive brain network model is utilized to foresee directions and set possible example waypoints as the ideal way. In [10], a Gaussian cycle (GP) is utilized to gain proficiency with the movement examples of walkers, and a way arranging is performed by integrating probabilities into the expense capability of irregular quick tree search. Albeit these techniques are successful to guarantee that the robot stays away from the walkers, the freezing robot issue (FRP) [11] may happen when confronted with dynamic people on foot. For instance, because the passerby expectation model contains a vulnerability, the robot will most likely be unable to track down a protected way through the group.



Figure1:Mobile robot in crowds

This study proposes a learning strategy for the passing movement given profound support learning (DRL). A methodology of start-to-finish movement organizer in light of DRL is exceptionally viable in challenging to demonstrate conditions, like groups with numerous people on foot. The proposed strategy prepares a passing movement utilizing a basic person on foot passing recreation. The got the hang of passing movement organizer can be straightforwardly incorporated into the route of a versatile robot, and exploratory outcomes have been acquired on a genuine robot.

2. Related work

With the quick improvements in the AI field and DRL, scientists have as of late begun involving brain networks for robot routes in powerful conditions [12]. These start-to-finish route learning techniques rely upon the climate of the preparation information; consequently, utilizing them outside the prepared environment is troublesome. Thusly, they are joined with way arranging strategies, like A*, to learn just the movement age [13, 14].

The strategy portrayed in [15] incorporates a circulated multi-specialist crash evasion calculation in light of profound support learning. This exploration was subsequently reached out by altering the award capability to guarantee that the specialists stick to normal practices [16]. Since these models center around moving people on foot, they experience the ill effects of stoppages and impacts when confronted with unnoticed walkers or fixed obstructions. In a genuine climate, these issues should be tended to because certain individuals stop in light of multiple factors, for instance, to check shows out. Subsequently, the point of this examination is to add fixed people on foot to the growing experience to guarantee that the framework figures out how to act successfully in genuine conditions.

Generally speaking, the organization yield is an unpleasant discretized esteem, like straight speed or rakish bearing at a specific time. Assuming that the acquired ways of behaving are straightforwardly applied to the speed orders of the robot, abrupt robot speed and posture changes might happen. Such abrupt changes in speed make walkers anxious, thusly are not appropriate for robots that work among them. The proposed passing movement gaining framework figures out how to speed up and decelerate flawlessly from the ongoing pace as the robot explores. What's more, it involves a matrix guide of the robot's environmental elements as its present status and results in speed control orders straightforwardly from its feedback. This wipes out the requirement for committed hubs to compute speed orders and can be effortlessly supplanted with existing movement plans.

The primary commitment of this study is that it proposes a travel movement learning strategy that can be straightforwardly coordinated into the independent route of genuine robots. The primary elements of the proposed technique are the following: 1) the partition of the section movement from the way arranged makes the learning movement successful in different conditions. 2) the technique gains from moving walkers as well as from fixed people on foot. 3) the entry movement arranging can learn smooth speed increase and deceleration movements to compute the speed order yields. In the showing test at the display, the viability of the proposed strategy is affirmed by carrying out it on a genuine robot.

3. Learning the passing motion for mobile robot navigation

Reenactment climate with walkers cruising by the learning of passing movement is completed by utilizing a reproduction that addresses the groups with people on foot and robots. To mimic the passing movement of a robot and a person on foot, it is expected that the walker and robot move deliberately in a restricted space. The recreation model addresses walkers with a basic circle model. To create a genuine group, the proposed reproduction incorporates fixed walkers too.

Figure 2 (a) shows the portrayal of a passerby model in recreation, where the place of the person on foot is addressed as a green circle with a range rp . The walker circle is swelled by the sweep of the robot rr , which means the impact region. The anticipated scope of the person on foot development has attracted the course of the passerby speed as a cone with a focal point of 30 degrees. To master moving without upsetting people on foot, the recreation incorporates the anticipated region. The anticipated region portrayal of the 30 degrees cone is developed by alluding to the forward point of the walker's field of view in the passerby display depicted in [17]. The size of the expectation region is scaled utilizing the person on foot speed. The shade of the prescient region is addressed by a grayscale with a 2-second reach at every 0.5 seconds.

The reproduction considers two conditions as per the arrangement of people on foot. One is an unhampered space (figure 2 (b)), while the other contains haphazardly positioned fixed walkers (figure 2 (c)). Strolling people on foot push toward the contrary side from where they are put in a circle. The robot plans to move from the underlying position (blue spot) to the objective (red speck). The underlying place of the robot and objective position is inside the circle. To address a unique climate, people on foot move in two different strolling designs: a single setting, where a passerby strolls alone, and a social scene, where two walkers walk next to each other. Strolling walkers are introduced in irregular settings, and at most three individuals are available in the climate at a time. People on foot move as indicated by the ORCA strategy. The fixed walkers are organized in arbitrary numbers and positions.

