Transportation Research Interdisciplinary Perspectives 12 (2021) 100473

Contents lists available at ScienceDirect

Transportation Research Interdisciplinary Perspectives

journal homepage: www.sciencedirect.com/journal/transportation-research-interdisciplinary-perspectives

Optimal path planning of autonomous navigation in outdoor environment via heuristic technique

S. Julius Fusic, G. Kanagaraj *, K. Hariharan, S. Karthikeyan

Department of Mechatronics, Thiagarajar College of Engineering, Madurai, TamilNadu 625015, India

A R T I C L E I N F O

Keywords:
Localization
Satellite image
Path planning
Particle swarm optimization

A B S T R A C T

Path planning for automated guided vehicles (AGVs) operating in an outdoor environment is a key task in logistic applications. This paper highlights a new approach for finding collision-free path for AGVs in an outdoor environment using satellite images. Satellite images are transformed into occupancy grids that divide the environment, obstacles (building, trees and pedestrian path etc.,) as black grids and free routes as white grids in order to find an obstacle free path. The proposed navigation control strategy is to localise the AGVs vehicle route until any approaching obstacle is detected and to turn to the safest area before continuing its path. The navigational model was developed in the MATLAB/Simulink 2D virtual environment to visualise the path navigation. Particle swarm optimization and its five variants were used to obtain the obstacle free path. Experiments were conducted in various environments to verify the efficiency and performance of the algorithm. Validation with a bench mark instance ensures that the proposed algorithm found a shorter path with less computation time.

Introduction

Mobile robot navigation is a critical problem in a variety of fields, including industry, autonomous vehicles, and safety. In addition, the most well-known navigation systems, such as GPS, are now subjected to natural and artificial problems in a variety of operating environments. Automated Guided Vehicles (AGVs) path planning is a critical topic that has been the subject of research for a long time. Despite advanced research studies in this field, the real time unknown environment-based path planning is difficult to handle by AGVs vehicles in smart logistics applications. The vast development of Rapid technology has modernized the industrial sector in Industry 4.0. The logistics application serves as lifeblood of industry 4.0 revolutions and provides a key contribution in the Industry sector. AGVs are turned out to be an integral part of the solution in an autonomous logistics system to transport packages and accessories from one place to another with less or no human intervention. In recent times due to pandemic and industrial restriction ecosystems, the labour cost hike and shortage of labourers have forced industrial sectors to take significant solutions permissible to stay competitive in the global business market. A detailed review of unmanned automated systems such as AGVs that transport packages, materials, accessories and all other products in warehouse/go down, distribution and logistics environment to reduce labour costs, other additional costs and increase the productivity, profitability, flexibility and reliability in the system in the context of task planning architecture for service robotics (Serrano and Santiago, 2021). The introduction of AGVs, drones is an advanced solution to replace existing vehicles for goods transportation. Predictive path planning for mobility optimization and navigation control using vector fields in confined environments has been analysed (Azpúrua and Rezende, 2021). GPS and GNSS satellite data for localize the autonomous vehicles in Industrial 4.0 logistic applications (Hadi et al., 2021). AGVs comprises various components and algorithms to make a decision on a specific task during loading and unloading goods operation. However, the efficiency of finding a path in a real time environment remains a difficult task. Many researchers are trying to develop algorithms and effective process methods to perform localization and navigate the path effectively. Path planning in an unknown environment is a difficult task for mobile robots. To achieve navigation efficiency with an urban geographical chart, the integrated navigation observability and navigation performance analysis were used. Designing effective driving safety interventions is imperative as traffic crashes are the leading cause of injury and death among adolescents. Ji *et al* (Ji et al., 2021) adopted a fusion algorithm for global path planning to show the effectiveness to avoiding unnecessary bumpy roads. Mapping an unknown environment is difficult and requires significant energy. To navigate in such an environment requires a lot of pre

* Corresponding author.
E-mail addresses: sjf@tce.edu (S. Julius Fusic), gkmech@tce.edu (G. Kanagaraj), khh@tce.edu (K. Hariharan), skarthi%20@student.tce.edu (S. Karthikeyan).

https://doi.org/10.1016/j.trip.2021.100473
Received 19 March 2021; Received in revised form 20 July 2021; Accepted 11 September 2021
Available online 1 October 2021

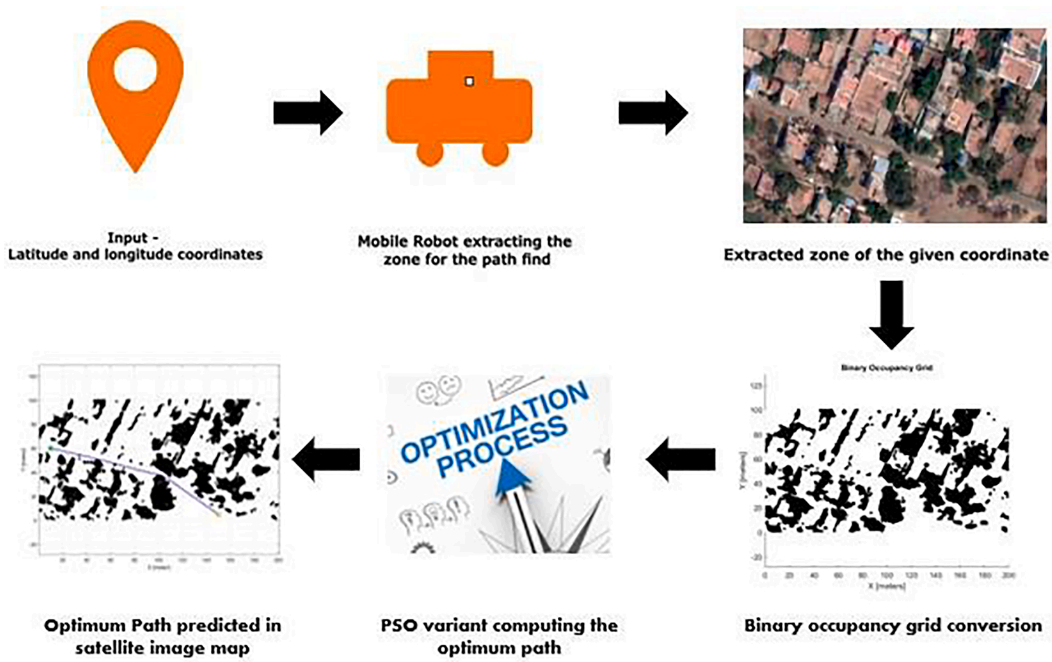

Fig. 1. Sequential workflow of the proposed navigation approach.

Fig. 2. The input satellite image (environment E1).

