A novel improved elephant herding optimization for path planning of a mobile robot

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ABSTRACT

Swarm intelligence algorithms have been in recent years one of the most used tools for planning the trajectory of a mobile robot. Researchers are applying those algorithms to find the optimal path, which reduces the time required to perform a task by the mobile robot. In this paper, we propose a new method based on the grey wolf optimizer algorithm (GWO) and the improved elephant herding optimization algorithm (IEHO) for planning the optimal trajectory of a mobile robot. The proposed solution consists of developing an IEHO algorithm by improving the basic EHO algorithm and then hybridizing it with the GWO algorithm to take advantage of the exploration and exploitation capabilities of both algorithms. The comparison of the IEHO-GWO hybrid proposed in this work with the GWO, EHO, and cuckoo-search (CS) algorithms via simulation shows its effectiveness in finding an optimal trajectory by avoiding obstacles around the mobile robot.

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1. INTRODUCTION

In recent years, research on mobile robots has seen a remarkable evolution because of their large application. In addition to designing new robots for different tasks, researchers are working on improving and proposing new methods and intelligent control systems for the autonomous navigation of mobile robots, whether in industry, agriculture, and autonomous vehicles. Indeed, in most cases, the environment of mobile robots is either totally unknown or partially unknown, and either static or dynamic, which makes the autonomous navigation of mobile robots a complicated task. One major task for mobile robot navigation is path planning, which has become one of the indispensable research axes in the development of mobile robots.

Trajectory planning is one of the critical tasks when developing a driving system for a mobile robot. The goal here is to plan a safe trajectory, allowing the robot to avoid obstacles in its environment to reach the desired goal. Numerous research works in the last decades address this issue by developing methods based on artificial intelligence. The algorithms and methods proposed by researchers can be classified into three categories. Algorithms based on heuristics, including fuzzy logic [1], [2], neural networks [2], the neuro-fuzzy technique [3], [4], probabilistic neuro-fuzzy [3], and the Q-learning [5], [6], which is known in the planning of trajectories of mobile robots, by its capacity of self-learning without requiring an a priori model of the environment. Nature-inspired algorithms, used to optimize the length of the path, including, genetic algorithm (GA) [7], [8], particle swarm optimization (PSO) [9]–[11], ant colony optimization (ACO) [12],

[13], the grey wolf optimizer (GWO) [14], [15], dragonfly algorithm [16], and cuckoo-search (CS) [17], [18], the use of those algorithms is based on the optimization of an objective function ensures the search for an optimal path by taking obstacles into account. Hybrid methods, in which a collaboration between two or more algorithms is used to improve the search of the optimal solution such as: fuzzy logic-ACO [19], fuzzy-GA [20], based on an improved genetic algorithm, and a fuzzy obstacle avoidance of a soccer robot, IWO-PSO based on the use of invasive weed optimization (IWO) and PSO to search for the optimal trajectory for several robots in a non-stationary environment [21], firefly-fuzzy hybrid algorithm [22] used for trajectory planning of an unmanned aerial vehicle (UAV), PSO-GWO [23]–[25] used in solving multi-objective path planning for an autonomous guided robot, and improved PSO-GWO (IPSO-GWO) as an improved method based on the use of laser range finder, GWO, and PSO [26].

The most common issue solved by these methods is the planning of an optimal trajectory. All methods select a path among various trajectory possibilities, to allow the robot to reach its goal and to reduce the navigation time. A successful method or algorithm quickly finds the optimal path, which positively influences the energy required by a robot to perform such a task, the battery life, the productivity of industrial mobile robots, the intervention time of robots used in critical areas.

The goal of this research work is to develop a new method based on the use of the elephant herding optimization algorithm (EHO) for the search for an optimal trajectory for a mobile robot in different locations. EHO is a recent algorithm belonging to the family of swarm intelligence algorithms, proposed by [27]. Its principle is based on the simulation of the behavior of elephant herding when solving optimization problems. This algorithm is known by a small number of parameters and has a very high capacity for space exploration [28]. In this paper, we have tried to improve some of the basic search principles of the EHO algorithm by proposing an improved elephant herding optimization (IEHO) algorithm to increase its search and optimization capabilities. Also, a hybridization of the IEHO algorithm with the GWO has been proposed to search for the optimal trajectory by taking advantage of the capabilities of both algorithms.

The rest of this paper is presented as follows: Section 2 and Section 3, present respectively the EHO algorithm and the GWO algorithm. In section 4, we will present the procedure followed to improve the EHO algorithm as well as the hybrid IEHO-GWO algorithm for optimal trajectory planning. A parametric study of this hybrid algorithm will be presented in section 5. In section 6 and 7, a comparison and discussion of the simulation results obtained by the proposed method IEHO-GWO and the application of the GWO, EHO, and CS algorithms is presented. At the end of this article, conclusions and perspectives are presented in section 8.