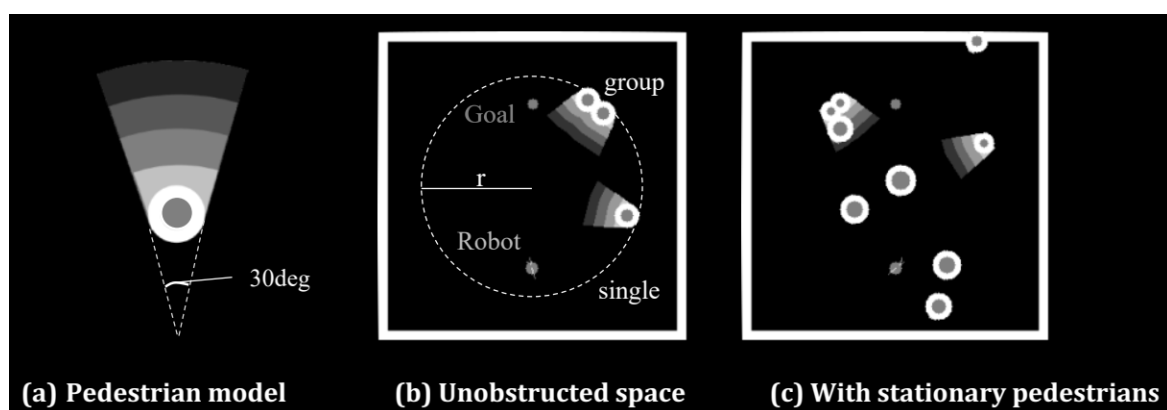


Figure 2: Model and climate in a reenactment

3.1. Simulation of passing motion learning

In Reinforcement learning (RL), the climate is formed as a Markov choice cycle with state

space $\mathbf{S}$, activity space $\mathbf{A}$, state progress likelihood lattice $\mathbf{P}$, reward capability R , and rebate factor $\gamma \in [0,1)$. The prize capability R assesses state $\mathbf{S}$ and returns a scalar award while moving from the state $\mathbf{st}$ to the following state $\mathbf{st}^{\%}$. The objective is to track down a strategy π that boosts the normal return for each state $\mathbf{S}$.

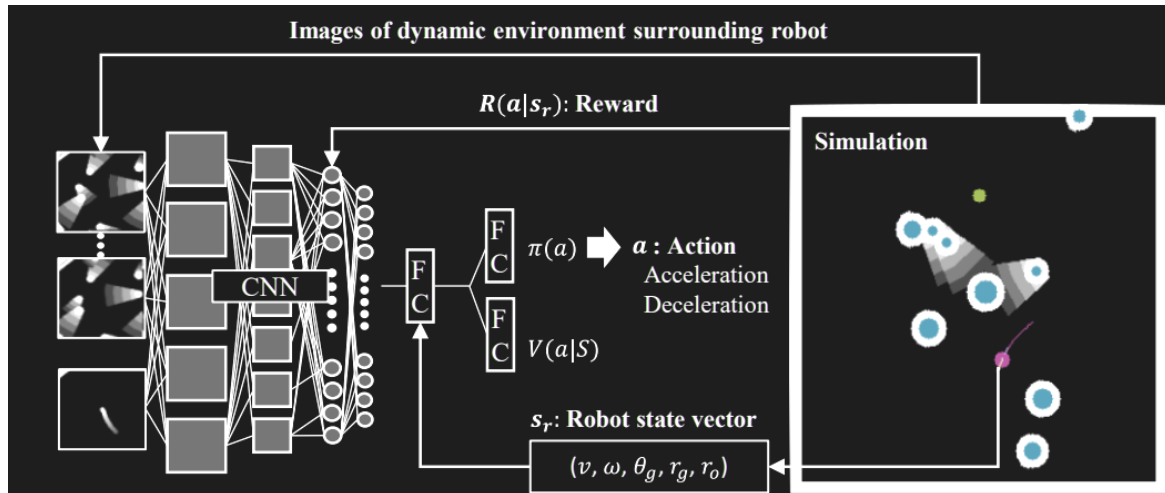


Figure 3: Passing movement getting the hang of utilizing reenactment

Figure 3 blueprints of the educational experience for passing movement arranging. In the proposed network model, the state space S is gotten from reenactment. One state is the robot state vector $\mathbf{sr} = 3v, \omega, \theta r, rg, ro7$, where v and ω are the direct and rakish speed of the robot, separately, θr is the robot present, rg is the distance to the objective, and ro is the distance to the nearest obstruction. The other state contains the data about powerful climate-encompassing robots. The recreation addresses dynamic climate data encompassing robots as a period series of pictures. The portrayal strategy is depicted exhaustively in area 3.3. The activity space $\mathbf{A}$ comprises control orders for speed increase and deceleration got from the ongoing rate, portrayed as a tuple of speed and turn. The $(\mathbf{a})$ returns the probability of being the ideal activity for every conceivable activity $\mathbf{a}$ given a present status $\mathbf{S}$. The approach $(\mathbf{a})$ is found by making moves and allowing the specialist to investigate its learning reproduction to amplify the aggregate prizes $(\mathbf{a}|\mathbf{sr})$. The prize capability $(\mathbf{a}|\mathbf{sr})$ assesses the robot state vector $\mathbf{sr}$ to guarantee that the robot can arrive at its objective without crashing into obstructions. The proposed network applies A3C [18] support learning system to empower dispersed learning.

3.2 A portrayal of environment in dynamic condition

The reproduction addresses the unique climate as a period series of pictures around the robot to process a passing movement. This portrayal technique alludes to GOSELO [19] to address the climate as a picture. The picture in current time t is created, which is a square with $10\ m$ long sides fixated on the robot's situation. Figure 4 (a) shows an edited segment of the picture encompassing the robot. The picture is turned to address the objective at the top. This picture

doesn't rely upon the robot position or passerby direction in the recreation; it learns just the general positional connection between oneself position and objective position. This is extremely successful as far as decreasing the learning time.