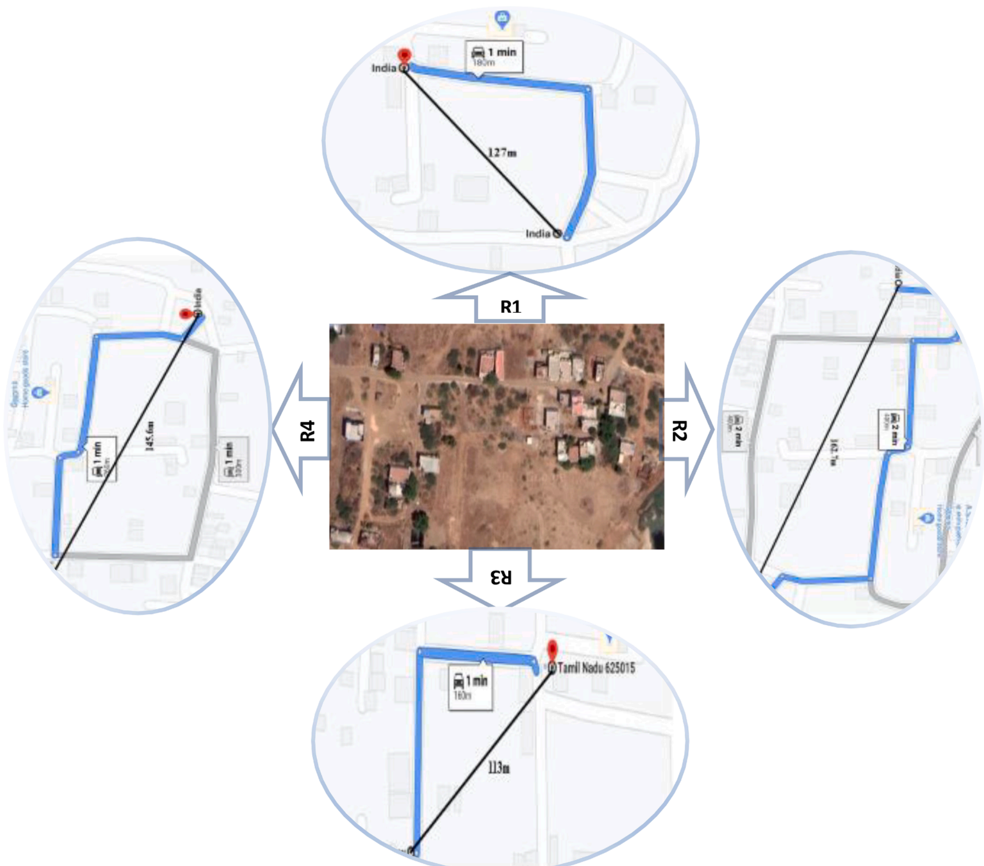

Fig. 3. The input satellite image (environment E2).

data in order to make a decision regarding the motion between two points. A realistic, 3D virtual simulation environment of the actual geo-fenced urban area used in (Li et al., 2021) was built for evaluating and developing the path planning and path tracking. Sun et al (Sun et al., 2019) adopted an online motion planning method that can guarantee the safe and smooth navigation of Mecanum-wheeled robots in an industrial environment. A multi-objective approach was adopted in design a decision support system for underwater cleaning robots used in the tank cleaning operations to explore all feasible paths (Mahmud et al., 2021). Similarly, meta- heuristic optimisation approaches are now practiced in order to see the improvisation of algorithms with better computation power. In the past, Particle swarm optimisation (PSO) algorithm approaches were handled with less computation power compared to today's computation power. Similar to Neural networks, PSO, Ant colony and Genetic algorithms can also be improvised and better results can be achieved as to neural networks with latest the computation development (Rajput and Kumari, 2017). Many researchers have stated that GPU hardware creates differences in Neural networks-based navigation complex problems. Anish pandey discussed the performance of the controllers based on time using optimization algorithm in current generation (Pandey and Parhi, 2017). Darsana et al., proposed a method to use an autonomous mobile robot for outdoor vehicles. The algorithms they have proposed is to reduce the number of turns that have to be taken by the mobile robot in order to achieve the shortest path for the destination.

The robot path planning problems (RPP) was addressed by many classical methods like A*, Voronoi diagram, Dijkstra's, cell decomposition, breadth search, first depth search, potential field, roadmap and gravitational search (Fusic et al., 2018; Hwang and Ahuja, 1992; Kloetzer et al., 2015; Anbarasu and Anitha, 2018; Wang et al., 2018; Li et al., 2017; Purcaru et al., 2013; Goswami et al., 2020). The introduction of classical approach for robotic application has complexity in computation process, time taken to find solutions. To overcome certain problems due to classical method, the RPP focused on heuristic optimization algorithms like Ant colony optimization (ACO), Improved ant colony optimisation, Genetic Algorithm (GA), Neural Network (NN), Particle swarm optimization (PSO), and hybrid approach techniques addressed robotic trajectory and path planning problems. The heuristic approaches made the computation process simple and effective time bound.

Out of that, the particle swarm optimization (PSO) is a bio-inspired heuristic optimization algorithm approach which was created and introduced for all complex optimisation problem by Kennedy and Eberhart in 1995. Particle swarm optimization is a natural inspired algorithm based on a swarm of birds searching for a food. In PSO, the solution or member in each population were denoted as particles and the group of members were represented as swarm in classical PSO heuristic approach. In the PSO model all particles in a 'n' population have fitness values. The fitness values of each particle are evaluated using fitness function which is need to be optimized, and have velocities which direct the flying of the particles. Each bird (particle) of each population addresses the change in position from obtaining the food which is the best solution in the proposed environment. In case of mobile robot path planning problem statements, the food will be the next position of xy coordinates of robot. And the swarm heuristic algorithm will search for the position without interfering obstacles in the given environment (Baygin et al., 2018). The Ant colony algorithm-based path planning approach was so popular among robotic applications. Xin et al., (Xin et al., 2019) proposed the optimal solution for complex robotic problem by comparing Particle swarm optimization and Ant colony optimization algorithm. The PSO optimal solution is achieved with less performance attributes. Also, PSO has been widely used for the search optimization

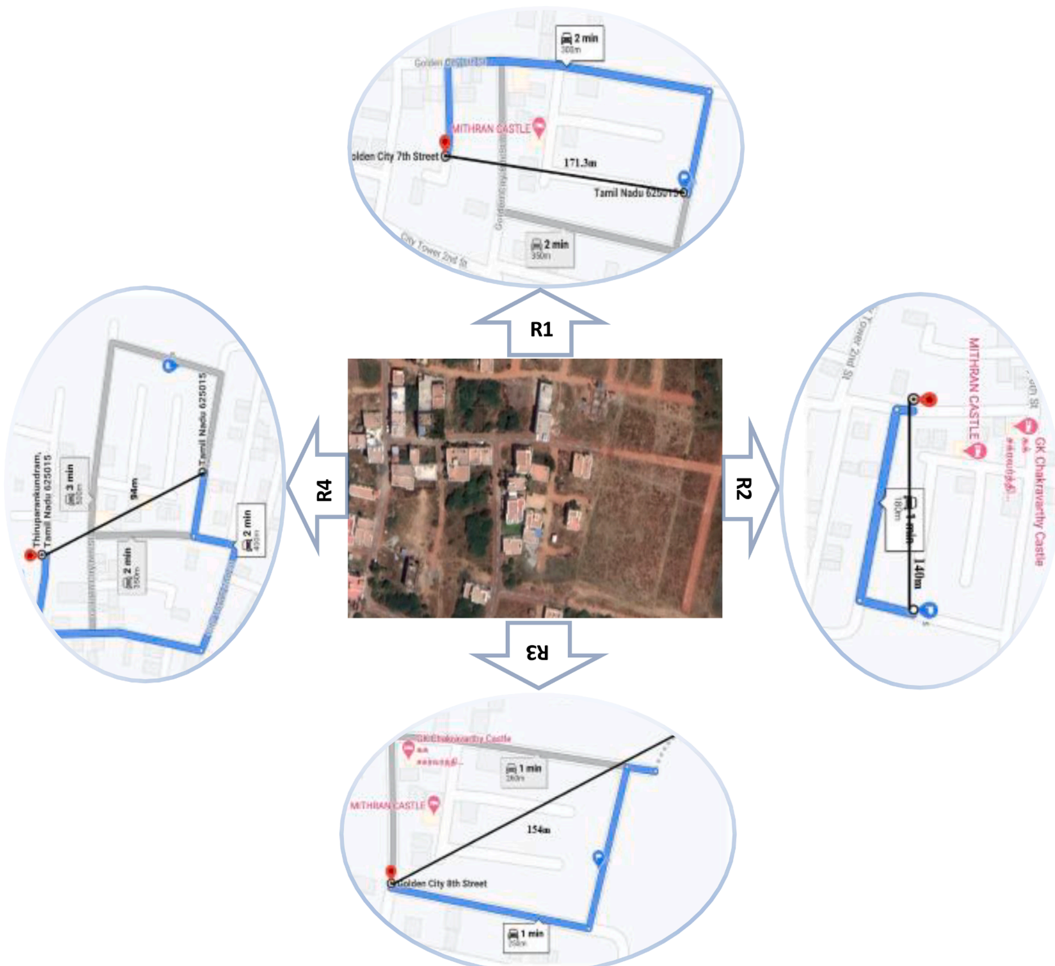

Fig. 4. The input satellite image (environment E3).