2. ELEPHANT HERDING OPTIMIZATION ALGORITHM

Elephant herding optimization (EHO) is an algorithm that belongs to the nature-inspired optimization algorithms. It is one of the most recent swarm intelligence algorithms proposed by Wang *et al.* [27], and its application lies in optimization problems. Even though it is a fairly recent algorithm, EHO has already been successfully applied to various numerical problems [29]–[31].

In general, solving optimization problems using swarm intelligence algorithms is based on the fact that the search for the optimal solution requires two capabilities; global search is used to explore the search space so that the algorithm avoids the local minimum. Local search in which the algorithm tries to find the best solution in small areas of the search space. The elephant herding optimization algorithm balances these two capabilities. The behavior of EHO is described as follows: An elephant population is composed of k clans. Each clan has a leader elephant called the matriarch m_i, see Figure 1. In each generation, some male elephants leave the clans to live alone away from their original clan. The intelligence of swarms in EHO is therefore based on the fact that the clans represent local search, while the elephants leaving the clan describe the process of a global search. In terms of optimization, the matriarch is the optimal solution with the best fitness function value in the clan. On the other hand, male elephants moving away from the clan are the solutions with the worst fitness function values. The implementation procedure of EHO is generally based on clan updating and separating operators, as the two major phases of the algorithm.

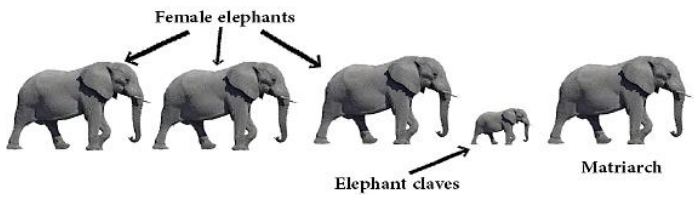


Figure 1. The social hierarchy of EHO algorithm

2.1. The clan updating operator

According to the elephants' natural hierarchy, a matriarch is responsible for guiding the elephants of each clan. The new position of each elephant is always controlled by the matriarch. The clan updating operator models this behavior as follows: for each clan $c_i (i = 1,2,\ldots.,k)$ in the population and each elephant $j(j = 1,2,\ldots.,n)$ in the clan c_i, the updating of the old solution $x_{c_i,j}$with a new solution $x_{new,c_i,j}$ is done by (1).

$$x_{new,c_i,j} = x_{c_i,j} + \alpha(m_i - x_{c_i,j})r \tag{1}$$

where, $x_{new,c_i,j}$ is the new position of elephant j in clan c_i, and $x_{c_i,j}$ its old position, m_i is the best solution in the clan c_i (the matriarch of the clan c_i), $\alpha \in [0,1]$ designates the influence of the matriarch m_i, and r is a random number between 0 and 1. Equation (1) models the fact that each elephant in the clan follows its matriarch to move. The matriarch himself has to look for a new position to continue guiding his clan, so it is necessary to check for the matriarch by the comparison between $x_{c_i,j}$ and m_i. If those solutions are equal, then the new position $x_{new,c_i,j}$ of m_i is calculated by (2).

$$x_{new,c_i,j} = \beta x_{center,c_i} \tag{2}$$

where $\beta \in [0,1]$ controls the effect of the center x_{center,c_i} of the clan c_i on the new position $x_{new,c_i,j}$ of the matriarch. The center x_{center,c_i} of the clan $c_i$can be calculated as (3).

$$x_{center,c_i} = \frac{1}{n_{c_i}} \sum_{j=1}^{n_{c_i}} x_{c_i,j} \tag{3}$$

where n_{c_i} is the number of elephants in the clan c_i. At this stage of the calculation, it is also necessary to check the limits of the new solution $x_{new,c_i,j}$ against the limits of the search space.

2.2. The separating operator

According to the social behavior of elephants in the wild, at each generation, the male elephant leaves his family group to live separately. In terms of optimization, this elephant is considered to be a worst solution to the optimized problem. This process is modeled by the separation operator as follows; in each clan of the population, the elephant with the worst fitness function value x_{worst,c_i} leaving the group is replaced by another elephant generated randomly using (4).

$$x_{worst,c_i} = x_{min} + (x_{max} - x_{min} + 1) * rand \tag{4}$$

where the parameter $rand \in [0,1]$ is a uniform random distribution, while x_{min} and x_{max} are respectively the lower and upper limits of the search space. The pseudocode of the elephant herding optimization algorithm is given in Table 1.

