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An Intelligent Gain-based Ant Colony Optimisation Method for Path Planning of Unmanned Ground Vehicles

Sangeetha V.[#,*], K.S. Ravichandran[#], Sellammal Shekhar[!], and Anand M. Tapas[@]

[#]*School of Computing, SASTRA Deemed University, Thirumalaisamudram, Thanjavur - 613 401, India*
[!]*DRDO-Extramural Research and Intellectual Property Rights, DRDO HQrs, New Delhi - 110 004, India*
[@]*DRDO-Defence Research and Development Laboratory, Hyderabad - 500 058, India*
[*]*E-mail: sangeetha@sastra.ac.in*

ABSTRACT

In many of the military applications, path planning is one of the crucial decision-making strategies in an unmanned autonomous system. Many intelligent approaches to pathfinding and generation have been derived in the past decade. Energy reduction (cost and time) during pathfinding is a herculean task. Optimal path planning not only means the shortest path but also finding one in the minimised cost and time. In this paper, an intelligent gain based ant colony optimisation and gain based green-ant (GG-Ant) have been proposed with an efficient path and least computation time than the recent state-of-the-art intelligent techniques. Simulation has been done under different conditions and results outperform the existing ant colony optimisation (ACO) and green-ant techniques with respect to the computation time and path length.

Keywords: Ant colony optimisation; Green-ant; Pheromone gain; Collision-free path

1. INTRODUCTION

In recent days, intelligent systems have attracted many researchers and developers from many branches of engineering and sciences, especially in the field of path planning to bring up innovations in Autonomous motion planning approaches. Their applications vary from data collection, delivery, surveillance to crucial military purposes. Such Autonomous or Unmanned vehicles can be broadly classified into four categories as unmanned underwater vehicles (UUVs), unmanned aerial vehicles (UAVs), unmanned surface vehicles (USVs) and unmanned ground vehicles (UGVs). Each one has its own application ranging from ocean exploration, remote sensing, and imagery collection to military surveillance. The proposed research work is mainly focused on the intelligent path finding for UGVs. UGV navigation is generally described as a sequence of collision-free movements from starting to the destination position in the provided configuration space. From the study[1], UGV navigation has three steps:

(i) World perception – the area for path planning is perceived and studied for obstacles, start and destination points.
(ii) Pathfinding and generation – intelligent algorithms are applied on the studied configuration space and path is found.
(iii) Motion planning- UGV is navigated through the found path to reach the destination

The problem of path planning is NP-complete. Researchers have been implementing many methods to find the optimal path in various environments. Hanlin[2], *et al.,* proposed a path planning algorithm combining Voronoi diagram, visibility algorithm and Dijkstra's search algorithm to find optimal path for USV and the path was computed in *O(nlogn).* Finite Angle A* algorithm was proposed by Yang[3], *et al.,* for path planning on satellite images using a modified Line of Sight with a branching factor of 16 for increasing the efficiency of the FAA* algorithm. Duchon[4], *et al.,* proposed Modified A* algorithm with modifications like theta*, phi*, rectangular symmetry reduction, jump point search and implemented on both symmetrical and asymmetrical environments. A survey of Motion planning algorithms was made by Goerzen[5], *et al.,* from the perspective of UGV guidance. The problem of path planning was discussed in aspects like complexity, mapping with existing standard algorithms.

Over the last decade, nature-inspired algorithms have motivated researchers to work in all fields of optimisation. Such algorithms can efficiently provide near optimal solution with better efficiency and least computational complexity even in large environments. Angus[6], solved the problem of path planning using ant colony optimisation and tested on mound, volcano, valley terrains using both vector and multiplication combination methods. Behzadi[7], *et al.,* developed a genetic algorithm for solving the shortest path problem using the graph connectivity and implemented on road maps of Tehran, the capital city of Iran. An extensive survey on the available heuristic methods for path planning discussing the pros and cons was provided by Mac[8], *et al.,* A hybrid algorithm through the combination of genetic algorithm and the adaptive fuzzy logic controller was implemented by Bakdi[9], *et al.,* for pathfinding on a two-wheeled indoor mobile robot. The piecewise cubic hermite interpolating polynomial is then applied on it to get a