Table 1
Parameters values for the algorithms.

PSO Type	Parameter	Value	Definition
CCPSO 2	pFactor	0.5	User specified probability value
LSS-PSO	W Max	0.9	Maximum inertia
	W Min	0.1	Minimal inertia
	c1	1.250	Confidence in oneself
	c2	1.250	Confidence in the swarm
	pr	0.5	User specified probability value
	r	0.1	Small constant
OBL-PSO	Phi	0.1	Manual parameter
SPSO	W	0.5	Inertia weight
	C1, C2	1.1	Learning coefficients
VCPSO	M	10	Minimal interval for each segment

problem. Bevilacqua et al., (Bevilacqua et al., 2017) made a racing circuit simulation in MATLAB software using particle swarm optimization to resemble the racing environment.

Proposed navigation approach

The proposed navigation approach is to find the path for an AGVs from a start point to end point before it starts. The start and end points are predicted using the satellite navigation system to identify the loading and unloading of goods geographical positions in logistic applications (Sekaran et al., 2020). The input for the mobile robot in the proposed work is satellite image of terrain where the warehouse and destination customer end are located. The travelling zone for the mobile robot is captured as an image. The captured image is then converted to occupancy grids. The occupancy grids are the spaces filled by objects and spaces and represented as one and zero in a grid coordinate system. The mobile robot also follows the same coordinate system. The approach is only based on the satellite image taken prior. PSO and its five variants able to find the obstacle free optimal path to travel from start to end point.

Fig. 1 shows the sequential workflow of the proposed navigation approach to find the path in an outdoor environment. The input latitude and longitude coordinate of the loading and unloading points are localized using satellite navigation system proposed in (Hadi et al., 2021; Sekaran et al., 2020) to the mobile robot. Based on localization point the satellite image is given as an input to AGVs controller for predicting the shortest path. Initially the raw satellite terrain image is given as input to the controller for pre-processing using filters like Sobel, Canny and binary occupancy grid to avoid the complexity of AGVs to understand the obstacles and free moving path from the given image. Among the filters the binary occupancy grid filtering technique is well suited (Kloetzer et al., 2015) filter for the proposed work to convert image attributes into coordinates. After pre-processing the image is created as an input for proposed PSO variants to predict the shortest path Figs. 2-4.

The captured satellite map cannot be used directly. Image processing techniques has to be applied in order to recover information from the image to use it. There are filter techniques like sobel and canny but these filters are very much colour pixel based. Sometimes the edge detected by the sobel filter cannot be distinguished between road and buildings. Three environments (E1, E2 and E3) are derived from satellite images

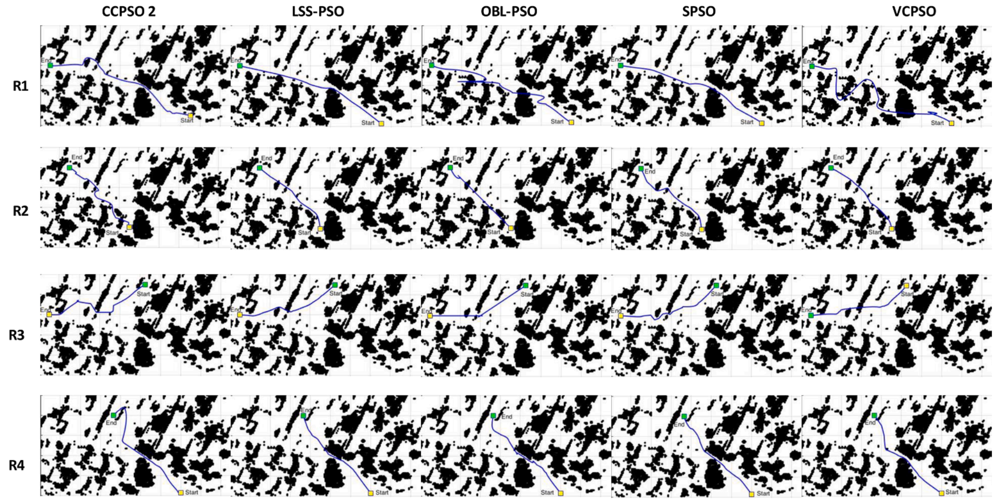

Fig. 5. Optimal path obtained from PSO variants for Environment 1.

Table 2
Comparison of results.

Environment	Route	Coordinates		Actual D (m)	CCPSO		LSS-PSO		OLB-PSO		SPSO		VCPSO	
		Start Point	End Point		D (m)	T (min)	D (m)	T (min)	D (m)	T (min)	D (m)	T (min)	D (m)	T (min)
E 1	*R 1*	9° 49’ 15.03’’ N 77° 59’ 48.7’’ E	9° 49’ 19.02’’ N 77° 59’ 41.6’’ E	151.2	157	38	155	37	227	42	154	37	223	41
	R 2	9° 49’ 15.36’’ N 77° 59’ 45.42’’ E	9° 49’ 18.7’’ N 77° 59’ 44.30’’ E	84.8	101	30	88*	28*	96	29	93	29	87	28
	R 3	9° 49’ 18.73’’ N 77° 59’ 46.54’’ E	9° 49’ 18.54’’ N 77° 59’ 42.4’’ E	100.1	111	34	106	32	113	34	101.8	30	105	31
	R 4	9° 49’ 20.172’’ N 77° 59’ 45.5’’ E	9° 49’ 18.67’’ N 77° 59’ 41.6’’ E	99.6	128	37	105	33	117	35	103	32	108	33
E 2	*R 1*	9° 52’ 36.9’’ N 78° 5’ 14.68’’ E	9° 52’ 40.34’’ N 78° 5’ 11.94’’ E	127.3	131.6	20	134.6	21	143.3	24	128.3	17	129.6	19
	R 2	9° 52’ 36.84’’ N 78° 5’ 15’’ E	9° 52’ 40.08’’ N 78° 5’ 7.8’’ E	162.7	172.5	32	166.78	30	190	35	166.18	29	164.8*	28*
	R 3	9° 52’ 40.21’’ N 78° 5’ 12.66’’ E	9° 52’ 38.352’’ N 78° 5’ 9.24’’ E	113.1	160	27	156.7	26	156.6	26	118	20	122.5	21
	R 4	9° 52’ 37.1244’’ N 78° 5’ 15.7’’ E	9° 52’ 40.368’’ N 78° 5’ 8.88’’ E	145.6	151.3	26	146.5*	24*	170.4	30	147.2	26	146.9	26
E 3	*R 1*	9°52’42.7“N 78°04’35.7”E	9°53’12.2“N 78°05’09.5”E	171	194.6	48	240.80	58	188.5	42	172.1	39	196.5	43
	R 2	9°53’12.2“N 78°05’09.5”E	9° 53’ 12.25’’ N 78° 5’ 5.14’’ E	140.1	158.74	39	145.48	36	148.3	37	141.78	33	183.18	44
	R 3	9° 53’ 14.3’’ N 78° 5’ 11.4’’ E	9° 53’ 11.8104’’ N 78° 5’ 5.03’’ E	154.3	183.18	44	156.51	39	155.07*	38*	159.34	41	193.26	48
	R 4	9° 53’ 11.44’’ N 78° 5’ 6.36’’ E	9° 53’ 16.08’’ N 78° 5’ 4.56’’ E	94.1	99.2	18	110	20	128	24	96.3	17	97.8	18