Table 1. The pseudocode of the EHO algorithm

EHO algorithm
Initialize the population while ($t < Maxit$) Sort all the elephants according to their fitness for all clans in the population do   for all elephants in the clan c_i do   Update $x_{c_i,j}$ and generate $x_{new,c_i,j}$ by (1)   if m_i=$x_{c_i,j}$ then   Update $x_{c_i,j}$ and generate $x_{new,c_i,j}$ by (2) end if end for end for for all clans in the population do   Replace the worst elephant x_{worst,c_i} in the clan c_i by (4) end for   Evaluate the population by the newly updated positions   *t=t+1* end while Return The best-found solution in the population

3. GREY WOLF OPTIMIZER ALGORITHM

The GWO algorithm is one of the optimization algorithms proposed in recent years, its principle is based on the simulation of the social hierarchy of gray wolves and their hunting mechanism described by three main steps; the pursuit of the prey, encircling the prey, and the attack towards the prey. Grey wolves in general are grouped according to a social hierarchy. The leader of the group alpha (α), followed by a second category of beta (β) wolves and a third composed of delta (δ) wolves, as well as omegas (ω); the wolves in the last category in this hierarchy [23].

The solution of the optimization problems by the GWO algorithm is found by considering alpha as the first best solution, beta as the second-best solution, and delta as the third best solution. The omegas in the mechanism of the GWO algorithm, present the candidate solutions used to search for the optimal solution in each iteration. The updating of the position of the omegas (X_ω) is based on the positions of the other wolves, which reflects the fact that each omega in the group follows the alpha, beta, and delta wolves, respecting their social hierarchy. GWO is known for its high exploration capacity which allows the algorithm to perform a global search in space avoiding the situations that lead the algorithm to stuck in a local minimum. The capacity of global search and the limited number of parameters presents the GWO algorithm as one of the reliable and exploitable methods for the search for the optimal trajectory of a mobile robot. The procedure of this algorithm is described in [14], [32], [33].

4. HYBRID IEHO-GWO ALGORITHM PROPOSED FOR PATH PLANNING

The basic EHO algorithm as already mentioned above looks for the optimal solution using clan update and separation as two main operators. The idea of the algorithm is that each elephant in a clan follows its matriarch Figure 2. In each clan, there is a better solution m_i presented by the matriarch. Equation (1) shows that at each iteration, all the elephants in the group change their position relative to the matriarch's position, while the same equation does not update the position of the group leader. This is why in the basic EHO algorithm, this problem is solved using (2). By observing this equation, we notice that at each iteration, the update of the position of the matriarch takes into account the center of the clan with an influence factor β. In each generation, the new position of the matriarch m_i is chosen between the origin and the clan center x_{center,c_i} as shown Figure 2(a). This step in the algorithm shows an unjustified convergence of matriarch towards the center of its clan, which can limit the algorithm in terms of space exploration capability and consequently the search for the optimal solution.

Another weakness of EHO exists in the separation operator. Indeed, with each generation, the male elephant leaves their clan. In terms of optimization, these elephants present a bad solution to be replaced, to ensure a reliable convergence of the algorithm towards the optimal solution. This is mathematically translated by (4). Using this equation to replace randomly those solutions, does not guarantee that in the next generation, a good candidate solution will be generated. This procedure can influence the algorithm in general rather than its convergence speed, especially if the randomly generated solution is a bad choice.

The objective of this work is to propose a new method for planning the trajectory of a mobile robot by trying to improve the EHO algorithm. The improvement that we propose is firstly to develop (2) so that we can improve the exploration capability and the convergence speed of the EHO algorithm adapted to the trajectory planning. The principle is based on the fact that the updating of the position of the matriarch in each clan, is done according to the center of the clan x_{center,c_i}, its current position m_i, and the position of the best global solution m_g. This solution presents the matriarch who has the best position among all the matriarchs in the population. This can be described as follows: each elephant in a clan follows its matriarch m_i, and each matriarch in the population follows the matriarch m_g with the best position in the group as shown in Figure 2(b). Equation (2) becomes:

$$x_{new,c_i,j} = m_i + \beta x_{center,c_i} + \Gamma(m_g - m_i)r \quad (5)$$

with m_i the current position of the matriarch and $x_{new,c_i,j}$ its new position. The term $\beta x_{center,c_i}$ keeps the matriarch close to its clan with an influencing factor $\beta \in [0,1]$ while $\Gamma(m_g - m_i)r$ allowing m_i to track m_g with an influencing factor $\Gamma \in [0,1]$; $r \in [0,1]$ is a uniform random distribution. The second improvement is the one used to replace the solutions with the worst fitness function values, The x_{worst,c_i} will be replaced by an x element calculated based on the procedure of the GWO algorithm. The cooperation between both IEHO and GWO algorithms consists in that at each generation, the GWO algorithm exploits the elements of each clan as search agents to search for the best solution x. By using this proposed solution, we will be sure that x_{worst,c_i}will be replaced by a better solution, which further influences the exploration ability and convergence speed of the proposed hybrid IEHO-GWO algorithm. Table 2 presents the pseudocode of the hybrid IEHO-GWO algorithm.

