Generation of cost functions for Particle Swarm Optimization using Artificial Potential Fields

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***Abstract*—This work is focused on the generation of a new set of cost functions for the Particle Swarm Optimization (PSO) algorithm using Artificial Potential Fields (APF).**

First, APFs were proposed to model areas with collapsed structures as an optimizable function. The idea behind this was to use the PSO algorithm to find a path for the agents of the swarm towards a specific goal. From these tests, the best parameters for the PSO algorithm and each of the collapsed structures' scenarios were defined. Our experiments showed that the majority of agents converged to the global minimum in every test case. From these tests it was concluded that artificial potential fields are optimizable candidate functions for the PSO algorithm. Looking towards a future implementation in search operations, it was determined that the Choset model with multiplicative behaviour was the model with outperformed the rest in terms of convergence and number of iterations.

***Index Terms*—artificial potential fields, particle swarm optimization, search and rescue**

I. Introduction

This work aims at implementing a PSO algorithm combined with APFs to allow navigation of a multi-agent system in an obstacle-filled environment. Our main objective is to develop a methodology to generate cost functions that can model real life disaster scenarios, such as collapsed structures. This could potentially be used to guide robots in search and rescue missions.

The experimental setup of the work consisted in setting up search spaces and modeling them with different functions. Then, the parameters for the PSO and the APF models were selected heuristically in order to determine the optimal PSO model. The amount of agents that converge to the local minimum and the iterations it takes the algorithm were used to select the best combination of APF model and PSO algorithm.

In this work, we selected the best combination of APF and PSO looking forward to a future implementation of the method in the search area. This area has been a major object of study and various studies have been carried out to assist effectively in the search of people and in order to reduce the risk to rescuers. Regarding the situation in Guatemala, many people live in a situation of very high risk or in conditions of threat of collapse and flood [5]. In addition, the seismic potential of the region is variable, earthquakes of maximum magnitudes can be generated with different recurrence laws thanks to earthquakes associated with the Depression of Honduras, the activity of the source of volcanoes in Central America, the Chixoy-Polochic-fault system Motagua and the subduction pit associated with the Cocos and Caribbean plate boundary [6].

II. Background

According to [10] and [14], the PSO algorithm is defined as follows:

$$X_i^{t+1} = X_i^t + V_i^{t+1} \tag{1}$$

$$V_i^{t+1} = K(\omega V_i^t + \beta_l r_1 (P_i - X_i^t) + \beta_g r_2 (P_g - X_i^t) + \gamma r_3 \hat{V}_i^t) \tag{2}$$

where

- X_i^t and X_i^{t+1} are the positions of *ith* particle in iteration t and $t+1$ respectively.
- V_i^t and V_i^{t+1} are velocity vectors of the *ith* particle in iteration t and $t+1$ respectively.
- r_1, r_2 y r_3 are random numbers between 0 and 1.
- P_i is the best candidate location for the *ith* particle.
- P_g is the best candidate location for the entire swarm (also known as *gbest*).
- ω, β_l y β_g are user defined coefficients used to control inertia, exploration, and exploit attributes of each particle respectively.
- γ the diversity preservation coefficient.
- K is a constriction factor used to control velocity.

According to [8], an APF is a differentiable real-valued function that assigns an energy value to each in space. The idea behind an APF is to obtain a force vector field by calculating the gradient of the energy function. A complete APF is composed by two forces: repulsive and attractive. The model can be compared to a positive-charged particle that moves in a gradient vector field. The negative-charged goal attracts the particle, while positive-charged obstacles generate a force that repels the particle away from them. Both forces combine to drive the particle towards the goal.

The most common APF model found in literature [9], [11], [12] and [13] is the Choset model, defined as follows: [8]:

$$U_{\text{rep}}(q) = \begin{cases} \frac{1}{2}\eta \left(\frac{1}{d_i(q)} - \frac{1}{Q^*}\right)^2 & d_i(q) \leq Q^* \\ 0 & d_i(q) > Q^* \end{cases} \tag{3}$$

$$U_{\text{att}}(q) =$$

$$\begin{cases} \frac{1}{2}\zeta d^2(q, q_{\text{goal}}) & d(q, q_{\text{goal}}) \le d^*_{\text{goal}} \\ d^*_{\text{goal}}\zeta d(q, q_{\text{goal}}) - \frac{1}{2}\zeta(d^*_{\text{goal}})^2 & d(q, q_{\text{goal}}) > d^*_{\text{goal}} \end{cases} \quad (4)$$

For $U_{\text{rep}}(q)$, $d_i(q)$ is the minimum euclidean distance of the agent relative to any obstacle, η is a proportional constant determined heuristically, and Q^* is a threshold distance to ignore obstacles that are too far.