portrays the major scenario of crowd part in south India. The environment E1 details the crowded scenario, the environment E2 mentioned about the least crowded scenario and the environment E3 details the moderate crowded scenario. For each environment four routes (R1, R2, R3 and R4) are marked with same start point and four destination points. The actual shortest distance for the four routes is obtained from google map. Most of the time the google map route struggle with obstacles. To avoid such circumstances the proposed PSO variants find the obstacle free path.

PSO algorithm implementation

The various state of art PSO variance types like cooperative coevolving particle swarm optimization (CCPSO 2), Vector Coevolving Particle Swarm Optimization (VCPSO), Local Stochastic Search Particle Swarm Optimization (LSS-PSO), Opposition-Based Learning Competitive Particle Swarm Optimizer (OBL-CPSO). The random grouping method shows improved search capability which enhances the optimization while planning the path. The LSS-PSO is proposed by Ding et al. (Ding et al., 2014) details about the identification of particle velocity using geometry functions as diversity enhancing mechanism and Local Stochastic Search strategy. The LSS-PSO algorithm local stochastic search were used to calculate the velocity of the particle for recognizing the local best (pbest). The OBL-CPSO variance optimisation algorithm is proposed by the Zhou et al. (Zhou et al., 2016) where the competitive learning and opposition-based learning are used to analyse the fitness factor of identifying pbest in the given problem. The velocity and position of particles are updated based on opposition-based learning method. The VCPSO optimisation algorithm is proposed by Zhang et al (Zhang et al., 2017) in which the particles in the given populations are converted in to various segments and find the nearby position as pbest. The hybrid relationship of centralized operator in hill and lake operation is used to converge the iteration at quicker rate. Table 1 shows the PSO algorithm parameters that are used during simulation.

Algorithm to convert image into occupancy grid

Input: $imageresize[200,100]$
Output: $Binaryoccupancygridimage$
1. **Initialize occupancy grid**
2. **Convert** *colour image into Grey scale*
3. *Set threshold value* $= 80$
4. **For** $(1toX_t)$
   5. **For** $(1toY_t)$
      6. $a = compareoccupancyvalueforXY$
7. **If** $a == 1$
   Obs X $= x_{ob}$; (X, Y are coordinate axis; Obs X, Obs Y refers the obstacle position at ×, y)
   Obs Y $= y_{ob}$;
   Obs R $= r_{ob}$; size of the obstacle
   a = a++
   8. **End**
9. **End**

SPSO Algorithm

Input: Binary occupancy grid model $startandendpointcoordinates(x_s, y_s, x_t, y_t)$, **t**
Output: $No.ofPointsbetween(x_s, y_s, x_t, y_t)$ (s position of the source in map; t target position in the map)
Initialize Particles$(nP, X_t^i, V_t^i, w_t, c1_t^i c2_t^i)$
Calculate $ViolationofParticleV_i$ **for all** i
Calculate (P_{best}) **for populated particles Local best of i**th **particle**
If $(P_{best} > G_{best})$ **then substitute** $(G_{best} = P_{best})$
Find best particle based on Violation ==0 and updateG_{best}
$i_{iteration} = 1$
while $i_{current} < Max_{itr} orViolation() iszero$ **do**
  Update Velocity function $V_i^{x,y}$
  $X_{t+1}^i = w_i.V_t^i + c1_t^i.rand_1 * (P_{best} - X_t^i) + c2_t^i.rand_2 * (G_{best} - X_t^i)$
  $V_{t+1}^i = X_t^i + V_t^i$ **update position for each particle**
If $X_t^i issuperiorthanP_{best}$
    select$P_{best} tobeX_t^i$
  End if
  If $X_t^i issuperiorthanG_{best}$
    select$G_{best} tobeX_t^i$
  End if
  Update V_t^i, X_t^i **based on** $Violationvalue$
  $i_{iteration} = i_{iteration} + 1$
end while
Return

The proposed SPSO heuristic algorithm is coded in MATLAB 2020b environment. All the simulation experiments are run on the PC with Intel(R) Core (TM) i5-6500 CPU @ 3.20 GHz, 8 GB RAM. The procedural steps of SPSO algorithm are illustrated here.

Step: 1 **Initialization:** Initial population is generated randomly (say $nP = 1000$). The position of i th particle $(X_0^i)$is selected randomly corresponding to environment coordinates. The ×, y coordinates of i th particle position is randomly generated in the lower and upper bound coordinates limits [0200], [0100] respectively. The initial velocity of each particle is assigned as 0.

Step: 2 **Cost Function:** The cost function i th particle is calculated using the Eq. (1). The best particle position of each iteration where the violation = 0 is chose as local best position P_{best}. Each selected particle from local best with zero violation is considered as global best position G_{best}.Currently the SPSO heuristic algorithm identify the optimal best position as point between***startandendpointcoordinates***(x_s, y_s, x_t, y_t)

$$X_t^i = \sqrt{(x_s - x_t)^2 + (y_s - y_t)^2} \quad (1)$$

$$Violation_{i+1} = Violation_i + \frac{mean\left(1 - \sqrt{(x_x - x_{ob})^2 + (y_y - y_{ob})^2}\right)}{r_{ob}} \cdots \quad (2)$$

$x_{ob} - Splineinterpolationoccupancygridobstacleinxcoordinate$

$y_{ob} - Splineinterpolationoccupancygridobstacleinycoordinate$

$r_{ob} - Radiusoftheoccupancygridobstacle$

Step: 3 For each iteration, the particle position X_t^i and velocity v_t^i is updated and the output point is generated across (x_s, y_s, x_t, y_t). Each iteration particle cost function is ranked as P_{best} compared with the G_{best}.

$$Position, X_{t+1}^i = x_t^i + v_{t+1}^i \cdots \quad (3)$$

$$Velocity, V_{t+1}^i = V_t^i + c_1 rand_1 (P_{best} - X_t^i) + c_2 rand_2 (G_{best} - X_t^i) \cdots \quad (4)$$

$P_{best} - bestindividualparticleposition$

$G_{best} - Globalbestparticleposition$

$C_1 C_2 - cognitiveandsocialconstant$

$rand_1, rand_2 - randomnumbersbetween0and1$

Step: 4 The best fit value particle is ranked and marked between (x_s, y_s, x_t, y_t) as assumed as global best solution for t = 1. If violation occur with the best position, then the iteration is not feasible point and the loop move on to next iteration. The step 3 and 4 is repeated until the target coordinate point reached. At end the points generated in each iteration are connected and path is plotted between the starting coordinate point to target coordinate point.

