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An improved ant colony optimization algorithm for unmanned surface vehicle local path planning with multi-modality constraints

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ABSTRACT

The increase application of machine learning and artificial intelligence in the field of robotics, have emerged the need for real time algorithms for autonomous unmanned aircraft and surface vehicles. In recent years, various studies have been conducted for path planning of unmanned surface vehicle (USV), especially to maritime transportation. Most of the traditional approaches include optimization algorithms for finding the shortest or fastest path. However, USV motion in complex environments demand multi-objective optimization and multi-modality constraints to cope with dynamic environments and moving obstacles. To this end, an improved Ant Colony Optimization with Fuzzy Logic (ACO-FL) is proposed to deal with local path planning for obstacle avoidance by taking into account wind, current, wave and dynamic obstacles. The proposed algorithm was compared to original ACO and popular Bug algorithm in simulation tests. The results showed that ACO-FL reached better performance compared to the other algorithms under examination in terms of optimal solution and convergence speed. Thus, the proposed algorithm can be considered as an effective approach for path planning of USVs.

1. Introduction

The field of autonomous robotics has gained a lot of attention due to the development of artificial intelligent approaches that support real time applications. Scientists focus on the development of completely autonomous vehicles that could understand the surrounding environment and interfere with it without the need of human interaction. For instance, Unmanned Ground Vehicles (UGVs) can be found in industrial applications (González et al., 2018; Wu et al., 2021); agricultural applications (Gonzalez-De-Santos et al., 2020; Negrete et al., 2018); military applications (Czapla and Wrona, 2013); and disaster rescue (Kamel et al., 2020) among others. Unmanned Aircraft Vehicles (UAVs) have widely been used mostly for monitoring and mapping (Lindner et al., 2016; Ren et al., 2019) and security (Birk et al., 2011; Shakhatreh et al., 2019) applications for safety, communication and environmental monitoring, among other tasks.

Another type of unmanned vehicle that has attracted the attention of the scientific community, lately, is the Unmanned Surface Vehicle (USV). USVs have not been widely applied like UAVs and UGVs but they play important role to specific areas such as ocean sampling and monitoring (Vasilijević et al., 2017; Yang et al., 2018), rescue (Wilde and Murphy, 2018) and cooperation with UAVs and/or UGVs for monitoring (Yan et al., 2010; Zhou et al., 2020). A vital part of the unmanned vehicles is the autonomy and the ability to move within a complex dynamic environment depending the obstacle detection and the environmental conditions (Zhou et al., 2020). To this end, various methodologies have been developed for local path planning and obstacle avoidance. However, most of these approaches are implemented for known environments and static objects. In our study, an improved Ant Colony Optimization algorithm with fuzzy logic (ACO-FL) is proposed to address the problem of local path planning for dynamic obstacle avoidance in complex environments. ACO-FL will generate a local path to avoid a detected obstacle with respect to the wind, current and wave at that time. Based on the USVs automation and intelligent level classification (Zhou et al., 2020), the aforementioned problem belongs to Level five where partially it has been addressed by a limited number of studies. In (Ma et al., 2018), a multi-objective nonlinear optimization model was formulated for path planning of USV with currents effects. To address this problem the dynamic augmented multi-objective particle swarm optimization algorithm was proposed based on Pareto optimal path set. A* algorithm was used in (Singh et al., 2018) for optimal path planning of USV with dynamic obstacles and ocean currents.

Specifically, a path planning algorithm based on reinforcement learning was proposed for path optimization of marine vehicles in ocean

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currents (Yoo and Kim, 2016); and for collision avoidance and path planning in unknown environments (Wang et al., 2019). In this study the effects of ocean currents were taken into account in the movement of the USV for extracting an optimal path. In (Song et al., 2017) a time-variant maritime path planning problem of USV was addressed by developing a multi-layer fast marching path planning algorithm. The anisotropic fast marching algorithm was adopted as the baseline algorithm to search for an optimal trajectory, while an obstacle prediction process was proposed for changing the position of USV. The proposed method contributed to the minimization of the negative impact of the environmental factors, such as current.

Current approaches are limited to traditional optimization methodologies, focusing on minimizing over one objective or using Pareto optimality for multi-objective path planning problems. Moreover, path-search approached, such as Dijkstra and A* have been proven computationally consuming when it comes to complex environments and enlarged maps (Li et al., 2019; Zhang et al., 2018). To this end, in order to cope with the aforementioned limitations, an improved ACO is proposed enhanced with Fuzzy Logic for evaluating the effect of various criteria on the path optimality. To the best of our knowledge, such an approach has not been adopted and studied towards USV path planning in an environment composed from static and moving obstacles in addition to surface currents. USVs are mostly equipped with limited computational resources in addition to limited endurance. This study focuses on the effectiveness of the proposed approach in terms of computational time to generate optimal paths in simulation area under various environmental conditions.

The contribution of our study to the current literature consists of:

- Integrating Fuzzy Logic to generate an optimal route that will balance among the aforementioned optimization criteria, such as traveled distance, path smoothness and fuel consumption for USV obstacle avoidance multi-objective path planning.
- Incorporating constraints relevant to current effects in a dynamic environment with static and moving obstacles
- Competitive evaluation in simulation environment under various scenarios with Ant Colony Optimization algorithm and Bug 2.

2. Methodology

2.1. Problem formulation

In this study we focus on multi-objective path planning for obstacle avoidance in case of USV. To generate a local path to avoid a static or moving obstacle the minimization of the deviation from the initial route, the brut alteration in the direction of the initial route and the energy consumption due to current effects are taken into account.