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smoothened path. Huang[10], *et al.,* experimented with a time-delayed neural network (TDNN) to find a global optimal path on the online public cordeau instances and New York Instances. The principle behind this experiment was that earliest auto-wave that hits the destination decides the shortest path. Comparisons with Dijkstra's and pulse coupled neural network proved the efficiency of TDNN based path planning. Ant colony-based decisional navigation system was developed and implemented by Lazarowska[11] on USVs. A safe ship control including both the static and dynamic consideration was proposed through ACO.

2. ACO ALGORITHM

Ant colony optimisation, proposed by Dorigo[12], *et al.,* based on swarm intelligence is a random stochastic population-based heuristic algorithm that simulates the real-time behaviour of ants. The foraging behaviour of ants in finding the shortest path between the nest and food source has always been a spark of interest for many types of research. Many experiments have been conducted on the foraging behaviour of real ants[12-13]. Ants deposit a chemical liquid called pheromone on their way of traversal. This helps the following ants to communicate with each other. The usability of the path is either increased by pheromone reinforcement or decreased through pheromone evaporation. The intensity of the pheromone reduces when there is no further traversal on the path. The successor ants choose the path with a higher concentration of pheromone quantity. Artificial ants are the counterparts of real ants in a simulating discretised environment. Unlike the real ants, artificial ants have an internal state and memory.

3. GAIN BASED MODEL FOR UGV ENERGY REDUCTION

During path selection, ants choose the path with more pheromone as the next path. Using this principle, Gain based function is introduced in this paper. When UGV encounter an obstacle, many paths will be constructed initially around the obstacle thus requiring time to settle down all the ants on an optimal path. The advantage of the proposed algorithm is to help in choosing the next path efficiently and reduce the time taken to settle-down all the ants on an optimal path.

3.1 Gain-based Ant Colony Optimisation

In the proposed gain based algorithm, energy reduction is obtained by eliminating the need to traverse all paths around an obstacle. The pseudocode representation for modified ACO called gain based ant colony optimisation (GACO) is given below:

```
1  begin
2  Initialise $\tau_o, \alpha, \beta, \rho$ ,start,destination
3  while( not termination)
3.1  Initialise population of N ants ;
3.2  Compute $\tau_{ij}^{new} = \left(1-\rho\right)\tau_{ij}^{old} + \sum_{k=1}^{N} \Delta\tau_{ij}^{k} \pm Gain_{ij}^{k}$
3.3 Compute Node Transition Probability (NTP) for each $k \in N$ and update visit$_k$ ;
3.4  Compute $d_{ij}$ , for each k∊N
3.5  Update the best path among N;
3.6  If( solution converged)  break;
3.7  Update pheromone trail;
3.8 do;
4  end
```

Parameters used in above routine are given in Table 1.

Consider a configuration space of 20 x 20 as shown in Fig. 1.

Table 1. Parameters of ant colony algorithm

Parameter	Description
N	Total number of ants
τ_o	Initial pheromone amount
τ_{ij}	Amount of pheromone deposited while traversing from *i* to *j*
η_{ij}	Heuristic function indicating the visibility of route between *i* and *j*; $\eta_{ij} = \frac{1}{d_{ij}}$
d_{ij}	Cost of route (*i*,*j*) obtained by k^{th} ant
α	Influence of pheromone on the choice of next vertex
β	Influence of heuristic function on the choice of next vertex
ρ	Rate of pheromone evaporation; $0<\rho<1$
$visit_k$	A table containing nodes that are allowed to be visited by k^{th} ant
Q	Constant quality function related to the pheromone quantity
E_{ij}^{k}	Energy consumed by k^{th} ant over *ij*