Results and discussion

The navigation algorithm for the five variants of PSO were coded in MATLAB2020b environment and used same hardware for all the variants. All the simulation experiments were run on the PC with Intel(R) Core (TM) i5-6500 CPU @ 3.20 GHz, 8 GB RAM. The optimal routes obtained by PSO variants for the three environments (E1, E2 and E3) are shown in Fig. 5 respectively. Figs. 8–10 shows the convergence plots for the five variants of PSO for the three environments. Table 2 shows the corresponding distance and travel time obtained for the four routes in the three environments. From Fig. 5, CCPSO, LSS-PSO, OLB-PSO and VCPSO almost deduct the optimal path by overlapping with obstacles. But SPSO wins all the five routes with shortest distance and travel time. LSS- PSO reach the shortest route by crossing the obstacles in two or three instances. Fig. 6 indicates the optimal path related to environment 2 by all the PSO variants. Similar trend observed out of the five PSO variant, SPSO perform better in terms of distance and time. From Fig. 7, OLB-PSO slightly outperform in E3 but struggle with obstacles in few places. The convergence plots in Figs. 8-10 delineates that SPSO outperforms better convergence for the three environments among all the PSO variants.

Fig. 5 (Environment-1 crowded scenario) Consider the Smart Logistic industry A warehouse-1 is located in the starting point and the ending point is the consignee who ordered the goods. The shortest path irrespective of obstacle is 151.2 m. This case is modelled and the proposed five variances of different particle swarm optimisation iteration is processed. Out of five variants (at Max Iteration = 100) the SPSO reach the

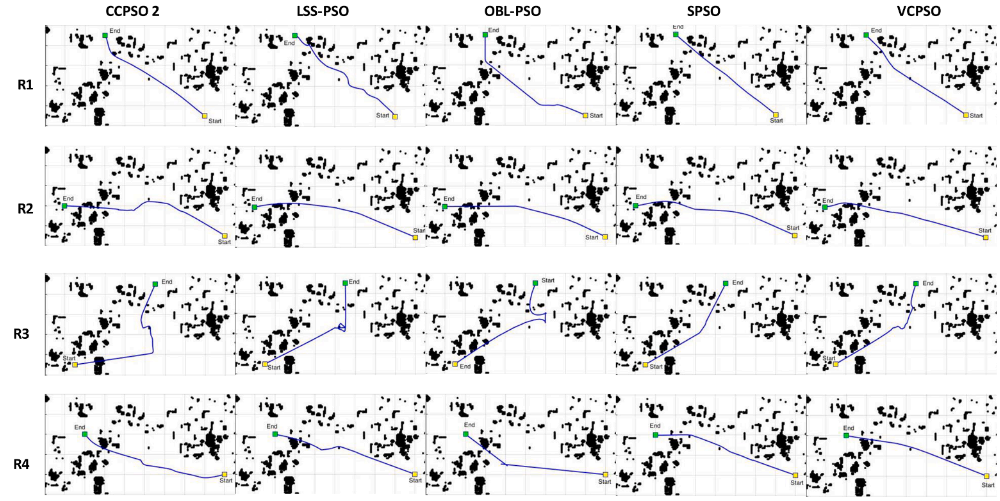

Fig. 6. Optimal path obtained from PSO variants for Environment 2.

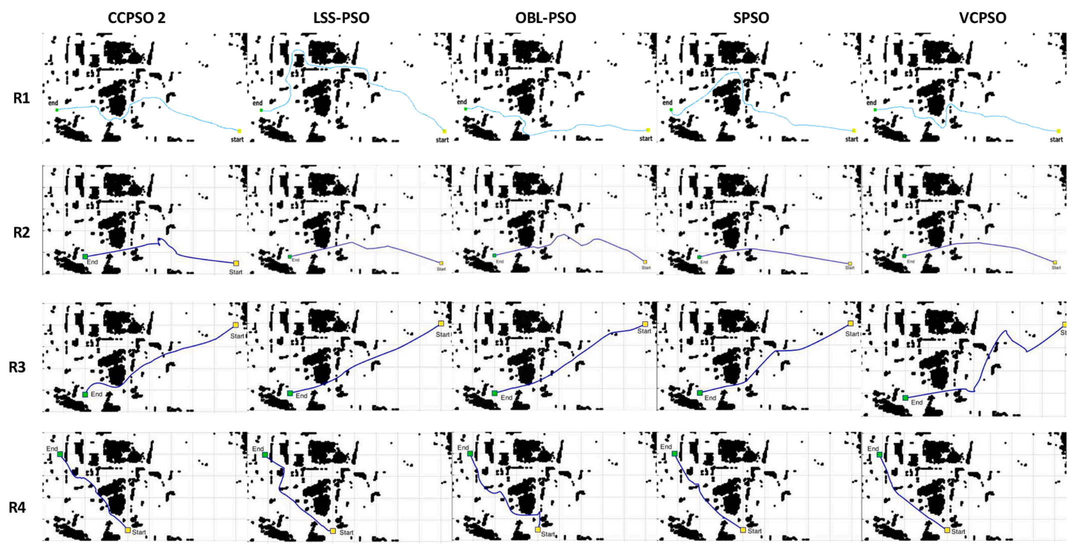

Fig. 7. Optimal path obtained from PSO variants for Environment 3.

destination at 154 m distance and 37 min time without disturbing the obstacles in the path navigation. A warehouse-2 is located in the starting point and the ending point is the customer who ordered the package to be deliver. For case 2 the shortest path navigate between two point is 84.8 m. Even though the LSS PSO variant reach the destination at 88 m but it gets collide with obstacle at point (52,68). Whereas the SPSO safely reach the destination without damaging the vehicle by colliding the obstacle. Thus, the case 2 the obstacle avoidance best fit is better in SPSO than other four variants. The starting point defines the warehouse-3 where the case 3 scenario and ending point mention the consignee who billed the delivery product. The GPS navigation latitude and longitude details are changed into (x, y) coordinate points. The actual shortest distance between warehouse-3 and consignee is 100.1 m. Out of five variants the SPSO reach the consignee at minimum distance of about 101.8 m which is feasible path in a crowded environment while compare to other four variants.

Fig. 6(Environment-2 least crowded scenario): Consider the competitor for smart logistic industry A have created a warehouse in the starting point and the ending point is the customer who ordered their consignment from the competitor warehouse. In this case the actual shortest distance without considering the obstacles is 99.6 m. Thus, the applied five variants to the proposed case 4 displayed a result. In that the SPSO variant reach the costumer with consignment at shortest feasible path. In the E2 the cluster of obstacles are less compare to other two environment. Thus, the starting point is the Smart logistic industry warehouse-1 and the end point mention the goods to unload. The actual shortest distance between the start and end point is 127.3 m. From the given environment all the five variants of PSO performs well. The SPSO outperformed all other variants and reach the unloading point as short navigation path 128.3 m. The smart logistic industry warehouse-2 located in the starting point as coordinate (180,10) and the end point where the ordered goods need to unload. Even though the given environment is having less obstacles but few variants provide the non-feasible path. Thus, the VCPSO variant reach the destination with minimum distance 164.8 m than SPSO 166.17 m. But the VCPSO collide with the obstacle thus produce non-feasible path. Whereas the SPSO even though reach at 166.17 m distance that path is feasible not collide with any obstacles. The warehouse-3 located in the starting point coordinate of about (30,10) in which the AGV vehicle load the consignment and reach the destination at (110,90) xy coordinates. The shortest distance between the two points are 113.1 m. Out of five variants the SPSO variant reach the destination at 118 m distance with high feasible path than other four variants. The E2 last case study where the consignment and warehouse is separated by a short distance range of