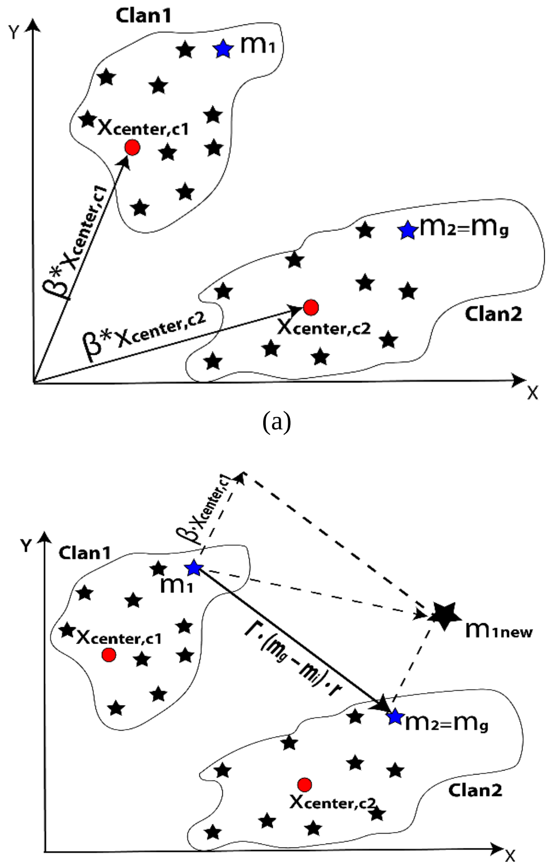


Figure 2. Position updating of the matriarch in: (a) EHO algorithm, and (b) IEHO algorithm

Table 2. The pseudocode of the hybrid IEHO-GWO algorithm

Hybrid IEHO-GWO algorithm
Initialize the population while ($t < Maxit$) Sort all the elephants according to their fitness for all clans in the population do   for all elephants j in the clan c_i do   Update $x_{c_i,j}$ and generate $x_{new,c_i,j}$ by (1)   if m_i=$x_{c_i,j}$ then   Update $x_{c_i,j}$ and generate $x_{new,c_i,j}$ by (5)   end if   Implement the GWO algorithm for all elephants in the clan c_i end for end for for all clans in the population do   Replace the worst elephant x_{worst,c_i} in the clan c_i with the x found with the GWO algorithm. end for   Evaluate the population by the newly updated positions t=t+1 end while Return m_g

5. PARAMETRIC STUDY

The objective of this section is to study the proposed IEHO-GWO algorithm. This study will focus on the influence of its parameters on its ability to find the optimal path. As already mentioned in the previous paragraphs, in addition to the number of populations, clans, and iteration, the IEHO-GWO algorithm requires a set of the three parameters α, β, and Γ for a complete adaptation to find the optimal path planning, see Figure 3.

In order to choose adequate values for the three parameters, we observe the evolution of the best cost (path length) during the iteration for each value of α, β, and Γ as shown in Figure 3(a) to (c). To do so, a fixed number of populations, clans, and iterations is chosen using an arbitrary environment for the mobile robot. The analysis of the results obtained in Figure 3, allows us to choose the right value for each parameter. Taking into consideration that an adequate value of each parameter, allows the algorithm to converge to an optimal solution as much as possible for a minimum number of iterations which will positively influence the mobile robot's navigation time. The proposed parameters for the IEHO-GWO algorithm used for the trajectory planning problem are presented in Table 3.

Table 3. The parameter values considered for the different algorithms

Algorithm	Number of iterations	Specific parameters
IEHO-GWO	200	Population Size=250
		Number of clans=25
		α=0.9; β =0.3; Γ =0.2
EHO	200	Population Size=250
		Number of clans=25
		α=0.9; β =0.3
GWO	200	Number of search agents=250
CS	200	Population Size=250
		Abandon probability Pa = 0.25
		Lévy flights settings α = 0.1; λ = 1.5