The last info pictures are displayed in Figure 4 (b). Since the info picture considers your previous developments and those of the person on foot, the info pictures are made out of six-channel pictures: time-series of the picture on occasion t , $t - 0.5$, $t - 1.0$, $t - 1.5$, and $t - 2.0$ seconds, and the direction pictures of the portable robot throughout recent seconds. The robot's direction is a picture that addresses its self-situating direction regarding the date. The information pictures are binarized to bring down the number of aspects and learning costs. The significant region has a pixel worth of 255 (white) and the crash region has a pixel worth of 0 (dark). The anticipated passerby regions have dark pixel upsides of [50, 100, 150, 200] relying upon the closeness to walkers.

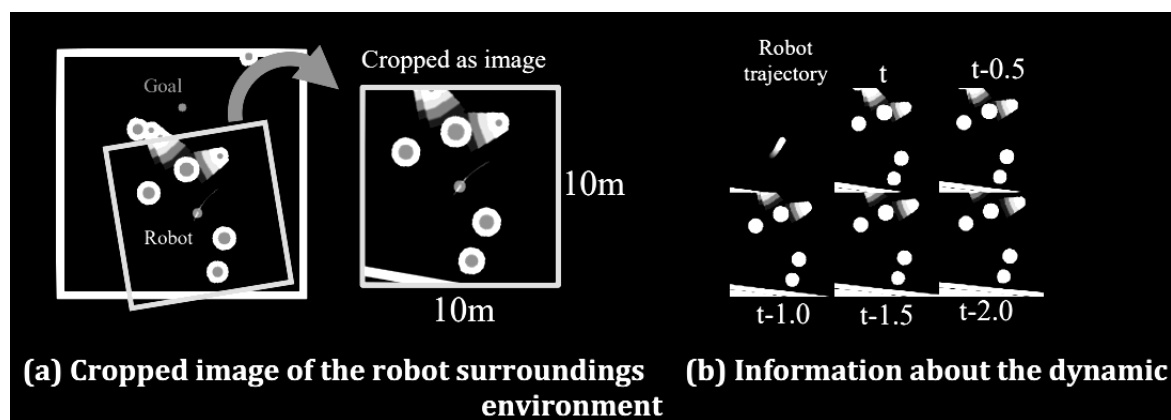


Figure 4: Creating input pictures as a guide state

3.3 Action and Reward plan

The speed order for the robot $ut = (vt, \omega t)$ comprises direct speed vt and rakish speed ωt . The activity space A is a mix of speed increase and deceleration in light of the ongoing velocity ut . The brain network decides the following activity $a = (\Delta v, \Delta \omega)$ utilizing activity space A . The lattice of the activity space is still up in the air by the boundary $[v_a)^{*+}, \omega_a)^{*+}, Rv, R\omega]$, where $v_a)^{*+}, \omega_a)^{*+}$ address the most extreme speed increase and deceleration of the speed order, and Rv and $R\omega$ address the goal of the activity space. The speed order u_0 is determined from the got activity a by:

$$v^t = \begin{cases} v_{max} & (v^t > v_{max}) \\ v_{min} & (v^t < v_{min}) \\ v^{t-1} + \Delta v & (else) \end{cases}, w^t = \begin{cases} w_{max} & (w^t > w_{max}) \\ w_{min} & (w^t < w_{min}) \\ w^{t-1} + \Delta w & (else) \end{cases}$$

where $v)^{*+}, v)78, \omega)^{*+}$, and $\omega)78$ address the most extreme and least velocities. This computation model depends on the DWA [1], which is intended to forestall unexpected speed and posture changes.

The target of the prize capability is to empower the organization to get familiar with the activities that are best inside a given state sr . For this reason, the scanty prize capability is set

as follows:

$$R(a|s_r) = \begin{cases} R_g = 15 & (\text{if reached goal}) \\ R_c = -15 & (\text{if collision}) \\ R_d + R_o + R_p & (\text{else}) \end{cases}$$

The prize capability grants the specialist R_g when it arrives at the objective and punishes it with R_c at the point when it slams into people on foot or impediments. The movement is assessed by three capabilities: R_d , R_o , and R_p . R_d assesses whether the robot moves toward the objective at each step. It is determined from the distance to the objective dt as $R_d = 2.5 \cdot (dt - dt_{\text{and}})$. R_o assesses the separation from the nearest hindrances and keeps walkers and deterrents from attacking the specialist safe place. On the off chance that the distance do between the specialist and obstruction is more modest than the edge dt ; it doles out the punishment $R_o = -0.02 \cdot do$ (if $do < dt$; $= 2.0$). R_p assesses the anticipated place of the robot. It is determined by utilizing the anticipated place of robot $\mathbf{pr}$ and pixel worth of the nearby guide ($\mathbf{p}$), as $R_p = -0.001 \cdot (255 - (\mathbf{pr}))$. The anticipated place of the robot $\mathbf{pr}$ is characterized as the positioning gauge when the robot moves from its ongoing situation at the current speed for 2.0 s.