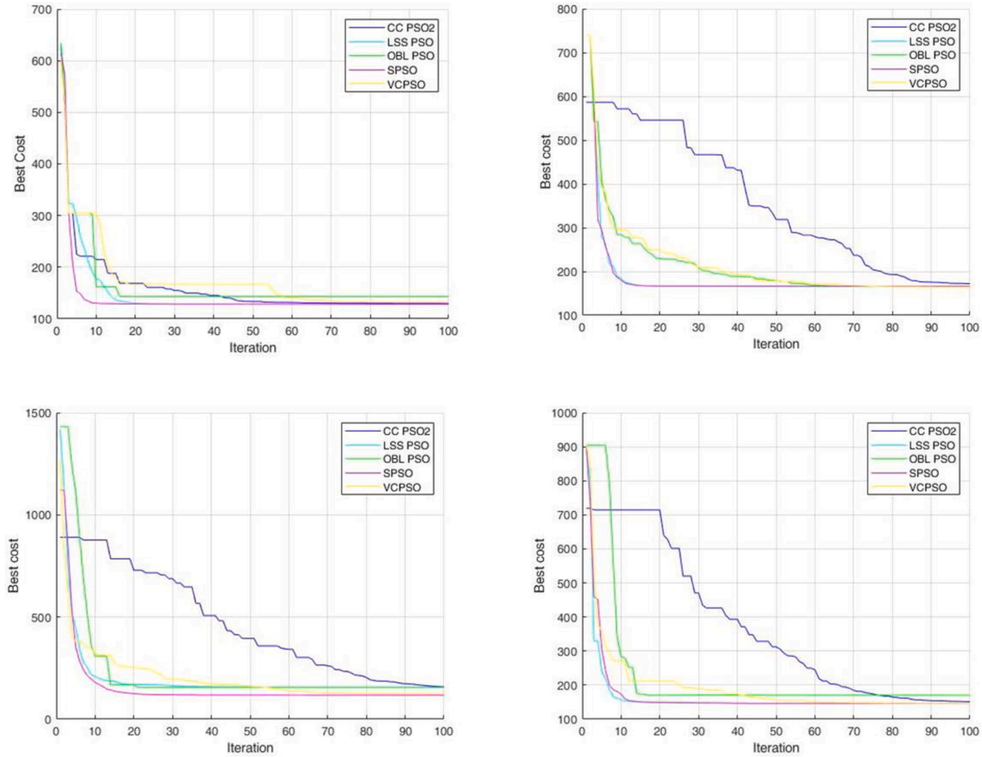

Fig. 8. Convergence plots for Environment 1.

about 145.6 m. The SPSO outperformed and provide a feasible path while compare to the LSS PSO.

Fig. 7(Environment-2 moderate crowded scenario): Consider the Logistic ware house is located in the starting point of coordinate in the given environment (E3) and the goods are loaded and the ending point provide the coordinate point for destination where the goods need to unload. The actual shortest distance is 171 m. Out of five variants, the SPSO plans the optimal path to reach the destination at 172.1 m distance. As in this scenario when the consignment loaded from the warehouse-2 and the ending point where the ordered customer location as coordinates. The shortest path irrespective of obstacles is 140.1 m. For the given scenario, the five PSO variants are used to find the feasible

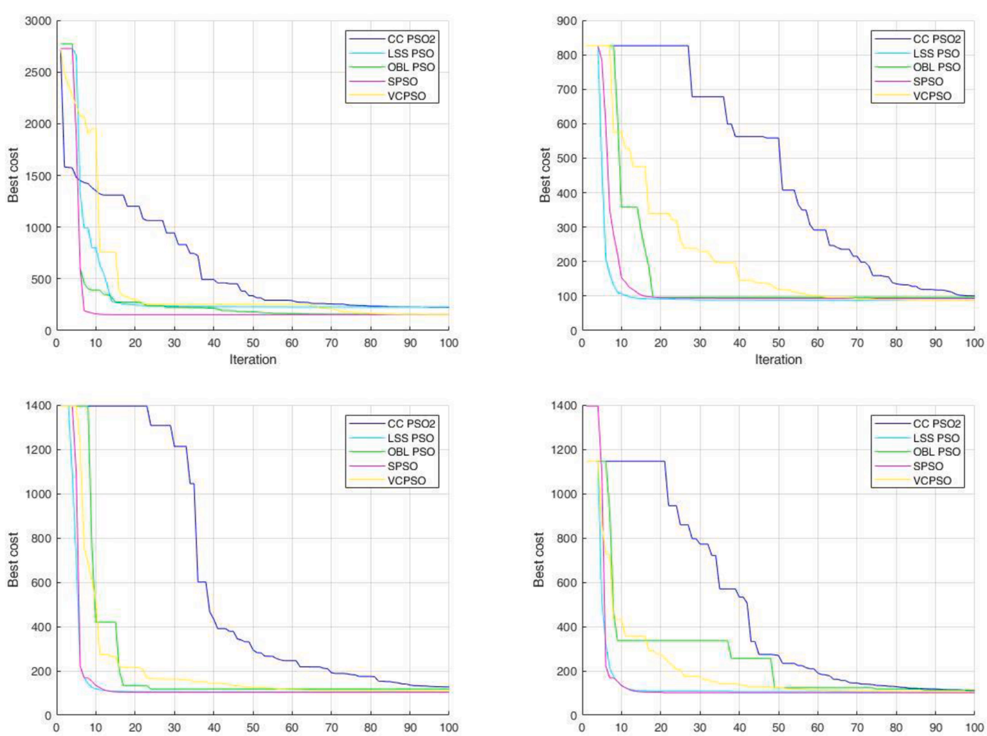

Fig. 9. Convergence plots for Environment 2.