Objective function 1: Shortest path deviation

$$minD = \sum_{i\in\mathscr{N}} \sum_{\substack{j\in N:\\(i,j)\in E}} d_{ij} = \sum_{i\in\mathscr{N}} \sum_{\substack{j\in N:\\(i,j)\in E}} \left(\sqrt{(j_x - i_x)^2 + (j_y - i_y)^2}\right)$$

Where $\mathscr{N}$ is the set of nodes that form the graph and $\mathscr{E}$ the set of edges of the graph; d_{ij} is the distance metric between node i and node j. In our formulation the Euclidean distance was adopted. i_x , j_x and i_y, j_y are the geographical coordinates of nodes i and j on horizontal and vertical axes, respectively. This term minimizes the traveled distance in order to avoid the obstacle.

Objective function 2: Smoothest maneuvering

$$min\theta = \sum_{i\in\mathscr{N}} \sum_{\substack{j\in N:\\(i,j)\in E}} \sum_{\substack{k\in N:\\(j,k)\in E}} \theta_{ijk}$$

Where θ_{ijk} is the angle that is formed from the edges (i,j) and (j,k). The term aims to minimize the brut change in the direction of the initial route when an obstacle must be avoided.

Objective function 3: Energy efficiency

$$minFC = \sum_{i\in\mathscr{N}} \sum_{\substack{j\in N:\\(i,j)\in E}} \frac{d_{ij}}{V + v_c} f$$

Where f is the fuel consumption per unit time (kg/h), V is the velocity of the USV and v_c the velocity of the currents. This term minimizes the energy consumption of the USV in case of route alteration for obstacle avoidance. To this end, the term forces the USV to move in accordance with the direction of the currents so less energy will be needed for the USV to perform the route. Based on the literature if a USV is moving against the currents more energy is needed to retain a certain velocity during a route (Chen et al., 2019; Ma et al., 2018; Song et al., 2017; Xia et al., 2019).

2.2. Ant Colony Optimization algorithm with Fuzzy Logic (ACO-FL)

To find an optimal solution under various objectives, as the one presented above in section 2.1, most of the studies focusing on multi-objective (MO) path planning (Ariyasingha and Fernando, 2015; Falcón-Cardona et al., 2020; Leguizamón and Coello Coello, 2011) adopt the conventional strategy of weighted sum method (WSM) or Pareto optimality. WSM combines the objectives into one single objective scalar function. This generates an efficient solution for the MO problem, however, this approach is highly dependent to the selection of the weights since wrong choice of value can lead to local optima traps. On the other hand, the Pareto optimality approach overcomes the above limitations by providing multiple solutions making its adoption most popular. In that cases, the number of improved objectives, the extent of these improvements and, also, the preference information of each objective are not considered during the calculation procedure. Furthermore, these limitations are crucial in real applications since only one 'compromise' Pareto solution is the preferable. Consequently, an additional multi-criteria decision making method is necessary for avoiding subjective or undesirable choice of a solution (Hasuike et al., 2013; Ntakolia and Iakovidis, 2021; Shen and Ge, 2019).

To solve the aforementioned multi-objective path planning problem for obstacle avoidance, ACO algorithm is employed enhanced with Fuzzy Logic (ACO-FL) in order to find a balanced route among the minimization criteria for obstacle avoidance. ACO is a popular algorithm used to solve graph-based problems. It is based on the ability of ants to trace their food sources by depositing pheromone along the path (Blum, 2005). In brief, ACO is based on two processes, the calculation of the transition probability, p_{ij}, of each edge in the graph (1) and the pheromone update process which recalculates the pheromone deposit, τ_{ij}, on each edge (2):

$$p_{ij} = \frac{\tau_{ij}}{\sum_{(k,l)\in\mathscr{E}} \tau_{kl}} \tag{1}$$

$$\tau_{ij} = (1-\rho)\tau_{ij} + \rho \sum_{a\in\mathscr{P}} \frac{Q}{L_a} \tag{2}$$

where $\rho \in [0,1]$ is the evaporation coefficient that decreases the pheromone deposit, $\mathscr{P}$ is the set of ants that compose the population, L_a is the cost of the path that the ant a chose to travel and Q is a constant associated with the amount of remaining pheromone (Blum, 2005; Dorigo et al., 2006; Dorigo and Blum, 2005; Mellal and Williams, 2018). The pseudoalgorithm of ACO algorithm is presented bellow in Algorithm 1.

Algorithm 1. ACO pseudoalgorithm

Algorithm 1: ACO pseudoalgorithm

Input: variables of ACO
$InitializePheromoneValues(\tau)$ // at the start of the algorithm the pheromone values (τ_{ij}) are all initialized to a constant value $c > 0$
$\mathfrak{s}^* \leftarrow NULL$ // current best solution does not exist
while termination criteria are not met **do**
  $\mathcal{G}_{iter} \leftarrow \emptyset$ // the set of the path at the current iteration is empty
  for $j = 1, \ldots, n_a$ **do**
    $\mathfrak{s} \leftarrow ConstructSolution(\tau)$ // A solution construction starts with an empty partial solution $\mathfrak{s}^p = \langle\,\rangle$. Then, at each construction step the current partial solution $\mathfrak{s}^p$ is extended by adding a feasible solution component based on the transition probabilities and the heuristic information (1).
    if $(f(\mathfrak{s}) < f(\mathfrak{s}^*))$ or $\mathfrak{s}^*$ $is\ NULL$ **then** $\mathfrak{s}^* \leftarrow \mathfrak{s}$
    $\mathcal{G}_{iter} \leftarrow \mathcal{G}_{iter} \cup \{\mathfrak{s}^*\}$
  end for
  $ApplyPheromoneUpdate(\tau, \mathcal{G}_{iter}, \mathfrak{s}^*)$ // based on (2)
end while
Output: current best solution $\mathfrak{s}^*$

In our study we integrate FL to the pheromone update process where the cost of the path is calculated based on the defuzzification value. Specifically, four membership functions are used, one for each objective function – input variables and one for the output variable which indicates the path optimality with respect to the objective terms (Fig. 1). Table 1 shows the fuzzy rules used in this study.