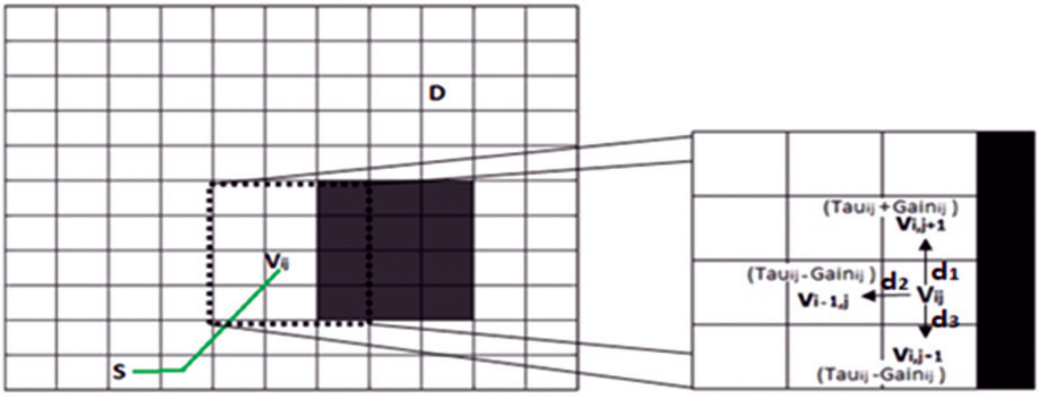


Figure 1. Pictorial representation of Pheromone gain process.

Calculating $Gain_{ij}^{k}$

A new amount of pheromone is added to the best path found so far to enable quicker pathfinding by reducing the energy calculation in all paths around the obstacle. Pheromone gain is given by Eqn. (2).

$$progress = \frac{v_{dest} - v_{current}}{Total\ Distance} \tag{1}$$

$$Gain = \frac{1}{\left(1 + e^{-\lambda * progress}\right)} \tag{2}$$

where V_{dest} is destination; $V_{current}$ is current node; λ is the learning parameter ranging from 0 to 1; $Total\ Distance = |S - D|$.

For all values of and progress, the value of the gain always lies between 0 and 1. The sigmoidal function will help in the smooth transition of UGV with less number of turns. $Gain_{ij}^{k}$ can be either positive or negative. If $Gain_{ij}^{k}$ is positive ,ant moves in the shortest path and if negative moves in other paths. The algorithm starts from *S*. Upon reaching V_{ij} (current position), the next node to be visited is searched. The node with minimum distance ($V_{i,j+1}$) is selected as next node to be visited and its pheromone trail is updated. While updating, $Gain_{ij}$ is added to τ_{ij}^{new} of $V_{i,j+1}$ and subtracted from the τ_{ij}^{new} of $V_{i,j-1}$ and $V_{i-1,j}$. In case if all neighbour nodes of current node have same distance, then gain is added to all nodes. Mathematically the procedure can be written as,

$$\delta_{ij} = min\left(d_1,\ d_2,\ d_3\right);$$

where $d_i = |currentposition - destination|$ for i = 1, 2, 3.

If path provides minimum δ_{ij} then $Gain_{ij}$ will be added along with the current pheromone quantity, otherwise subtracted as given in Eqn. (3)

$$\tau_{ij}^{new} = \begin{cases} \tau_{ij}^{new} = (1-\rho)\tau_{ij}^{old} + \sum\limits_{K=1}^{N} \Delta\tau_{ij}^{k} + Gain_{ij}^{k}\ ,\ if\ \delta_{ij}\ is\ shorter \\ \tau_{ij}^{new} = (1-\rho)\tau_{ij}^{old} + \sum\limits_{K=1}^{N} \Delta\tau_{ij}^{k} - Gain_{ij}^{k}\ ,\ if\ \delta_{ij}\ is\ longer \end{cases} \tag{3}$$

Using δ_{ij} and τ_{ij}^{new}, $NTP_{ij}^{k}(t)$ is calculated and ACO continues till stopping criteria.