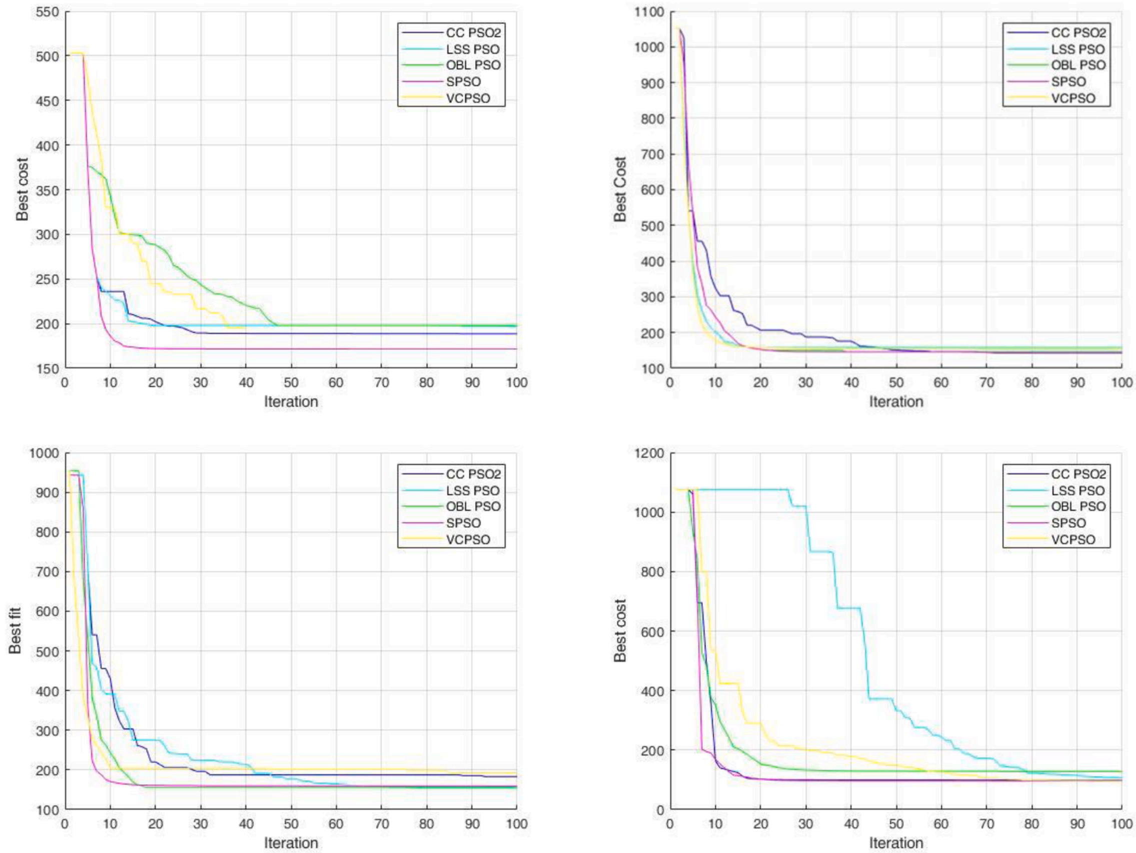

Fig. 10. Convergence plots for Environment 3.

shortest navigation path to reach the customer. The SPSO variant delivers a feasible path with distance of 141.78 m. In the given scenario with moderate obstacles, the starting point of AGV from warehouse-3 move forward to reach the unloading point. The least distance to reach the destination is 154.3 m. Even though the distance covered by the OLB PSO variant is minimal which is not a feasible solution. The OLB PSO variant navigate the destination by colliding with obstacles. Inspite of reaching the destination on time with least distance, it is necessary to ensure the safety of vehicle. In this regard, the SPSO reach the destination much safer than the OBL PSO. The end user and the logistic station are separated by the least distance of about 94 m. To navigate the shortest path from the tested five variants, the SPSO out performed all other PSO variant to reach the destination at 96.3 m.

To further verify the performance of PSO, a benchmark instance is taken from Yang et al., (Yang et al., 2015). The Finite angle algorithm (FAA* algorithm) proposed by Yang et al., (Yang et al., 2015) is for the images captured with thermal vision system while calculating path and also made specifically for the naval navigation purposes. The proposed algorithm is meant for the ground navigation and however the image filter applied in order to find the possibility of finding the path in waterways. And the inverse binary conversion made the possibility of providing the path plan. The compared method is made specifically for the naval way transport and however there is no detail for the navigation purposes in roadway transport. But SPSO can be used for both land and water way of transport by using suitable grid formation in order to generate the map. The time seems to be higher in case of SPSO it's because SPSO uses direct satellite image and convert them into binary. Whereas, FAA* uses thermal vision as in water way the shadows wouldn't be problem. However, we can't implement thermal vision conversion in roadways because the shadows might not consider for the path and it get varied depending on the noon time. Fig. 11 shows the best performance against the bench mark instance. Start and End point coordinates are 22°59′17.3″N 120°09′15.4″E and 22°58′56.6″N 120°08′49.6″E respectively. The optimum distance arrived in FAA* algorithm is 1677.90 but the optimum distance for the PSO route is 1524.61 which indicates that the PSO algorithm is capable finding best obstacle free route in a short time.

Conclusion

This paper presents the path optimization of AGVs in an unknown environment using satellite images. In order to find the obstacle free optimal path PSO and its five variants were tested. The satellite image was converted into occupancy grid using low level and medium level image processing approach. The mapping for an unknown environment can be done using satellite map data which might be previously recorded but the data about static objects become reliable here. Moreover, an unknown environment with limited data information gives an improved path planning for a mobile robot. The shortest distance covered in minimum time can be achieved in OBL-PSO and SPSO as compared with other variance for the given satellite image optimization problem. Three outdoor conditions with four different route scenarios were used to illustrate the success of PSO variants. SPSO achieves best among PSO variants. Furthermore, the findings indicate a strong connection between the number of obstacles faced and travel time. The lengths of the road factors and challenges often contribute to the difficulty of finding a secure navigating route. Furthermore, these tests should be replicated to determine the applicability of the suggested technique to a variety of scenarios.

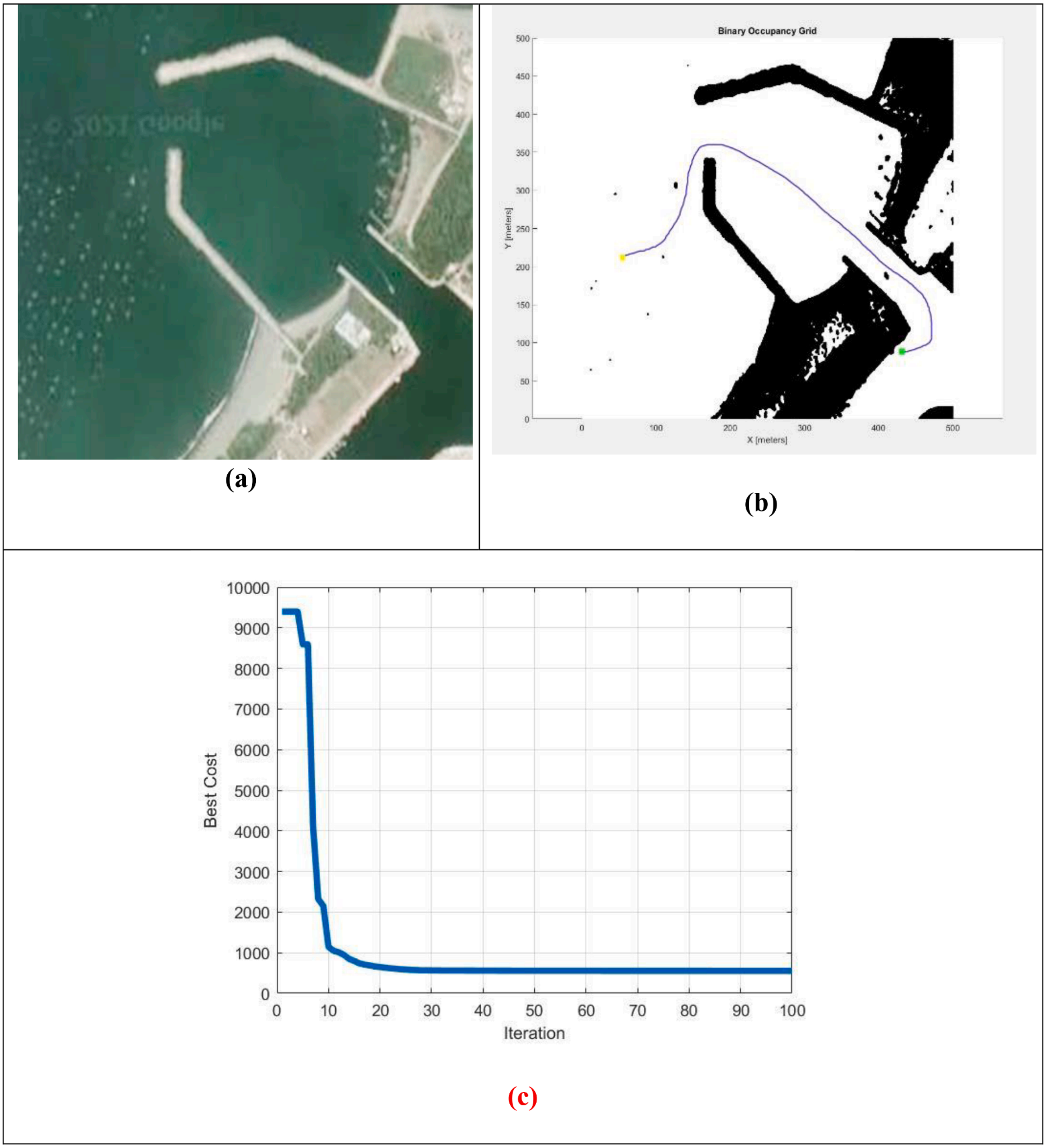

Fig. 11. Optimal route for benchmark instance (Yang et al., 2015).