In ACO-FL the pheromone update follows the process illustrated in Fig. 3. Specifically, in each iteration, each ant of the ant colony is retrieving a path. The cost of the path is calculated based on Mamdani fuzzy inference system (Harliana and Rahim, 2017). The crisp values of the objective terms are fuzzified into a fuzzy domain illustrated in Fig. 2. Then these values are aggregated based on the Mamdani inference system and the fuzzy rules (Table 1), and through the defuzzification process, a crisp value, that corresponds to the cost of the generated path, is calculated. This value replaces the $1/L_a$ in (2) in order to update the pheromones and consecutively the transition probabilities.

3. Experimental evaluation

3.1. Evaluation methodology

To evaluate the proposed approach, an excessive experimental evaluation is conducted based on a simulation area of the port of Piraeus (Fig. 3). The initial image is taken from Google Earth and following the environmental mapping approach, the area under examination is converted into the configuration space based on the regular occupancy grid, which is a popular mapping technique (Mooney et al., 2010). The axes in the presented images show the pixel scale used in the experiments that represents the longitudinal and latitude, respectively. ACO-FL is

Table 1
Fuzzy rules.

Path deviation	Smooth maneuvering	Energy efficiency	Path optimality
Short	Smooth	High	High
Short	Smooth	Medium	High
Short	Moderate	High	High
Moderate	Smooth	High	High
Short	Moderate	Medium	Medium
Moderate	Smooth	Medium	Medium
Moderate	Moderate	High	Medium
Moderate	Moderate	Medium	Medium
Long	Moderate or Brut	Medium or Low	Low
Moderate or Long	Brut	Medium or Low	Low
Moderate or Long	Moderate or Brut	Low	Low

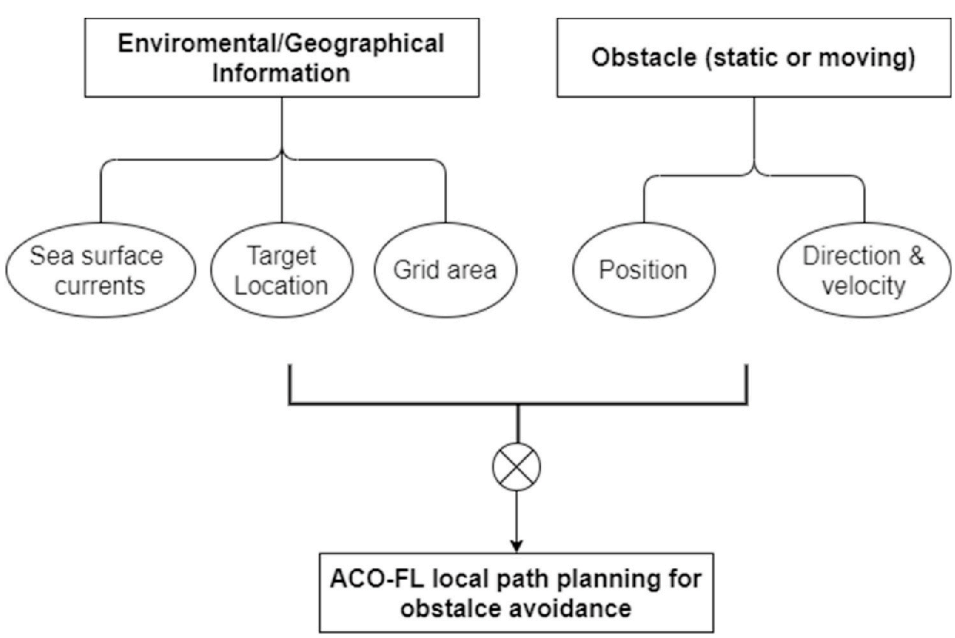

Fig. 1. Schematic of the proposed path planning approach.

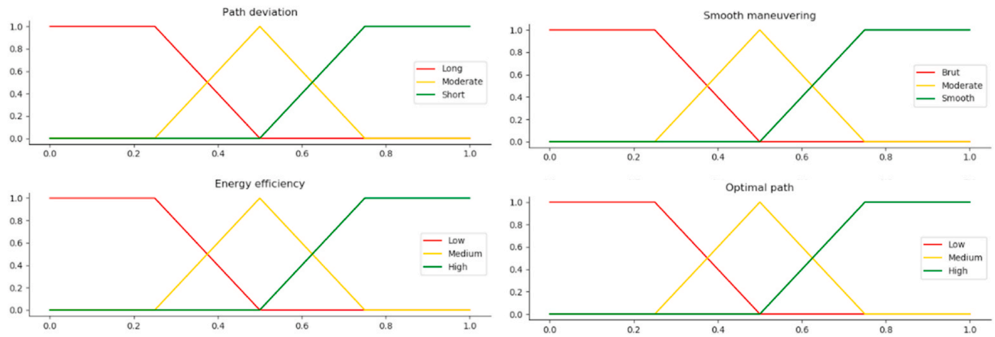

Fig. 2. Membership functions.