3.4. Integration with versatile robot route

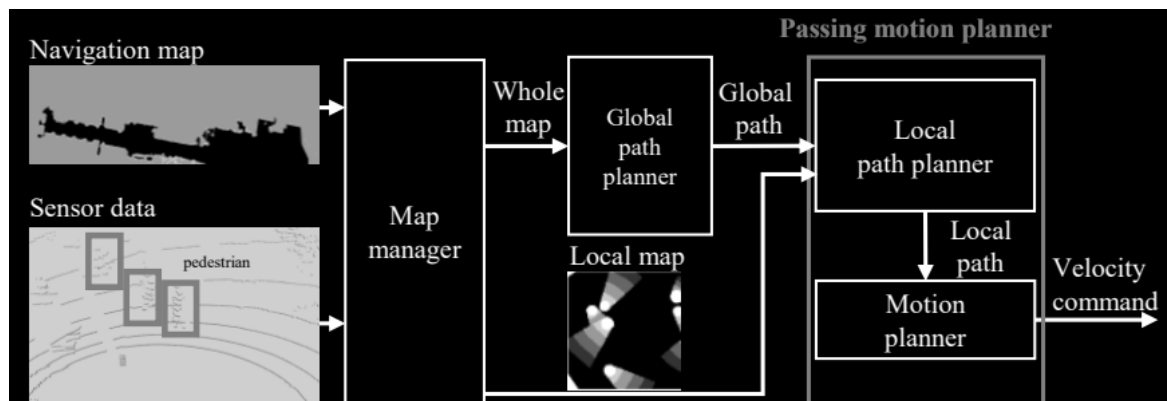


Figure 5: Versatile robot route with the proposed passing movement organizer

Figure 5 features the route structure containing the proposed passing movement organizer. The squares address every module and bolts address the data sources. The guide supervisor refreshes the route map with the ongoing snags given the procured sensor information. In a regular route structure, this module gives the route guide to two-way organizer modules. One is for worldwide way arranging, which ascertains the harsh way from the underlying situation to the objective given the whole route map, and the other is for neighborhood way arranging, which works out the way from the robot position to the put forth nearby objective on the worldwide way. To keep away from dynamic obstructions, it is executed at a high recurrence. At last, the movement arranging module computes the speed order to follow the nearby way. In the proposed route system, an entry movement organizer is applied rather than the two

ordinary modules (red boxes in Fig. 5).

4. Process evaluation

This segment depicts how the passing movement learning and proposed route structure were assessed. In the first place, the passing movement learning was assessed utilizing a straightforward test system with people on foot. Then, at that point, a reenactment of the versatile robot route was performed to assess the proposed route system. At long last, the proposed route structure was integrated into a portable robot and exhibited at a science gallery.

4.1. Process model training settings

The proposed network model purposes two CNN structures. The first is AlexNet [20], which is known for its superior presentation in picture acknowledgment undertakings. It comprises five convolutional layers and three completely associated layers. To decrease the preparation time, the AlexNet design utilized in this study can arrange the picture size from 224 pixels to 112 pixels. The second is a little CNN design comprising of three convolutional layers and four completely associated layers. The engineering portrayed in [21] was utilized as a kind of perspective to fabricate the CNN system utilized in this review. Figure 6 shows the small CNN engineering.

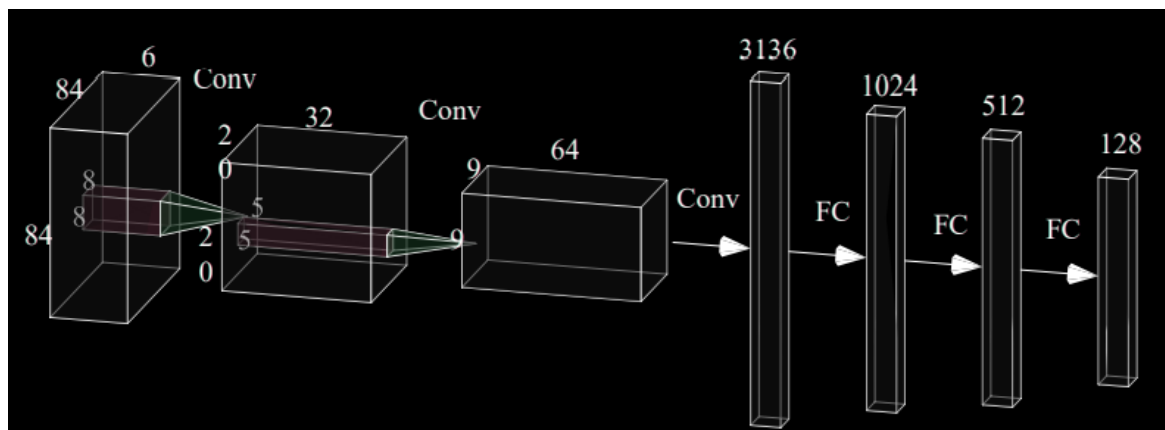


Figure 6: The minuscule CNN deep learning architecture

The preparation was done in a sum of 80 million stages. 30 million stages took place in the unhampered space climate, trailed by 50 million stages in the climate including fixed walkers. Table 1 reports the reenactment settings exhaustively. The quantity of fixed walkers is arbitrarily set in the reach 5 - 15.

Table 1: The reenactment setting subtleties

Environment		Robot	
L :Size of simulator	15m	r_r :Radius	0.3m
R :Resolution of image	0.05m	No. of action spaces	25 ($R_v=5, R_m=5$)
dt :Time interval	100ms/step	v :Linear velocity	[0.0,1.2]m/s
Pedestrian		m :Angular velocity	[-200,200]deg/s
r_p :Radius	[0.2,0.4]m	va_{max} :Max. linear acc.	1.0m/s ²
Motion policy	ORCA	ma_m :Max. angular acc.	100deg/s ²
Pref. velocity	1.2m/s		

4.2. Passing movement in a learning reproduction

The passing movement organizer is assessed with the climate including fixed people on foot as displayed in Figure 2. The underlying position and example of the walkers were arbitrary, as well as the underlying posture and position of the robot. As near baselines, (A*+DWA), ORCA, and CADRL techniques are utilized. A*+DWA is an ordinary route technique. ORCA is a common impact evasion technique, where a few free versatile robots or specialists try not to slam into one another with no correspondence between them. The CADRL is a decentralized multiagent impact aversion calculation in light of profound support learning. This strategy prepares the movement model thinking about just moving people on foot. Tests were led considering similar 500 episodes of randomized conditions for all pattern models.