3.2 Gain-based G-Ant

Whenever ant meets an obstacle, the Linear Regression based methodology proposed by[14-16,18], calculates energy consumption in all temporary paths thus increasing the computational cost. This can be avoided by adding the gain factor to the shortest δ_{ij} path. The pseudo-code for modified green-ant (G-Ant) algorithm called gain based green-ant (GG-Ant) algorithm for energy calculation proposed by[14-16] is given below:

```
System Input: w, m, v(t), a(t), $\theta(t)$, $\varepsilon(t)$,b,c, $V_{current}$,D
System Output :Energy E
1 Initialise Power=0;
2 Initialise parameters v(t) = velocity at t; m = mass of vehicle; a(t)=acceleration at t; w=weight of vehicle;
  $\theta$ = road grade; f=rolling resistance coefficient; C=Internal resistance coefficient; b= energy consumed by on-board equipment, $\varepsilon(t)$ = model error, with real time values;
3 for t = initial time to max-time with step size
  3.1 Get real-time values $w(t),\ \theta(t),\ f(t),\ m(t),\ a, c$;
  3.2 Calculate $F = W(t)*\theta(t) + f(t)*W(t) + m(t)*a + c$
    3.2.1 for k=S to $V_{current}$ // current node is got from path planning routine
      3.2.1.1 Compute for $V_{current}$ and $V_{neighbours}$
      3.2.1.2 if( $\delta_{ij}$ is shorter) then
        3.2.1.2.1 Compute $P(k) = F*v*k + b + Gain_{ij}^{k}$
        3.2.1.2.2 Compute $E = P*\Delta t$
        3.2.1.2.3 end;
      3.2.1.3 end
  3.2.2 end
  3.3 end
4 return E
```

The framework for the proposed GG-ANT is given in Fig. 2

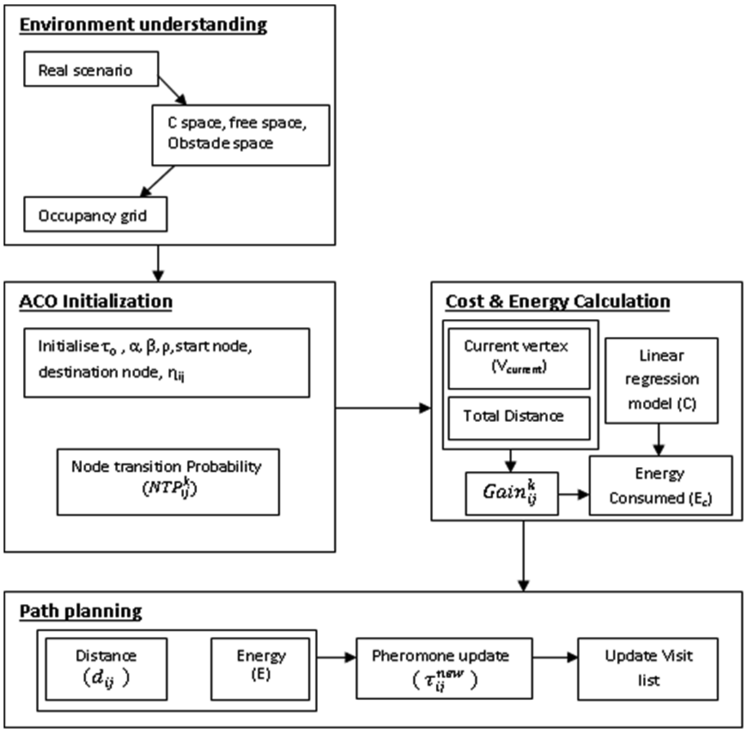

Environment understanding
Real scenario
C space, free space, Obstacle space
Occupancy grid
ACO Initialization
Initialise τ_0, α, β, ρ, start node, destination node, η_{ij}
Node transition Probability (NTP_{ij}^{k})
Cost & Energy Calculation
Current vertex ($V_{current}$)
Total Distance
Linear regression model (C)
$Gain_{ij}^{k}$
Energy Consumed (E_c)
Path planning
Distance (d_{ij})
Energy (E)
Pheromone update (τ_{ij}^{new})
Update Visit list

Figure 2. GG-ant system framework.