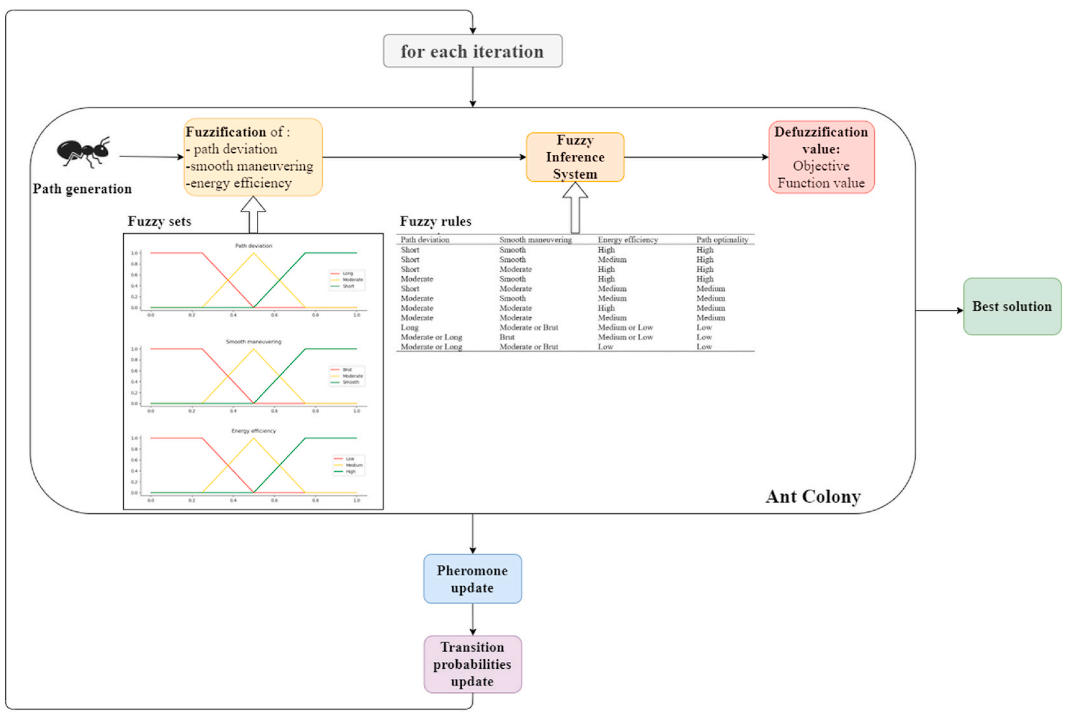

Fig. 3. ACO-FL flow diagram.

Table 2
Summarization of experiments.

Experiments	Description
Exp.1	1 static obstacle with sea surface currents of 1.5 m/s moving in anti-clockwise direction
Exp.2	1 static obstacle with sea surface currents of 2.5 m/s moving in anti-clockwise (AC) direction
Exp.3	1 static obstacle with sea surface currents of 1.5 m/s moving in clockwise (C) direction
Exp.4	1 static obstacle with sea surface currents of 2.5 m/s moving in clockwise direction
Exp.5	1 moving obstacle with sea surface currents of 1.5 m/s moving in anti-clockwise direction
Exp.6	1 moving obstacle with sea surface currents of 2.5 m/s moving in anti-clockwise direction
Exp.7	1 moving obstacle with sea surface currents of 1.5 m/s moving in clockwise direction
Exp.8	1 moving obstacle with sea surface currents of 2.5 m/s moving in clockwise direction

compared with ACO and a popular and simple algorithm commonly used for obstacle avoidance, Bug 2 (McGuire et al., 2019). Table 2 summarizes the various scenarios under examination. In total eight experiments were conducted in accordance with the standard experimental settings found in the literature (Antonelli et al., 2008; Campbell and Wynne, 2011; Fossen, 1999; Singh et al., 2018), divided with respect to: (i) obstacle avoidance into static obstacle and moving obstacle; (ii) the current intensity, i.e. moderate and strong current intensity; and (iii) current effect into clockwise and anti-clockwise. Fig. 4-d illustrates an example of the experiments under examination. The velocities are randomly generated during the initialization phase of the experiments. For ACO-FL and ACO, 30 iterations with 10 size population were used. The evaporation coefficient was set to 0.5, Q was set to 1 and $1/L_a$ was calculated based on the defuzzification value of the path optimality. Regarding the USV characteristics, f was set to 2 kg/h and V to 3 m/s.

The proposed experiments are simulated using Python and OpenCV, on Microsoft Windows 10 Environment as operational system, with AMD Ryzen 7 3800X 8-Core Processor at 3.89 GHz and 32 GB RAM.

In case of static obstacles, the node or nodes that correspond to the position of the detected obstacles are excluded from the graph as well as the relevant edges. The moving obstacles are modeled as ellipse, which is a common approach in marine environments (Tam et al., 2009). The edges in the trajectory are excluded from the graph to form a safe area where the USV can alter its route to avoid the obstacle.