This assessment looked at the accompanying measurements: achievement rate, appearance time, least distance to people on foot, and most extreme change in speed and posture inside a period step. The typical qualities in effective episodes were recorded. Table 2 reports the summed-up results. Figures 6 and 7 show two examinations of the development directions of walkers and robots in one episode. The strong blue circles address the robot, and different circles address walkers. The red star addresses the objective. The dark numbers on the direction address reproduction time.

With the customary route, the robot given A*+DWA goes directly to the objective as per the way plan, which prompts the robot to attempt to cross before the walkers as displayed in Figure 7 (a). A* can't change the robot way while digging out from a deficit, in this way, it crashes into the walker as displayed in Figure 8 (a). ORCA focuses on the speed toward the objective assuming there is no crash, consequently, inordinate methodology and unexpected differences in speed happen close to the middle where the person on foot and the robot meet. CADRL can perform hesitant moves while experiencing a moving passerby as displayed in Figure 7 (c). Be that as it may, it stalls out in a scene with a gathering of fixed walkers in front as displayed in Figure 8 (c) since it doesn't think about fixed obstructions. In figure 7, the proposed robot should be visible moving productively without upsetting the person on foot's development. Additionally, in figure 8 it very well may be seen keeping away from the person on foot coming in from the other side. In figure 8, the robot seems to trust that walkers will pass before continuing without upsetting them.

The proposed strategy made a higher progress rate and lower appearance time looking at all baselines except ORCA. ORCA accomplished improvement brings about these measurements since there were no crashes because of its plan strategy. Notwithstanding, an enormous change in act happened with ORCA. CADRL made the robot make a huge turn at an adequate distance to not hit a walker, and that implies it required greater investment to arrive at its objective. The achievement rate is low attributable to being stuck fixed people on foot. These outcomes exhibit that the proposed strategy ensured that the robot remained an adequate separation away from people on foot and moved proficiently without an unexpected difference in the present.

Table 2: Output of basic passing movement reproduction with various strategies

Method	Success[rateArriva --]	l	Min.dis.ofped.[m]	Max. Δv [m/sste p]	Max.[rad/ste p]	Δ ω
A*+DWA	0.30	10.9 $\pm$ 2.77	0.30 $\pm$ 0.16	0.08 $\pm$ 0.03	0.11 $\pm$ 0.05	
ORCA	1.00	7.45 $\pm$ 1.00	0.46 $\pm$ 0.12	1.20 $\pm$ 0.00	0.46 $\pm$ 0.12	
CADRL	0.42	11.3 $\pm$ 2.98	1.06 $\pm$ 0.99	0.79 $\pm$ 0.33	0.60 $\pm$ 0.49	
Proposed(AlexN et)	0.95	10.3 $\pm$ 1.19	1.00 $\pm$ 0.42	0.09 $\pm$ 0.03	0.04 $\pm$ 0.03	
Proposed (Tin CNN)	0.96	10.4 $\pm$ 1.54	0.93 $\pm$ 0.38	0.09 $\pm$ 0.05	0.03 $\pm$ 0.02	