The pseudo-code for GG-Ant is given below

```
1 begin
2 Initialise $\tau_o$, $\alpha$, $\beta$, $\rho$,start, destination
3 while( not terminated)
3.1 Initialise N ;
3.2 Compute $\tau_{ij}^{new} = (1-\rho)\tau_{ij}^{old} + \sum_{k=1}^{N} \Delta\tau_{ij}^{k} \pm Gain_{ij}^{k}$
3.3 Compute
 where $\eta_{ij} = \frac{1}{d_{ij}} + \frac{v_{ij}}{\varphi}$          (4)
(denotes speed at that instant, $\varphi$ indicates the maximum speed)
3.4 Update $visit_k$
3.5 Compute $d_{ij} = \sqrt{\sum_k^N = 1\left(v_k^i - v_k^j\right)^2}$, for each k)IN
3.6 Update the best path among N;
3.7 If( solution converged) break;
3.8 Update pheromone trail using Eqn. (5)
```

$$\Delta\tau_{ij}^{k} = \begin{cases} \dfrac{1}{d_{ij}^{k}} + \dfrac{1}{E_{k}^{ij}} & if\ k^{th}\ ant\ passes\ i\ and\ j \\ 0 & otherwise \end{cases} \tag{5}$$

$$E_{k}^{ij} = F * v * k * b + Gain_{ij}^{k} * \Delta t \tag{6}$$

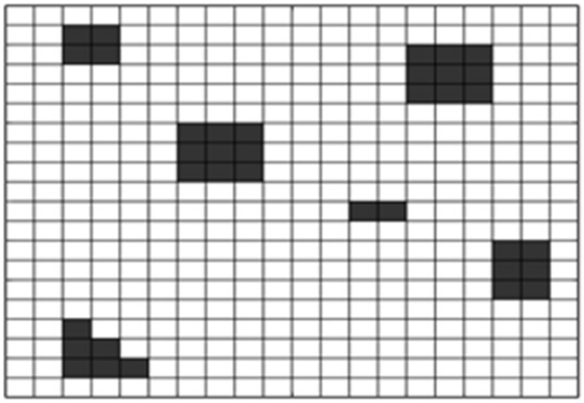
```
    3.9   do;
4   end
```

The algorithm continues until either shortest path is obtained or predetermined iterations have been completed.

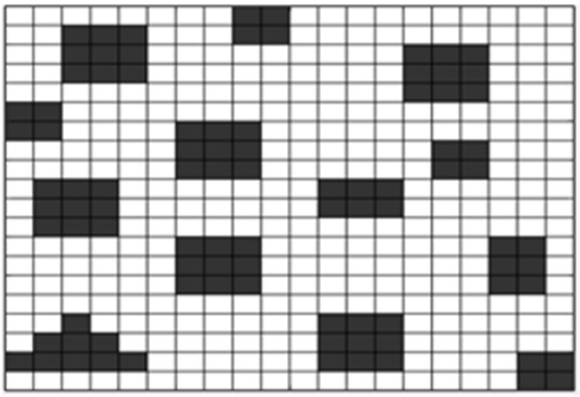
4. RESULTS AND DISCUSSION

The proposed GACO and GG-Ant were simulated in MATLAB R2016b under Windows 10under different conditions like a different number of iterations, a different number of obstacles, different sizes of population. The energy consumed while traveling was calculated using Eqn. (6). The values used in the simulation adopted from[14] and[17] are summarised in Table 2. The performance of GACO and GG-Ant have been compared with existing ACO and G-Ant and as given in Figs. 4(a) and 4(b). The simulations were done in 20 x 20 and 50 x 50 gridised environment with obstacles at various places. Based on the number of obstacles, the environment is categorised into simple and complex as given in Fig. 3(a) and 3(b).

Initially, a simulation has been done to verifying the effectiveness of GACO in a 20 x 20 environment. The results are as shown in Table 3. Population size and number of iterations are varied from 25 to 100 by step size 25. (25, 50, 75, 100). Start and destination are taken as 10 and 242 respectively.



(a)



(b)

Figure 3. (a) Simple type of 20 x 20 environment and (b) Complex type of 20 x 20 environment.