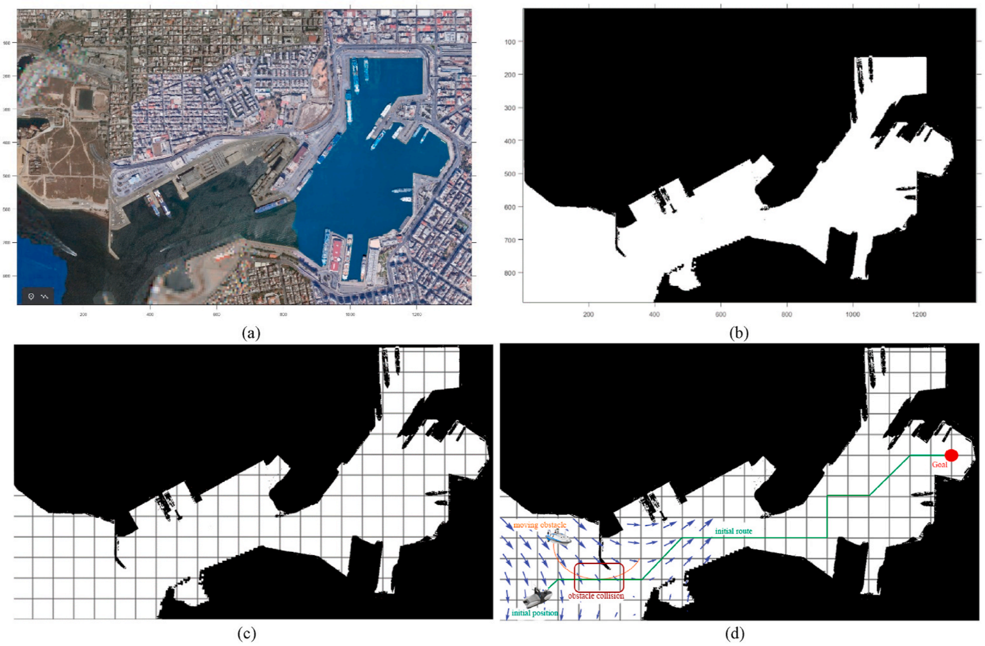

Fig. 4. (a) Satellite image of Piraeus Port, (b) its corresponding binary image (Source: Google Earth) in pixel scale, (c) the generated grid area used for path planning and (d) an example of experiment setting.

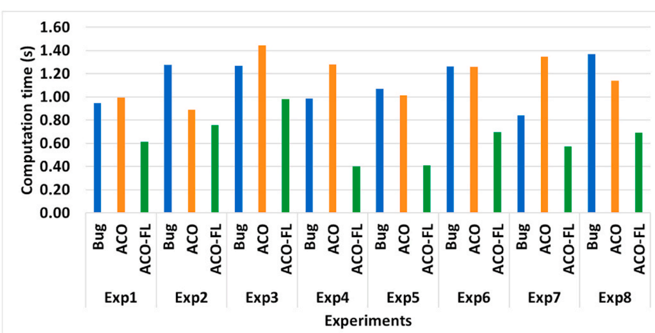

Fig. 5. Computation time per experiment per algorithm.

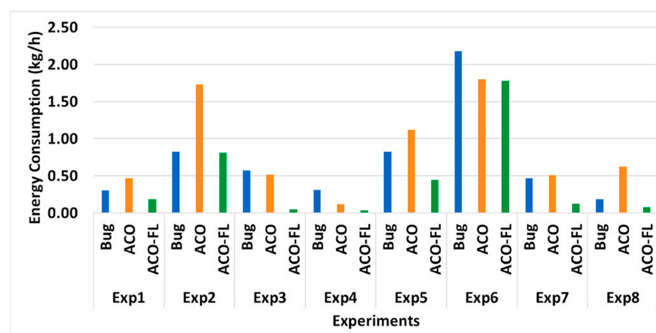

Fig. 7. Energy consumption for obstacle avoidance per experiment per algorithm.

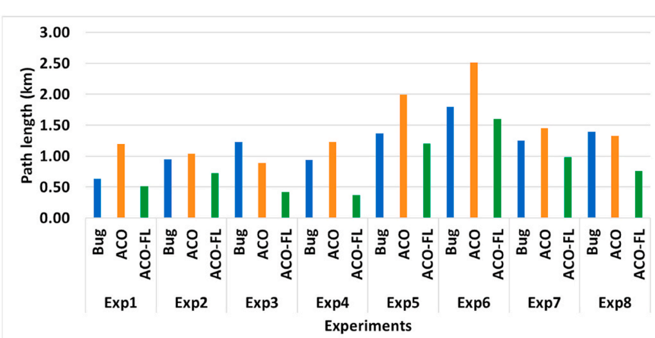

Fig. 6. Path length for obstacle avoidance per experiment per algorithm.

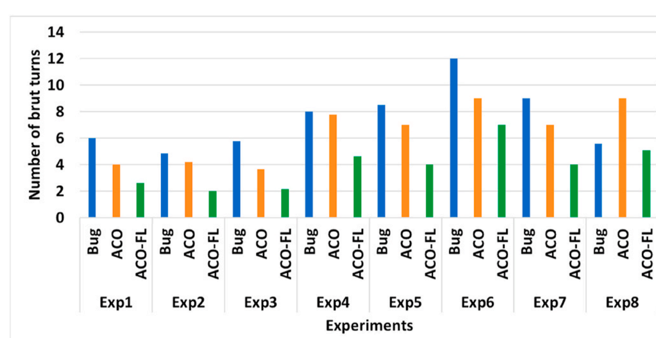

Fig. 8. Number of brut turns per experiment per algorithm.

3.2. Results

In this study 8 experiments with various conditions are conducted to compare the effectiveness of ACO-FL algorithm with ACO and Bug2 algorithms. Overall, the proposed algorithm achieved better performance in term of computation time for calculating an alternative path for avoiding the detected obstacle among a predefined path. Fig. 5 shows the computation time in seconds needed for each algorithm under examination for each experiment. We observe that in all cases, ACO-FL needed significant less computation time for finding the optimal path.