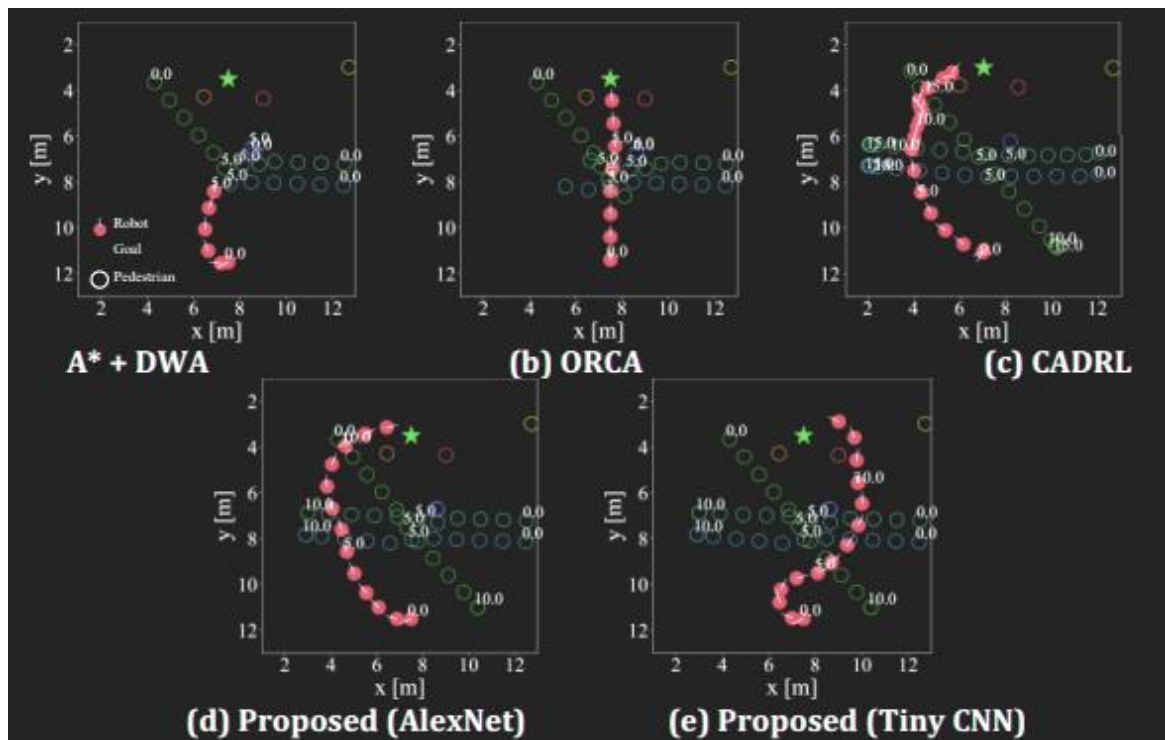


Figure 7: trajectory comparison of each method

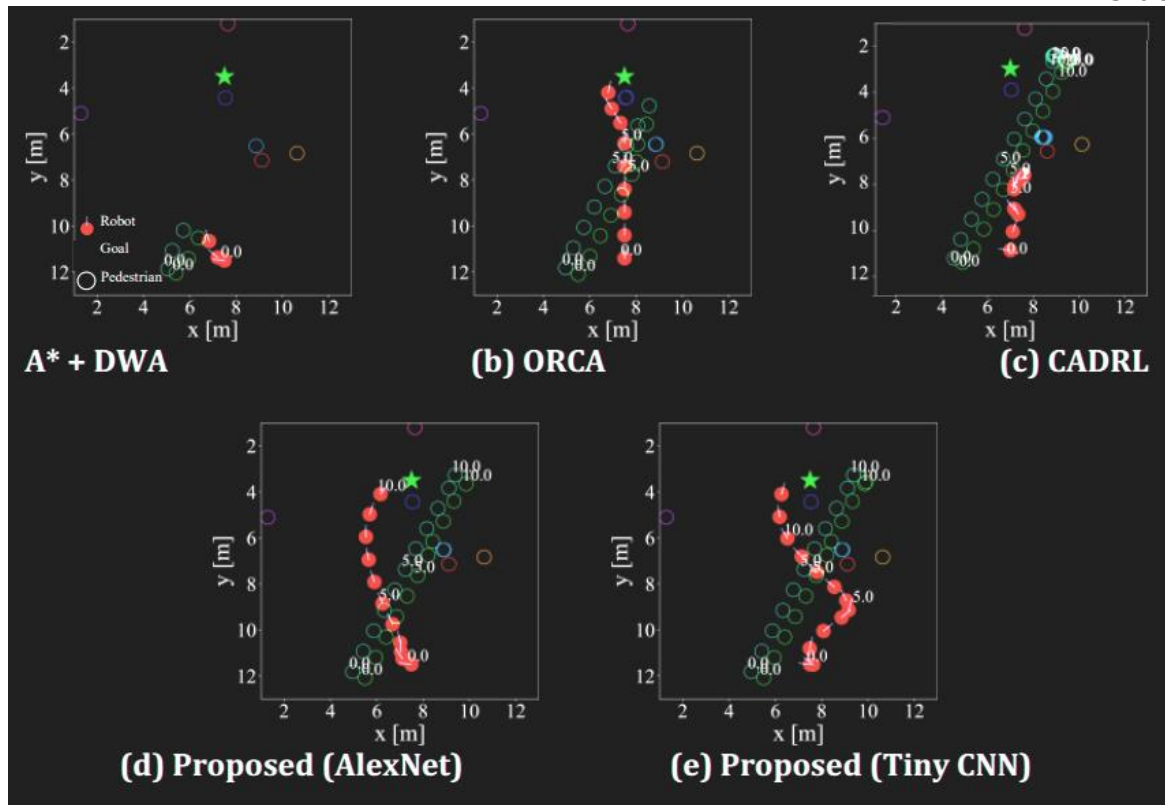


Figure 8: Correlation of direction with every technique

4.3. Portable robot route with passing movement

This segment shares the assessment of the proposed route system in the reproduction climate introduced in figure 9. This climate is a square with 50 m long sides. Ten moving walkers (addressed by green chambers) travel through the square, and forty people on foot stay fixed (addressed by red chambers). The people on foot haphazardly pick an objective among nine objections (in yellow) and stroll towards that objective as per the ORCA strategy.

The reproduction utilized the Pioneer P3-DX model (https://github.com/mario-serna/pioneer_p3dx_model) as the portable robot model. The robot was outfitted with 3D LIDAR (https://github.com/lmark1/velodyne_simulator) to perceive the general climate. In the trial, the robot arbitrarily chooses nine objections and performs an independent route. When it concludes its objective, nearby objectives are put at 7-m spans on the way drawn by A*. The robot moves to the following nearby objective when it is inside 2 m of the neighborhood objective. This cycle is rehased until the robot arrives at its objective or slams into hindrances. Gazebo [22] was utilized to execute the reenactment.

The route test ran 100 episodes for assessment. The proposed route structure was assessed and contrasted with the current route technique for A*+DWA. The accompanying measurements were examined: achievement rate, normal speed, distance to walkers, and speed and stance changes in a stage. The typical qualities in effective episodes were recorded. Table 3 records the outcomes. The proposed route system made a higher progress rate than that of the traditional one attributable to the proposed passing movement, which empowered walkers drawing closer from the side to stay away. The appearance time and normal speed

remained roughly equivalent when A^* was utilized, demonstrating that the proposed technique accomplished a proficient passing movement. The proposed techniques have no unexpected stance change. The primary driver of a crash with people on foot was the point at which the walker showed up at an objective and unexpectedly changed their way of behaving to arrive at the following objective.