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Acknowledgments

The authors would like to acknowledge the support of Thiagarajar College of Engineering in the production of this work.

References

Serrano, S.A., Santiago, E., Martinez-Carranza, J. et al. Knowledge-Based Hierarchical POMDPs for Task Planning. J Intell Robot Syst. 101(82). 2021. 1007/s10846-021-01348-8.

Azpúrua, H., Rezende, A., Potje, G. et al. Towards Semi-autonomous Robotic Inspection and Mapping in Confined Spaces with the EspeleoRobô. J Intell Robot Syst. 101. 69. 2021. 1007/s10846-021-01321-5.

Hadi, B., Khosravi, A. & Sarhadi. P. A Review of the Path Planning and Formation Control for Multiple Autonomous Underwater Vehicles. J Intell Robot Syst. 101(67). 2021. 1007/s10846-021-01330-4.

Ji, X., Feng, S., Han, Q., Yin, H., Yu, S., 2021. Improvement and Fusion of A* Algorithm and Dynamic Window Approach Considering Complex Environmental Information. Arabian Journal for Science and Engineering 46 (8), 7445–7459. https://doi.org/10.1007/s13369-021-05445-6.

Li, X., Zhu, S., Aksun-Guvenc, B., & Guvenc, L. (2021). Development and Evaluation of Path and Speed Profile Planning and Tracking Control for an Autonomous Shuttle Using a Realistic, Virtual Simulation Environment. Journal of Intelligent & Robotic Systems, 101(2), 1-23..1007/s10846-021-01316-2.

Sun, Y., Zhang, C., Sun, P., & Liu, C. (2019). Safe and Smooth Motion Planning for Mecanum-Wheeled Robot Using Improved RRT and Cubic Spline. Arabian Journal for Science and Engineering, 1-16..1007/s13369-019-04283-x.

Mahmud, M.S.A., Abidin, M.S.Z., Buyamin, S., Emmanuel, A.A., Hasan, H.S., 2021. Multi-objective route planning for underwater cleaning robot in water reservoir tank. Journal of Intelligent & Robotic Systems 101 (1), 1–16. https://doi.org/10.1007/s10846-020-01291-0.

Rajput, U., Kumari, M. 2017. Mobile robot path planning with modified ant colony optimisation. International Journal of Bio-Inspired Computation. 9(2), 106-113. 1504/IJBIC.2017.083133.

Pandey, A., & Parhi, D. R. 2017. Optimum path planning of mobile robot in unknown static and dynamic environments using Fuzzy-Wind Driven Optimization algorithm. Defence Technology. 13(1). 47-58. 1016/j.dt.2017.01.001.

Fusic, S.J., Ramkumar, P., Hariharan, K., 2018. In: Path planning of robot using modified dijkstra Algorithm. IEEE, pp. 1–5. https://doi.org/10.1109/NPEC.2018.8476787.

Hwang, Y.K., Ahuja, N., 1992. A potential field approach to path planning. IEEE Transactions on Robotics and Automation 8 (1), 23–32.

Kloetzer, M., Mahulea, C., & Gonzalez, R. (2015, October). Optimizing cell decomposition path planning for mobile robots using different metrics. In 2015 19th International Conference on System Theory, Control and Computing (ICSTCC). 565-570. IEEE. DOI: 10.1109/ICSTCC.2015.7321353.

Anbarasu, B., Anitha, G., 2018. Indoor scene recognition for micro aerial vehicles navigation using enhanced-GIST descriptors. Defence Science Journal 68 (2), 129. https://doi.org/10.1017/S0373463319000420.

Wang, W., Zhang, P., Liang, C., & Shi, Y. (2018). Design, path planning improvement and test of a portable massage robot on human back. International Journal of Advanced Robotic Systems, 15(4), 1729881418786631.

Li, M., Fu, J., Zhang, Y., Zhang, Z., Wang, S., Kong, H., & Mao, R. (2017). An improved searching algorithm for indoor trajectory reconstruction. International Journal of Distributed Sensor Networks, 13(11), .1177/1729881418786631.

Purcaru, C., Precup, R.E., Iercan, D., Fedorovici, L.O., David, R.C., Dragan, F., 2013. Optimal robot path planning using gravitational search algorithm. International Journal of Artificial Intelligence 10 (S13), 1–20.

Goswami, M., Mahato, S., Ghatak, R., Bose, A., 2020. Potential of Multi-constellation Global Navigation Satellite System in Indian Missile Test Range Applications. Defence Science Journal 70 (6). https://doi.org/10.1017/S0373463319000420.

BAYGIN, N., BAYGIN, M., & Karakose, M. (2018, September). PSO based path planning approach for multi service robots in dynamic environments. In 2018 International Conference on Artificial Intelligence and Data Processing (IDAP) (pp. 1-5). IEEE.. DOI: 10.1109/IDAP.2018.8620801.

Xin, J., Li, S., Sheng, J., Zhang, Y., Cui, Y., 2019. Application of improved particle swarm optimization for navigation of unmanned surface vehicles. Sensors 19 (14), 3096. https://doi.org/10.3390/s19143096.

Bevilacqua, M., Tsourdos, A., & Starr, A. (2017, May). Particle swarm for path planning in a racing circuit simulation. In 2017 IEEE International Instrumentation and Measurement Technology Conference (I2MTC) (pp. 1-6). IEEE. DOI: 10.1109/I2MTC.2017.7969735.

Sekaran, J.F., Kaluvan, H., Irudhayaraj, L., 2020. Modeling and Analysis of GPS–GLONASS Navigation for Car like Mobile Robot. J. Electr. Eng. Technol. 15 (2), 927–935. https://doi.org/10.1007/s42835-020-00365-1.

Ding, J., Liu, J., Chowdhury, K. R., Zhang, W., Hu, Q., & Lei, J. (2014). A particle swarm optimization using local stochastic search and enhancing diversity for continuous optimization.Neurocomputing,137,261–67. https://doi:10.1016/j.neucom.2013.03.075.

Zhou, J., Fang, W., Wu, X., Sun, J., & Cheng, S. (2016). An opposition-based learning competitive particle swarm optimizer. 2016 IEEE Congress on Evolutionary Computation (CEC). doi:10.1109/cec.2016.7743837.

Zhang, Q., Liu, W., Meng, X., Yang, B., & Vasilakos, A. V. (2017). Vector coevolving particle swarm optimization algorithm. Information sciences, 394, 273-298. .1016/j.ins.2017.01.038.

Yang, J.-M., Tseng, C.-M., Tseng, P.S., 2015. Path planning on satellite images for unmanned surface vehicles. International Journal of Naval Architecture and Ocean Engineering 7 (1), 87–99.