Table 2. Parameters and their values used for simulation in GG-ant[14,17]

Parameter	Value
α	0.4
β	0.6
ρ	0.3
φ	2 m/s
Time interval	3 Δt
Sampling interval	10 s
B	0 watts
M	30 kg

From Table 3, it could be inferred that as the number of iterations and population size increases, the length decreases, but the computation time increases. By considering proper tradeoffs between them optimal solution could be achieved.

Table 3. Simulation results for GACO under varying conditions

No of iterations	Population size	Length (No. of grids)	Time taken (s)
25	25	21.3137	4.9441
25	50	21.3137	8.2125
25	75	22.1421	12.2768
25	100	20.1421	15.7489
50	25	20.1421	8.8342
50	50	18.9706	14.8194
50	75	17.8995	23.6750
50	100	18.1421	28.3127
75	25	17.8995	11.6652
75	50	18.1421	21.6598
75	75	18.7279	31.6403
75	100	18.4853	42.0651
100	25	19.3137	15.0801
100	50	19.3137	30.2261
100	75	18.9706	43.6372
100	100	15.8995	44.5239

The proposed algorithms have been compared with existing Green Ant[18], ACO and results are tabulated in Tables 4-6. Since the algorithms discussed are meta-heuristic, each round of execution leads to different path convergence. Hence, the experiment is executed for 10 time and the average is tabulated. It can be observed from Figs. 4(a) and 4(b) that the path obtained from GACO and GG-Ant has less number of turns and least length than other paths. Lesser the number of turns, least is the energy consumed.

From Table 4, it is inferred that GACO takes less time than ACO in Simple and smaller environment by avoiding the unwanted paths around an obstacle.It can be inferred from the Table 5, that GACO performs better than ACO in case 2 and 3. If the obstacles are present sequentially, GACO performs little low than ACO (case 1).This drawback can be overcome when

Table 4. Performance Evaluation of GACO and ACO

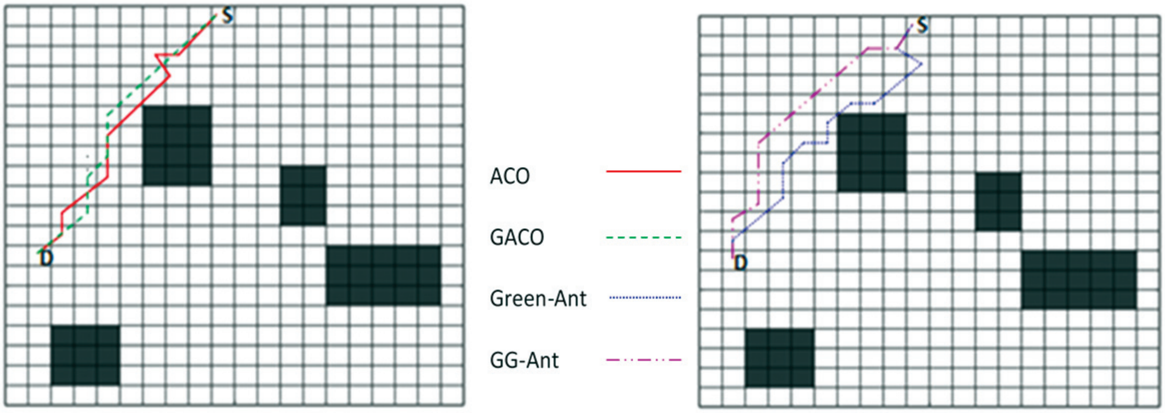
Complexity	**20 x 20**				**50 x 50**			
Configuration type	**Simple**		**Complex**		**Simple**		**Complex**	
Algorithm	**ACO**	**GACO**	**ACO**	**GACO**	**ACO**	**GACO**	**ACO**	**GACO**
Computation time (s)	4.653	4.260	5.205	4.918	53.301	42.161	56.372	57.490
Length (No. of grids)	26.292	26.229	28.527	26.932	30.325	30.316	33.002	33.764

Table 5. Performance Evaluation of GACO and ACO under difference cases of 50 x 50 Complex scenario