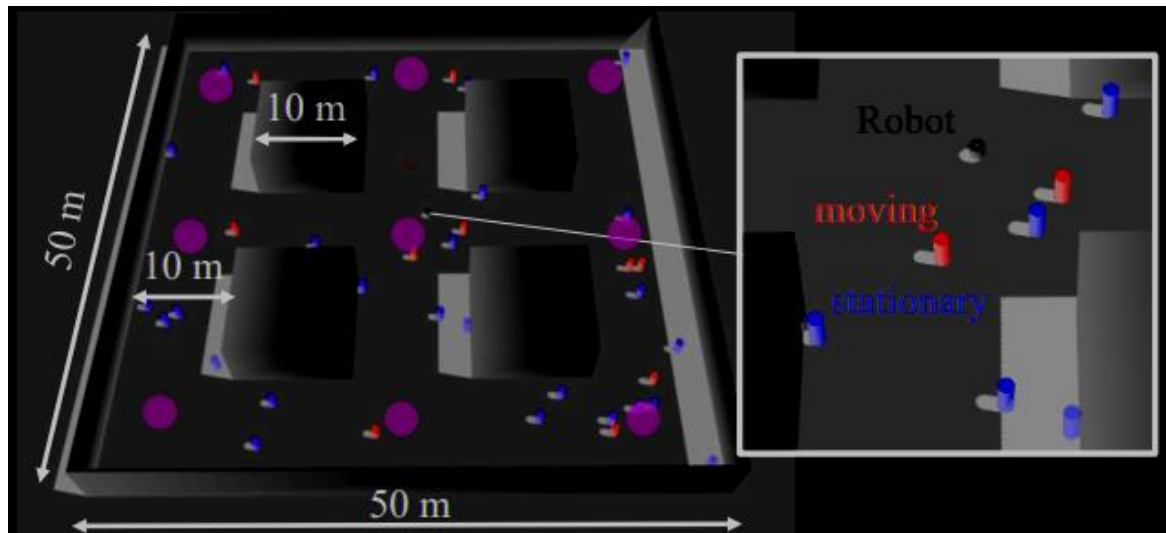


Figure 9: Recreation climate for assessing versatile robot route

Table 3: Aftereffect of mobile robot navigation in simulation process

Method	Success[--]	rateVelocity [m/s]	Min.dis.of[m]	ped.Max. Δv [m/sMax. step]	Max. [rad/step]
A^* +DWA	0.53	1.10	1.23 ± 0.52	0.11 ± 0.01	0.13 ± 0.11
Proposed(AlexNet)	0.87	1.17	0.93 ± 0.44	0.10 ± 0.02	0.11 ± 0.05
Proposed (Tiny CNN)	0.89	1.16	0.91 ± 0.42	0.09 ± 0.01	0.13 ± 0.05

3.4. Real-world show

The proposed route system was executed on a portable robot to test its genuine exhibition. Figure 10 (a) shows the versatile robot, which incorporates a PC (Intel, NUC10FNK) with an Intel Core i7-10710U CPU comprising six 2-strung centers. The robot is outfitted with 3D LIDAR (Velodyne VLP-32MR) and 6-hub IMU (Xsens Mti670) sensors. The 3D LIDAR recognizes the encompassing impediments and addresses them on the neighborhood map as point cloud information. The MCL-based 6-of restriction technique utilizing a 3D LIDAR and various IMUs is applied in the exhibition. For distinguishing moving walkers, a moving

item tracker (mo tracker) using test-based joint probabilistic information affiliation channels (SJPDAs) is applied. The restriction, way arranging, and movement arranging work at 10 Hz.

The exhibit try was done in a science historical center as displayed in figure 10 (b). Like the examination portrayed area in 4.3, three standard techniques were thought about: A*+DWA, proposed-Alex, and proposed-small CNN. To assess the proficiency of every strategy, an independent route was performed for 30 minutes utilizing every technique; the typical lap times were analyzed. The examination results as per the lap season of every technique are introduced in figure 10. The proposed technique runs at a more limited lap time than those of the customary strategies, which shows that the proposed strategy is more productive.

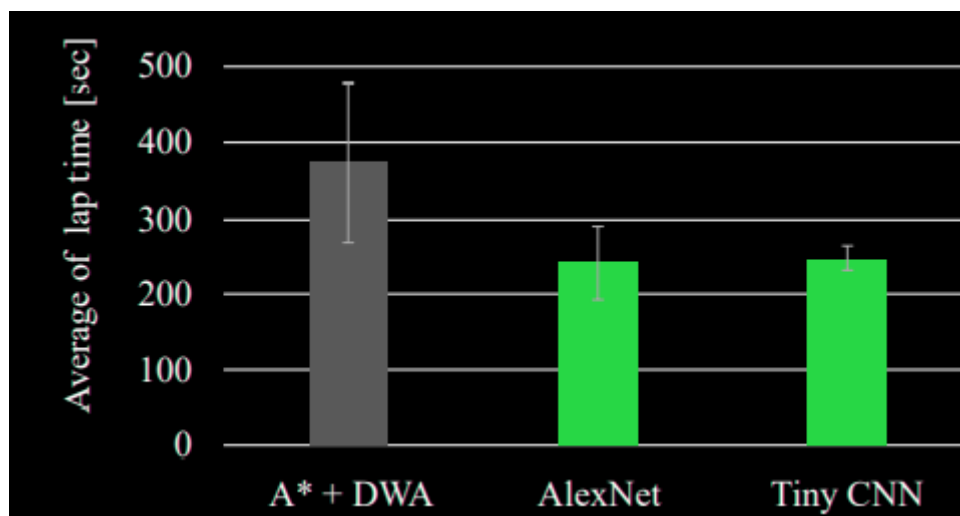


Figure 10: Normal lap time got utilizing every technique

4. CONCLUSION

This study presents a strategy for picking up passing developments for independent robots involving a test system in a powerful climate. The recreation incorporates static walkers to precisely reenact a packed climate. The proposed structure is intended to be effortlessly coordinated into genuine robots. A significant component of this system is its capacity to create smooth movement without disrupting the passerby. Likewise, attributable to isolating the gaining of the section movement from the way arranging, the learned movement is successful in different conditions. Tests show that the mastered passing movement makes a higher progress rate than those of ordinary strategies and a compelling passing movement with smooth speed increase and deceleration can be gotten. The proposed system was carried out on a portable robot in a science gallery, which effectively explored between walkers.