Regarding the length of the generated path for obstacle avoidance, ACO-FL outperformed the other competitive algorithms in all cases. Also, for static obstacle Bug2 performed better than ACO while ACO

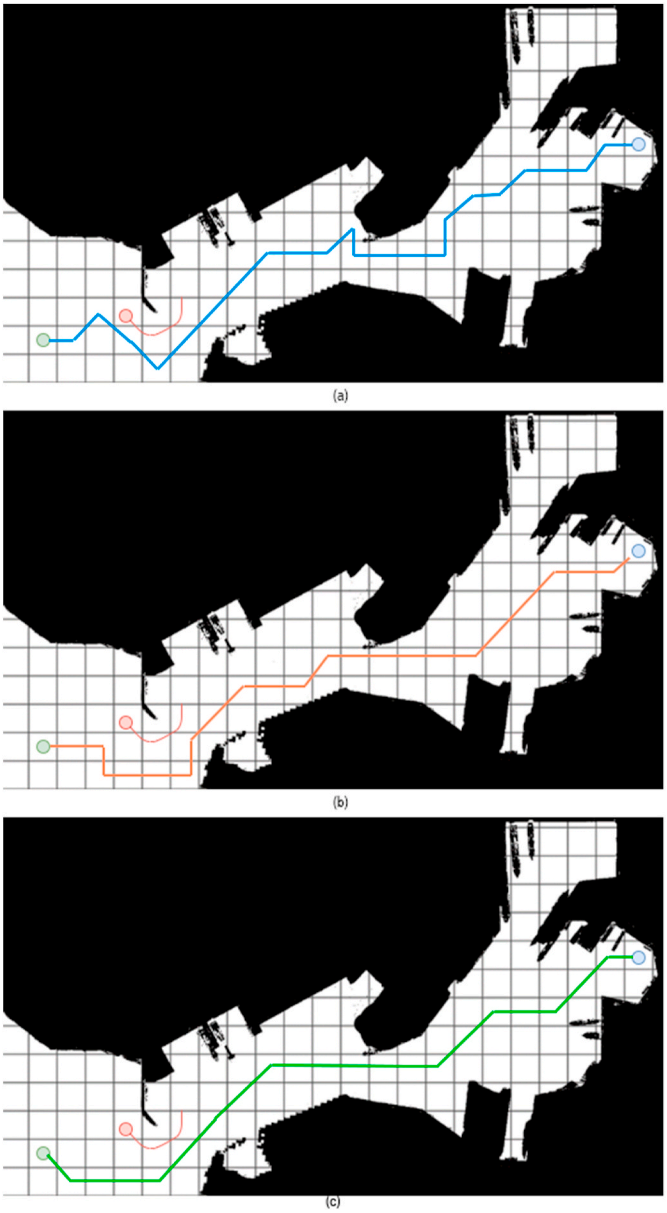

Fig. 9. Routes with obstacle avoidance from (a) Bug algorithm (b) ACO and (c) ACO-FL for experiment 6.

presented a better performance than Bug2 for moving obstacles (Fig. 6). Moreover, ACO-FL not only managed to find the optimal path in terms of distance but also was able to take into account the currents intensity and choose the optimal direction in order to minimize the energy consumption of the trip (Fig. 7). For instance, in case of strong currents (2.5 m/s) the effect was even more significant (Exp4 and 8), by almost erasing the need for fuel consumption. Fig. 8 illustrates the number of brut turns performed by the USV in order to impellent the generated path. For defining a turn as brut, a threshold of turn angle higher than 20° is used. This threshold is used after experimental evaluation and in order to make the comparison more challenging where even small turns are considered brut. ACO-FL is observed to have a better performance also in this optimization criterion for the tested scenarios. Hence, ACO-FL is capable of generating paths for obstacle avoidance with less path length, energy consumption and brut changes among the route for the presented experimental setup compared to the competitive algorithms, ACO and Bug2.

For instance, Fig. 9 illustrates the optimal path with obstacle avoidance found by Bug2, ACO and ACO-FL, respectively, for the experiment 6. The green circle represents the initial position of the USV and the blue circle the target position. The red circle represents the obstacle while the red line shows its trajectory. Initially, the squares that are used for the movement (squares with red line) of the obstacle (red circle) are excluded from the grid area that is permitted for the USV to move in. In experiment 6 the direction of the sea currents is set to be anti-clockwise which means that the sea currents are moving from the bottom to the top of the image. The qualitative results in Fig. 9 are aligned with the results in Fig. 8 that show that ACO-FL generates smoother paths. Also, ACO-FL alters the route mostly anti-clockwise moving in accordance with the sea currents direction. Bug algorithm performed clockwise movements which impacted the energy consumption as shown in Fig. 7.

4. Conclusions and future work

In this study, an improved ACO algorithm with Fuzzy Logic to calculate optimal paths in case of obstacle avoidance under dynamic environment for USVs. The path planning problem incorporated various minimization terms: (i) path length; (ii) smoothness of path; and (iii) energy consumption. An experimental evaluation was conducted taken into account various scenarios, such as sea surface current intensity and static or moving obstacle. Under these scenarios, ACO-FL was compared to Bug2 and ACO algorithms with respect to the optimization criteria. The simulation results show that the presented approach generates efficient way points for USV path planning in a computationally efficient manner against the conventional approaches, such as Bug2 and ACO without losing the optimality. The approach presented a robust performance and, therefore, it can be considered for solving real time path planning of USVs for obstacle avoidance in confined water.

Limitations of current study include the modeling of the moving obstacles with elliptic trajectories and the consideration of current effects. As future work, the study is planned to be extended to real world scenarios under dynamic complex environment with more moving and static obstacles, and dynamic ocean current velocities even in cases where the USV is very close to the obstacle taking into account the impact of waves and wind (Wu et al., 2020; Zhou et al., 2020). Also, the proposed algorithm is foreseen to be integrated in a path planning system of a prototype of a USV for real time application in a controlled environment. Last, the presented methodology was implemented under the project OPTINET and therefore can be adopted for the route planning of ships.

CRediT authorship contribution statement

Dimitrios V. Lyridis: Conceptualization, Methodology, Software, Writing – original draft, preparation, Visualization, Validation, Supervision, Project administration, Funding acquisition.

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.