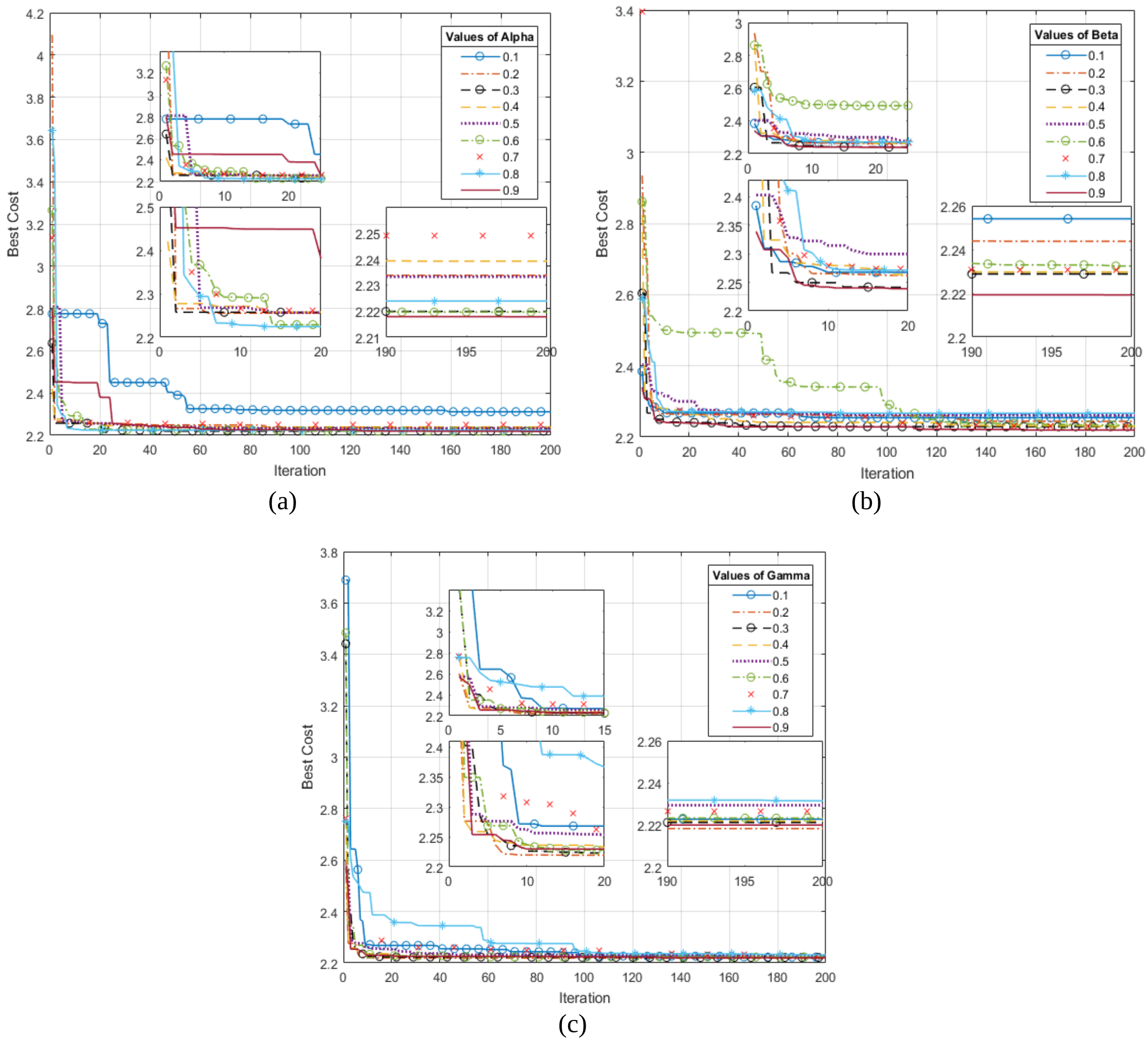


Figure 3. The evolution of the best cost for different values of: (a)- α, (b)- β, and (c)- Γ in 200 iterations

6. RESULTS AND DISCUSSION

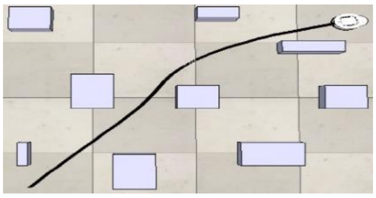
6.1. Simulation results

This section consists of validating by simulation the effectiveness of the proposed method for planning the optimal path of a mobile robot. The simulation results obtained for various environments are presented in Figures 4-5 using EHO in Figures 4(a)-5(a), GWO in Figures 4(b)-5(b), CS in Figures 4(c)-5(c), and IEHO-GWO presented in Figures 4(d)-5(d). The tests are performed using MATLAB and V-rep simulation software considering the parameter values presented in Table 3.