References

- [1] Fox, D., Burgard, W., & Thrun, S. (1997). The dynamic window approach to collision avoidance. *IEEE Robotics & Automation Magazine*, 4(1), 23-33.
- [2] Quinlan, S., & Khatib, O. (1993, May). Elastic bands: Connecting path planning and control. In [1993] *Proceedings IEEE International Conference on Robotics and Automation* (pp. 802-

807). IEEE.

- [3] Fiorini, P., & Shiller, Z. (1998). Motion planning in dynamic environments using velocity obstacles. *The international journal of robotics research*, 17(7), 760-772.
- [4] Berg, J. V. D., Guy, S. J., Lin, M., & Manocha, D. (2011). Reciprocal n-body collision avoidance. In *Robotics research* (pp. 3-19). Springer, Berlin, Heidelberg.
- [5] Helbing, D., & Molnar, P. (1995). Social force model for pedestrian dynamics. *Physical review E*, 51(5), 4282.
- [6] Pellegrini, S., Ess, A., Schindler, K., & Van Gool, L. (2009, September). You'll never walk alone: Modeling social behavior for multi-target tracking. In *2009 IEEE 12th international conference on computer vision* (pp. 261-268). IEEE.
- [7] Vemula, A., Muelling, K., & Oh, J. (2017, May). Modeling cooperative navigation in dense human crowds. In *2017 IEEE International Conference on Robotics and Automation (ICRA)* (pp. 1685-1692). IEEE.
- [8] Chen, Z., Song, C., Yang, Y., Zhao, B., Hu, Y., Liu, S., & Zhang, J. (2018). Robot navigation based on human trajectory prediction and multiple travel modes. *Applied Sciences*, 8(11), 2205.
- [9] Luders, B. D., Aoude, G. S., Joseph, J. M., Roy, N., & How, J. P. (2011). Probabilistically safe avoidance of dynamic obstacles with uncertain motion patterns.
- [10] Chiang, H. T. L., Faust, A., Fiser, M., & Francis, A. (2019). Learning navigation behaviors end-to-end with autorl. *IEEE Robotics and Automation Letters*, 4(2), 2007-2014.
- [11] Fan, T., Cheng, X., Pan, J., Manocha, D., & Yang, R. (2018). Crowdmov: Autonomous mapless navigation in crowded scenarios. *arXiv preprint arXiv:1807.07870*.
- [12] Pfeiffer, M., Shukla, S., Turchetta, M., Cadena, C., Krause, A., Siegwart, R., & Nieto, J. (2018). Reinforced imitation: Sample efficient deep reinforcement learning for mapless navigation by leveraging prior demonstrations. *IEEE Robotics and Automation Letters*, 3(4), 4423-4430.
- [13] Chen, C., Liu, Y., Kreiss, S., & Alahi, A. (2019, May). Crowd-robot interaction: Crowd-aware robot navigation with attention-based deep reinforcement learning. In *2019 International Conference on Robotics and Automation (ICRA)* (pp. 6015-6022). IEEE.
- [14] Everett, M., Chen, Y. F., & How, J. P. (2018, October). Motion planning among dynamic, decision-making agents with deep reinforcement learning. In *2018 IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS)* (pp. 3052-3059). IEEE.
- [15] Zhou, M., Dong, H., Wang, F. Y., Wang, Q., & Yang, X. (2016). Modeling and simulation of pedestrian dynamical behavior based on a fuzzy logic approach. *Information Sciences*, 360, 112-130.
- [16] Mnih, V., Badia, A. P., Mirza, M., Graves, A., Lillicrap, T., Harley, T., ... & Kavukcuoglu, K. (2016, June). Asynchronous methods for deep reinforcement learning. In *International conference on machine learning* (pp. 1928-1937). PMLR.
- [17] Kanezaki, A., Nitta, J., & Sasaki, Y. (2017). Goselo: Goal-directed obstacle and self-location map for robot navigation using reactive neural networks. *IEEE Robotics and automation letters*, 3(2), 696-703.
- [18] Krizhevsky, A., Sutskever, I., & Hinton, G. E. (2012). Imagenet classification with deep

convolutional neural networks. *Advances in neural information processing systems*, 25.

- [19] Fujita, Y., Nagarajan, P., Kataoka, T., & Ishikawa, T. (2021). ChainerRL: A Deep Reinforcement Learning Library. *J. Mach. Learn. Res.*, 22(77), 1-14.
- [20] Koenig, N., & Howard, A. (2004, September). Design and use paradigms for gazebo, an open-source multi-robot simulator. In *2004 IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS)*(IEEE Cat. No. 04CH37566) (Vol. 3, pp. 2149-2154). IEEE.
- [21] Ohsato, A., Sasaki, Y., & Mizoguchi, H. (2015, December). Real-time 6DoF localization for a mobile robot using pre-computed 3D laser likelihood field. In *2015 IEEE International Conference on Robotics and Biomimetics (ROBIO)* (pp. 2359-2364). IEEE.
- [22] Hatao, N., & Kagami, S. (2015). Cluster-based sjpdafs for classification and tracking of multiple moving objects. In *Field and Service Robotics* (pp. 303-317). Springer, Cham.