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References

Antonelli, G., Fossen, T.I., Yoerger, D.R., 2008. Underwater robotics. In: Siciliano, B., Khatib, O. (Eds.), Springer Handbook of Robotics. Springer, Berlin, Heidelberg, pp. 987–1008. https://doi.org/10.1007/978-3-540-30301-5_44.

Ariyasingha, I.D.I.D., Fernando, T.G.I., 2015. Performance analysis of the multi-objective ant colony optimization algorithms for the traveling salesman problem. Swarm and Evolutionary Computation 23, 11–26. https://doi.org/10.1016/j.swevo.2015.02.003.

Birk, A., Wiggerich, B., Bülow, H., Pfingsthorn, M., Schwertfeger, S., 2011. Safety, security, and rescue missions with an unmanned aerial vehicle (UAV). J. Intell. Rob. Syst. 64, 57–76. https://doi.org/10.1007/s10846-011-9546-8.

Blum, C., 2005. Ant colony optimization: introduction and recent trends. Phys. Life Rev. 2, 353–373. https://doi.org/10.1016/j.plrev.2005.10.001.

Campbell, J.B., Wynne, R.H., 2011. Introduction to Remote Sensing, fifth ed. Guilford Press.

Chen, Z., Zhang, Youming, Zhang, Yougong, Nie, Y., Tang, J., Zhu, S., 2019. A hybrid path planning algorithm for unmanned surface vehicles in complex environment with dynamic obstacles. IEEE Access 7, 126439–126449. https://doi.org/10.1109/ACCESS.2019.2936689.

Czapla, T., Wrona, J., 2013. Technology development of military applications of unmanned ground vehicles. In: Nawrat, A., Kuś, Z. (Eds.), Vision Based Systems for UAV Applications, Studies in Computational Intelligence. Springer International Publishing, Heidelberg, pp. 293–309. https://doi.org/10.1007/978-3-319-00369-6_19.

Dorigo, M., Birattari, M., Stutzle, T., 2006. Ant colony optimization. IEEE Comput. Intell. Mag. 1, 28–39.

Dorigo, M., Blum, C., 2005. Ant colony optimization theory: a survey. Theor. Comput. Sci. 344, 243–278. https://doi.org/10.1016/j.tcs.2005.05.020.

Falcón-Cardona, J., Leguizamón, G., Coello, C., Tapia, M., 2020. Chapter 1 Multi-Objective Ant Colony Optimization: an Updated Taxonomy and Review of Approaches.

Fossen, T.I., 1999. Guidance and Control of Ocean Vehicles. University of Trondheim, Norway, John Wiley & Sons, Chichester, England, Norway.

González, A., Olazagoitia, J.L., Vinolas, J., 2018. A low-cost data acquisition system for automobile dynamics applications. Sensors 18, 366. https://doi.org/10.3390/s18020366.

Gonzalez-De-Santos, P., Fernadez, R., Sepulveda, D., Navas, E., Armada, E., 2020. Unmanned ground vehicles for smart farms. In: Agronomy: Climate Change. BoD – Books on Demand.

Harliana, P., Rahim, R., 2017. Comparative analysis of membership function on Mamdani fuzzy inference system for decision making. J. Phys.: Conf. Ser. 930, 012029 https://doi.org/10.1088/1742-6596/930/1/012029.

Hasuike, T., Katagiri, H., Tsubaki, H., Tsuda, H., 2013. Interactive multi-objective route planning for sightseeing on time-expanded networks under various conditions. In: Procedia Computer Science, 17th International Conference in Knowledge Based and Intelligent Information and Engineering Systems - KES2013, 22, pp. 221–230. https://doi.org/10.1016/j.procs.2013.09.098.

Kamel, M.A., Yu, X., Zhang, Y., 2020. Formation control and coordination of multiple unmanned ground vehicles in normal and faulty situations: a review. Annu. Rev. Contr. 49, 128–144. https://doi.org/10.1016/j.arcontrol.2020.02.001.

Leguizamón, G., Coello Coello, C.A., 2011. Multi-objective ant colony optimization: a taxonomy and review of approaches. In: Integration of Swarm Intelligence and Artificial Neural Network, Series in Machine Perception and Artificial Intelligence. WORLD SCIENTIFIC, pp. 67–94. https://doi.org/10.1142/9789814280150_0003.

Li, D., Wang, P., Du, L., 2019. Path planning technologies for autonomous underwater vehicles-A review. IEEE Access 7, 9745–9768. https://doi.org/10.1109/ACCESS.2018.2888617.

Lindner, G., Schraml, K., Mansberger, R., Hübl, J., 2016. UAV monitoring and documentation of a large landslide. Appl Geomat 8, 1–11. https://doi.org/10.1007/s12518-015-0165-0.

Ma, Y., Hu, M., Yan, X., 2018. Multi-objective path planning for unmanned surface vehicle with currents effects. ISA (Instrum. Soc. Am.) Trans. 75, 137–156. https://doi.org/10.1016/j.isatra.2018.02.003.

McGuire, K.N., de Croon, G.C.H.E., Tuyls, K., 2019. A comparative study of bug algorithms for robot navigation. Robot. Autonom. Syst. 121, 103261 https://doi.org/10.1016/j.robot.2019.103261.

Mellal, M.A., Williams, E.J., 2018. A survey on ant colony optimization, particle swarm optimization, and cuckoo algorithms. In: Handbook of Research on Emergent Applications of Optimization Algorithms. IGI Global, pp. 37–51.

Mooney, P., Corcoran, P., Winstanley, A.C., 2010. Towards quality metrics for OpenStreetMap. In: GIS '10: Proceedings of the 18th SIGSPATIAL International Conference on Advances in Geographic Information Systems. Presented at the International Conference on Advances in Geographic Information Systems. ACM Digital Library, New York, NY, United States, pp. 514–517.