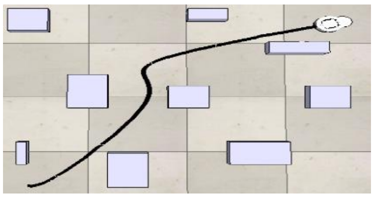
It is shown in Figures 4-6 and Table 4 that the proposed method IEHO-GWO allows the robot to find an optimal path in the environments considered. This method shows a high capacity in finding the optimal solution, comparing it with the EHO, GWO, and CS algorithms. The proposed IEHO-GWO method has successfully reduced both path length and simulation time in scenario-1 and scenario-2 as shown in Figure 6(a) and (b), respectively.

Table 4. Table comparative of simulation results

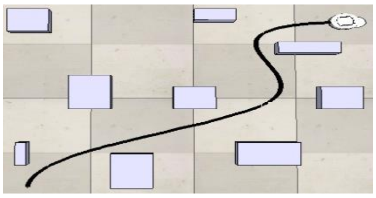
Scenario	method	length of path (m)	% of path saved	Simulation time (min)
	IEHO-GWO	**2.26**	----	**1.15**
Scenario-1	EHO	2.28	0.88	1.65
	GWO	2.50	9.6	2.52
	CS	2.59	12.74	2.72
	IEHO-GWO	**2.06**	----	**1.04**
Scenario-2	EHO	2.09	1.43	1.51
	GWO	2.24	8.03	2.56
	CS	2.36	12.72	2.80



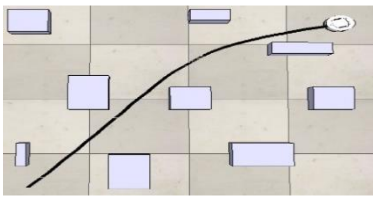
(a)



(b)

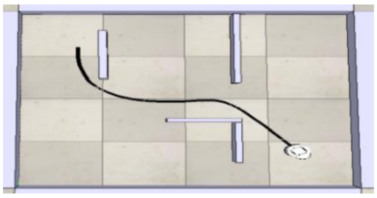


(c)

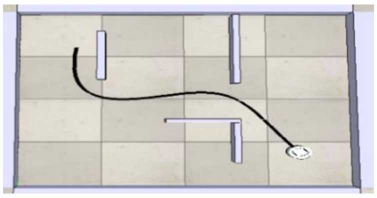


(d)

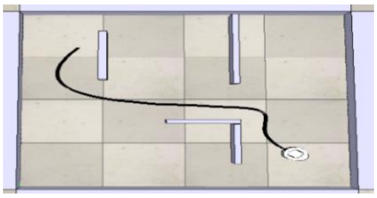
Figure 4. Paths obtained in scenario-1 using: (a) EHO, (b) GWO, (c) CS, and (d) IEHO-GWO algorithms



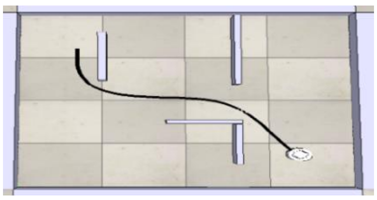
(a)



(b)



(c)



(d)

Figure 5. Paths obtained in scenario-2 using: (a) EHO, (b) GWO, (c) CS, and (d) IEHO-GWO algorithms

Figure 6 shows the evolution of the best solution (the path length) during the iteration run for the four methods. It can be seen that the IEHO-GWO converges quickly to the optimal solution better than the basic EHO algorithm which requires more iteration to reach the same solution. Both algorithms GWO and CS are very slow according to the results obtained, the number of iterations chosen is insufficient to converge towards the optimal solution, which confirms that the convergence speed of those algorithms is low compared to the IEHO-GWO and EHO.

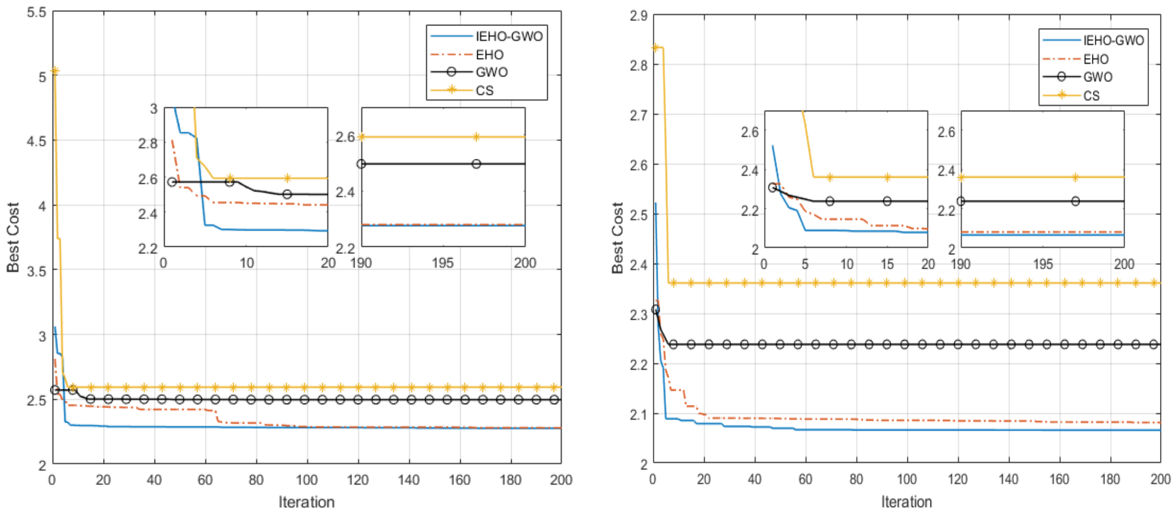
To test the proposed method, a comparison of the four algorithms in terms of the trajectory length is obtained by changing the maximum number of iterations as shown in Table 5 and Figure 7, and the size of the population in Table 6. Comparing this method with the basic EHO algorithm, it can be seen from Figure 7 that the EHO needs more iteration in Figure 7(a) as well as more individuals in Figure 7(b) to get closer to the solution found by the IEHO-GWO which confirms the higher speed of the proposed method compared to the one of the EHO algorithm. The IEHO-GWO does not require a very large number of individuals or iterations to find a better solution.