For $U_{\text{att}}(q)$, $d(q, q_{\text{goal}})$ is the minimum euclidean distance from the agent to the goal, ζ is a proportional constant determined heuristically, and d^*_{goal} is a threshold distance to define a conic or a parabolic function in terms of the relative distance from the agent to the goal.

Another model of APFs is found in the work of Kim, *et al.* [9] and its repulsive and attractive potential functions are given by:

$$U_{\text{rep}} = \sum_{j \in N} c_o \exp\left(-\frac{\|\psi^o_j\|^2}{l_o^2}\right) \quad (5)$$

$$U_{\text{att}} = c_g \left(1 - \exp\left(-\frac{\|\psi^g\|^2}{l_g^2}\right)\right) \quad (6)$$

For (5), j is the index of every obstacle in set N, c_o is the strength distance for obstacle avoidance, ψ^o_j is the minimum euclidean distance from the agent to j-th obstacle, l_o is the correlation distance for obstacle avoidance.

For (6), c_g is the strength distance to the goal, ψ^g is the minimum euclidean distance from the agent to the goal, l_g is the correlation distance to the goal.

One can combine the repulsion and attraction potentials by addition (7) or by the affine mapping (8), as proposed in [9].

$$U_{\text{tot}} = U_{\text{rep}} + U_{\text{att}} \quad (7)$$

$$U_{\text{tot}} = \frac{1}{c_g} U_{\text{rep}} \cdot U_{\text{att}} + U_{\text{rep}} \quad (8)$$

III. Experimental Setup

To tune the control parameters of the PSO, values were sampled for the parameters in the following ranges: $\omega \in [0.05, 1]$, $\beta_l \in [1, 500]$, $\beta_g \in [1, 35]$, and $\gamma \in [1, 11.5]$. Values were incremented by 0.05 for ω, 5 for $\beta_l \in [1, 50]$, 50 for $\beta_l \in [50, 500]$, 0.5 for γ. These ranges were defined by testing the algorithm in the search space shown in figure 8 with Choset model in additive behaviour [9]. The response values were taken as the percentage of agents that converged to the global minimum (successful agents), iterations that it took the algorithm to converge agents to global minimum and average fitness after 2000 iterations. Experiments were sampled with a system of 50 agents. The upper limit of the ranges described were taken as the response values remained static for a while.

An interview was conducted with the training manager of the Search and Rescue Brigade of the Volunteer Fire Brigade of Guatemala, Hector Sicajá, to gather information from local experience and point of view. In this interview, it was established that the most recurrent cases of collapsed structures locally (this includes Mexico, Guatemala, and El Salvador) are those corresponding to swallows nest, oblique and overlapping planes [7]. Three types of cases were generated according to the interview, which established that the most common cases were those of oblique collapse, total collapse and swallows nest. In addition to the interview, what was observed in similar works was taken as a basis [3].

The first set of experiments correspond to the oblique collapse case. We generated this case to simulate the obstruction of large objects that are usually found in offices and houses in an oblique case, such as desks, beds, walls and collapsed beams. A typical run is shown in Figure 7. The second set of experiments was generated to simulate the obstruction of a passage through medium-sized objects. This case corresponds mostly to a swallows nest case. A typical run is shown in Figure 8. The last set of experiments corresponds to the overlapping planes, where small spaces appear through the obstacles. In this cases, access to living spaces is reduced for rescuers. To simulate this case, the search space was hindered with numerous dispersed objects. A typical run is shown in Figure 9.

The idea behind having generated these cases is to be able to represent in a general way the most common cases of obstacles that agents can find in an area of collapsed structure. In addition, each case represents a different level of difficulty according to the number of local minima and size of obstacles scattered.

Once the APF models, PSO parameters and test cases were defined, we used fifty singular agents for each experiment. Each experiment now consisted of a test case modeled with an APF optimized by the PSO algorithm. The agents were randomly dispersed throughout a search space of 20 by 20 units. The prior dispersion of the swarm is used to simulate a method prior to PSO in which the agents are dispersed in the rescue area without following a defined algorithm. Each experiment was simulated twenty-five times, with response values as the percentage of agents that converged to the global minimum (successful agents) and iterations that it took the algorithm to converge agents to global minimum.

IV. Results

This section presents the results of the experimental procedure.