Negrete, J.C., Kriuskova, E.R., Canteñs, G.D.J.L., Avila, C.I.Z., Hernandez, G.L., 2018. Arduino board in the automation of agriculture in Mexico, A review. Int. J. Hortic. 8.

Ntakolia, C., Iakovidis, D.K., 2021. A swarm intelligence graph-based pathfinding algorithm (SIGPA) for multi-objective route planning. Comput. Oper. Res. 133, 105358 https://doi.org/10.1016/j.cor.2021.105358.

Ren, H., Zhao, Y., Xiao, W., Hu, Z., 2019. A review of UAV monitoring in mining areas: current status and future perspectives. Int J Coal Sci Technol 6, 320–333. https://doi.org/10.1007/s40789-019-00264-5.

Shakhatreh, H., Sawalmeh, A.H., Al-Fuqaha, A., Dou, Z., Almaita, E., Khalil, I., Othman, N.S., Khreishah, A., Guizani, M., 2019. Unmanned aerial vehicles (UAVs): a survey on civil applications and key research challenges. IEEE Access 7, 48572–48634. https://doi.org/10.1109/ACCESS.2019.2909530.

Shen, Y., Ge, G., 2019. Multi-objective particle swarm optimization based on fuzzy optimality. IEEE Access 7, 101513–101526. https://doi.org/10.1109/ACCESS.2019.2926584.

Singh, Y., Sharma, S., Sutton, R., Hatton, D., Khan, A., 2018. A constrained A* approach towards optimal path planning for an unmanned surface vehicle in a maritime environment containing dynamic obstacles and ocean currents. Ocean Eng. 169, 187–201. https://doi.org/10.1016/j.oceaneng.2018.09.016.

Song, R., Liu, Y., Bucknall, R., 2017. A multi-layered fast marching method for unmanned surface vehicle path planning in a time-variant maritime environment. Ocean Eng. 129, 301–317. https://doi.org/10.1016/j.oceaneng.2016.11.009.

Tam, C.K., Bucknall, R., Greig, A., 2009. Review of collision avoidance and path planning methods for ships in close range encounters. J. Navig. 62, 455–476. https://doi.org/10.1017/S0373463308005134.

Vasilijević, A., Nađ, Đ., Mandić, F., Mišković, N., Vukić, Z., 2017. Coordinated navigation of surface and underwater marine robotic vehicles for ocean sampling and environmental monitoring. IEEE ASME Trans. Mechatron. 22, 1174–1184. https://doi.org/10.1109/TMECH.2017.2684423.

Wang, C., Zhang, X., Li, R., Dong, P., 2019. Path planning of maritime autonomous surface ships in unknown environment with reinforcement learning. In: Sun, F., Liu, H., Hu, D. (Eds.), Cognitive Systems and Signal Processing, Communications in Computer and Information Science. Springer, Singapore, pp. 127–137. https://doi.org/10.1007/978-981-13-7986-4_12.

Wilde, G.A., Murphy, R.R., 2018. User interface for unmanned surface vehicles used to rescue drowning victims. In: 2018 IEEE International Symposium on Safety, Security, and Rescue Robotics (SSRR). Presented at the 2018 IEEE International Symposium on Safety, Security, and Rescue Robotics. SSRR), pp. 1–8. https://doi.org/10.1109/SSRR.2018.8468608.

Wu, G., Atilla, I., Tezdogan, T., Terziev, M., Wang, L., 2020. Long-voyage route planning method based on multi-scale visibility graph for autonomous ships. Ocean Eng. 219, 108242 https://doi.org/10.1016/j.oceaneng.2020.108242.

Wu, Y., Ding, Y., Ding, S., Savaria, Y., Li, M., 2021. Autonomous last-mile delivery based on the cooperation of multiple heterogeneous unmanned ground vehicles. Math. Probl Eng. 2021, e5546581 https://doi.org/10.1155/2021/5546581.

Xia, G., Han, Z., Zhao, B., Liu, C., Wang, X., 2019. Global path planning for unmanned surface vehicle based on improved quantum ant colony algorithm. Math. Probl Eng. 2019, e2902170 https://doi.org/10.1155/2019/2902170.

Yan, R., Pang, S., Sun, H., Pang, Y., 2010. Development and missions of unmanned surface vehicle. J. Mar. Sci. Appl. 9, 451–457. https://doi.org/10.1007/s11804-010-1033-2.

Yang, T.H., Hsiung, S.H., Kuo, C.H., Tsai, Y.D., Peng, K.C., Peng, K.C., Hsieh, Y.C., Shen, Z.J., Feng, J., Kuo, C., 2018. Development of Unmanned Surface Vehicle for Water Quality Monitoring and Measurement. Presented at the Proceedings of 4th IEEE International Conference on Applied System Innovation 2018. ICASI, pp. 566–569. https://doi.org/10.1109/ICASI.2018.8394316, 2018.

Yoo, B., Kim, J., 2016. Path optimization for marine vehicles in ocean currents using reinforcement learning. J. Mar. Sci. Technol. 21, 334–343. https://doi.org/10.1007/s00773-015-0355-9.

Zhang, H., Lin, W., Chen, A., 2018. Path planning for the mobile robot: a review. Symmetry 10, 450. https://doi.org/10.3390/sym10100450.

Zhou, C., Gu, S., Wen, Y., Du, Z., Xiao, C., Huang, L., Zhu, M., 2020. The review unmanned surface vehicle path planning: based on multi-modality constraint. Ocean Eng. 200, 107043 https://doi.org/10.1016/j.oceaneng.2020.107043.