Table 5. Path length for various iterations

Iterations	method	length of path (m)	% of path saved
100	IEHO-GWO	**2.0594**	-----
	EHO	2.0956	1.73
	GWO	2.5259	19.11
	CS	2.8947	28.86
150	IEHO-GWO	**2.063**	-----
	EHO	2.1435	3.75
	GWO	2.2377	7.81
	CS	2.8243	26.95
200	IEHO-GWO	**2.065**	-----
	EHO	2.0755	0.51
	GWO	2.1661	4.67
	CS	2.6759	22.83
250	IEHO-GWO	**2.0594**	-----
	EHO	2.0844	1.20
	GWO	2.184	5.71
	CS	2.616	21.28
300	IEHO-GWO	**2.0767**	-----
	EHO	2.0643	-0.60
	GWO	2.2545	7.89
	CS	2.6683	22.17
350	IEHO-GWO	**2.0871**	-----
	EHO	2.0691	-0.87
	GWO	2.2318	6.48
	CS	2.8325	12.40
400	IEHO-GWO	**2.0666**	-----
	EHO	2.0838	0.82
	GWO	2.1968	5.97
	CS	2.377	13.06
450	IEHO-GWO	**2.0842**	-----
	EHO	2.073	-0.54
	GWO	2.1943	5.02
	CS	2.3269	10.43
500	IEHO-GWO	**2.0561**	------
	EHO	2.154	4.54
	GWO	2.0938	1.80
	CS	2.4933	17.53
550	IEHO-GWO	**2.0502**	-----
	EHO	2.0775	1.31
	GWO	2.0757	1.23
	CS	2.3237	11.77

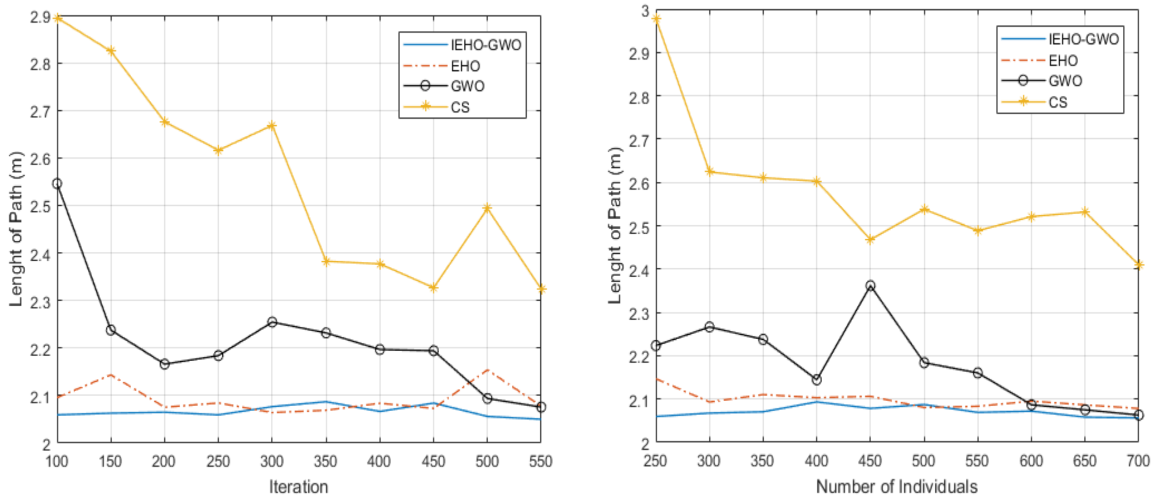
Table 6. Path length for various population sizes