	Case 1		**Case 2**		**Case 3**	
Algorithm	**ACO**	**GACO**	**ACO**	**GACO**	**ACO**	**GACO**
Computation time (s)	56.372	57.490	56.253	56.166	64.8126	58.696
Length (No. of grids)	33.002	33.764	31.714	30.510	35.0315	34.246

Table 6. Performance Evaluation of Green-Ant and GG-Ant

Complexity	**20 x 20**				**50 x 50**			
Configuration type	**Simple**		**Complex**		**Simple**		**Complex**	
Algorithm	**G-Ant**	**GG-Ant**	**G-Ant**	**GGAnt**	**G-Ant**	**GG-Ant**	**G-Ant**	**GG-Ant**
Computation time (s)	53.802	37.445	53.895	43.271	1823.298	1742.502	1890.376	1828.875
Length (No. of grids)	27.063	26.974	27.146	27.105	33.271	31.5504	33.351	32.337



(a)

(b)

Figure 4. (a) Comparison of ACO, GACO, Green-Ant and (b) Comparison of Green-Ant, GG-Ant.

using Ensembled GACO. Greater the number of obstacles in the environment, the more the deviations ant has to make to provide a clear path.

From Table 6, it can be observed that time taken and path length is reduced in GG-Ant. The energy is calculated only for the best paths found so far i.e., local optimum paths, while avoiding the other paths around obstacles. Hence optimisation is done at the lower level itself and the overall time and Energy Consumption is greatly reduced. The GG-Ant uses Sigmoidal function which provides a smoothed curve with less number of turns for the path. It can also be noted that the computation time increases as the complexity of the environment increases. GG-Ant provides best solutions in all cases, because it considers all vehicle parameters to its pathfinding. The proposed algorithm converges always unless there is a complete blocking i.e., No path between the source and destination. They will give local optimum at the worst case and the near global optimal solution at the best case. In case of smaller size environment, they will always provide global optimal solutions.

5. CONCLUSIONS

In this paper, new energy-based path planning approaches; GACO and GG-Ant have been proposed. Energy is computed using the progress of UGVs and incorporated in the path planning procedure of ACO. The algorithms are implemented in MATLAB and performances are evaluated against Green-Ant and ACO under conditions like different population size, number of iterations and different number of obstacle. Simulations are done in Simple and Complex configuration spaces. From the results, it is found that GACO and GG-Ant outperform the other approaches with less computation time and length. The paper can be extended further for energy reduction based path planning on a 3D environment. Also, path recommendation system can be developed.

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CONTRIBUTORS

Ms Sangeetha V. has received her BE (Computer Science Engineering) from Government College of Engineering, Salem and ME (Software Engineering) from Anna University Regional Centre, Coimbatore. She is currently doing her PhD in SASTRA Deemed University. Her areas of interest include Optimisation, nature inspired algorithms, machine learning.

In the current work, she has contributed to the design and implementation of the algorithm and testing.

Dr K.S. Ravichandran received his Master degree from Bharathidasan University and PhD from Alagappa University. He is currently the Associate Dean in School of Computing, SASTRA Deemed University.

His contributions are towards applications of soft computing in the field of image processing, multi-decision criteria making and engineering problems.

Mrs Sellammal Shekhar, obtained her BTech (Electronics & Communication Engineering) from University of Jodhpur, MTech from IIT Delhi and MS in Cyber Law & Cyber Security from National Law University, Jodhpur. Currently working as Scientist 'G' and Associate Director in the Directorate of Extramural Research & Intellectual Property Rights, DRDO Headquarters, New Delhi. Her research interests include: Information Security, cryptology, communication and signal analysis.

In the current study, she has contributed in enhancing the application aspect of the proposed algorithm.

Mr Anand M. Tapas received his BE (Electrical Engineering) from VRCE, Nagpur, in 1982 and a MTech (Control & instrumentation) from IIT Bombay, India, in 1985. Currently he is working as a Scientist in DRDO-Defence Research & Development Laboratory, Hyderabad. His research interest includes : Missile guidance, control, estimation and instrumentation.

He has contributed in analysing the literature and fine tune the research aspect of the manuscript