Individuals	method	length of path (m)	% of path saved
250	IEHO-GWO	**2.0597**	-----
	EHO	2.1469	4.06
	GWO	2.2234	7.36
	CS	2.979	30.86
300	IEHO-GWO	**2.0676**	-----
	EHO	**2.0932**	1.22
	GWO	2.2663	8.77
	CS	2.2641	21.21
350	IEHO-GWO	**2.0706**	-----
	EHO	2.1103	1.88
	GWO	2.2377	7.47
	CS	2.6106	20.68
400	IEHO-GWO	**2.0934**	-----
	EHO	2.1031	0.46
	GWO	2.1445	2.38
	CS	2.6029	19.57
450	IEHO-GWO	**2.0785**	-----
	EHO	2.1063	1.32
	GWO	2.3617	11.99
	CS	2.4679	15.78
500	IEHO-GWO	**2.0873**	-----
	EHO	2.0804	-0.33
	GWO	2.1839	4.42
	CS	2.5381	17.76
550	IEHO-GWO	**2.0692**	------
	EHO	2.0833	0.68
	GWO	2.1603	4.22
	CS	2.4884	16.84
600	IEHO-GWO	**2.0721**	------
	EHO	2.0952	1.10
	GWO	2.0867	0.70
	CS	2.5212	17.81
650	IEHO-GWO	**2.0582**	----
	EHO	2.0865	1.36
	GWO	2.075	0.81
	CS	2.5316	18.70
700	IEHO-GWO	**2.0565**	-----
	EHO	2.0782	1.04
	GWO	2.0631	0.32
	CS	2.4094	14.65



(a) (b)

Figure 6. BestCost evolution curve for: (a) scenario-1 and (b) scenario-2



(a) (b)

Figure 7. Path length evolution for (a) various iterations and (b) various individuals

7. DISCUSSION

The EHO algorithm has been applied in several works in order to solve optimization problems. The algorithm's structure, based on the social behavior of elephants in nature, gives the algorithm a good space exploration capacity. This capacity is still limited and risks minimizing the convergence speed of the algorithm because of its updating equation [28]. Sharma *et al.* [34] have developed an improvement of EHO by proposing a new update equation for EHO. The IEHO-GWO method proposed in this article tries to improve the basic algorithm in terms of convergence speed, by increasing its space exploration capacity. This method hybrid the capabilities of both algorithms GWO and IEHO. On one side, the unjustifiable convergence of the EHO algorithm towards the clan origin at each iteration presents a weakness of the algorithm, since it limits its space exploration capability and consequently its convergence speed. According to the modifications applied to the basic equations of EHO, the improved EHO (IEHO) proposed in this work, allows the algorithm to avoid the local minimum in its search space by leading the search with the best solution in all the population. On the other side, the implementation of the GWO algorithm in the path planning of mobile robots has shown, according to several works, that GWO has a high space exploration capability, which increases the possibility to find the global minimum easily [34], [35]. The PSO-GWO hybridization presented in [24] shows the utility of GWO in improving the exploration capability of the PSO algorithm. A comparison of PSO-GWO and IEHO-GWO has been performed in terms of optimal path planning in the same environment used in scenario-1. IEHO-GWO has a good performance (L=2.26 m) compared to PSO-GWO (L=2.36 m). Therefore, PSO-GWO requires more iterations and a larger population (130 iterations and 300 individuals) to reach a near solution to IEHO-GWO, which requires only 250 individuals and 60 iterations.

The cooperation between both algorithms IEHO and GWO, results in an IEHO-GWO method that outperforms the EHO algorithm in terms of space exploration and convergence speed. On the one hand, the IEHO-GWO method exploits the high space exploration capacity provided by GWO to avoid local minimums. On the other, IEHO affects the convergence speed of IEHO-GWO, making it faster than the EHO algorithm. IEHO-GWO finds the optimal solution in many iterations and with a lower population number than those required by EHO and GWO respectively.

8. CONCLUSION

In this paper, based on the EHO algorithm, a hybrid IEHO-GWO method is proposed for planning the optimal trajectory of a mobile robot in a static environment containing obstacles. The proposed method has been tested by comparing it with the EHO, GWO, and CS algorithms. In the simulation using MATLAB and V-rep software, the combination of the GWO's exploration and exploitation capabilities, as well as the convergence speed of EHO, allows the development of a new IEHO-GWO method that balances between the different capabilities to find very quickly the best solution in the search space. The results obtained make the IEHO-GWO algorithm an effective method for the path planning of a mobile robot in an uncertain environment. The future work consists of developing an intelligent system able to guide and locate a mobile robot in a dynamic environment.

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