A. PSO parameters analysis

Figure 1 present for β_l the associated value for successful agents. It is noted that the percentage of successful agents tends to decrease by increasing the β_l parameter. Figures 2, 3, 4, 5 present for each of the PSO control parameters the associated number of algorithm iterations. It is noted that the number of algorithm iterations tends to decrease by increasing any control parameter. The average fitness value associated with the control parameters presented a stationary tendency in any case. The number of successful agents associated with the β_g, γ and ω parameters also presented a stationary tendency.

The PSO control parameters were tuned according to the analysis as follows: 0.5 for ω, 200 for β_l, 25 for β_g and 12 for γ. The parameter values were chosen where the stationary tendency started in the case of the associated number of algorithm iterations. The β_l value was chosen taking into account that an increase in this parameter would mean a decrease in the number of successful agents.

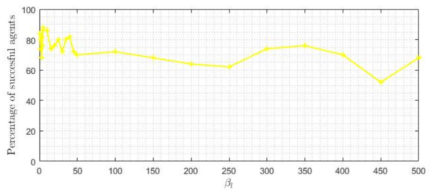

Fig. 1

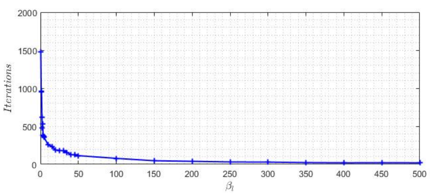

Fig. 2

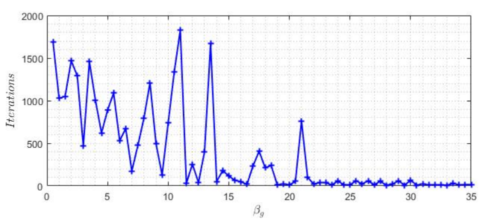

Fig. 3

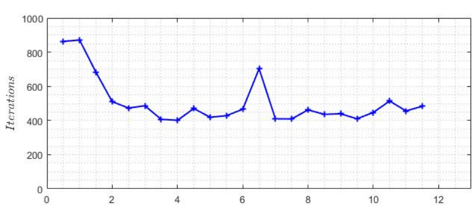

Fig. 4

B. Generated cost functions

This section presents the experimental results for the generated cost functions implemented in the PSO algorithm.

Figure 6 presents the typical fitness value decrease for every agent in the experiments made. It is noted that the fitness value is optimized and that the majority of the system reaches the global minimum.

Figures 7, 8, 9 show the typical trajectories of agents in the test cases generated.

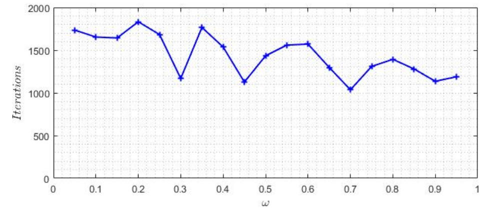

Fig. 5

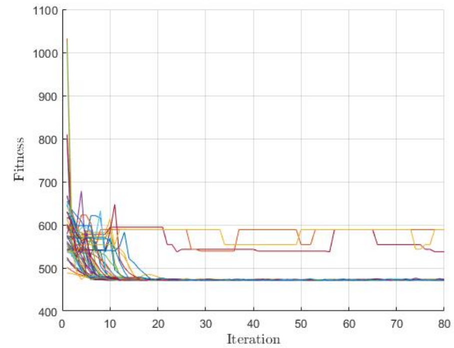

Fig. 6: Fitness value for every iteration in case C with Choset model in additive behaviour

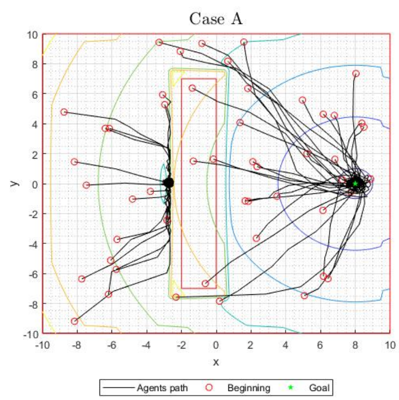

Fig. 7: Agents trajectories in case A simulation with Choset model in additive behaviour

Tables 1 presents the means and standard deviations of successful agents in the generated simulations. Table 2 presents means and standard deviations of the iterations necessary for the PSO to converge agents to global minimum.

V. Discussion and Conclusions

This paper investigated the generation of cost functions for the particle swarm optimization (PSO) algorithm using the (artificial potential field) APF method. The optimization of the value fitness of three test cases was executed with the PSO algorithm. From the figures 6,7,8 and 9 it can be seen that there is a problem of convergence towards local minima, which is a recurring problem in the implementation of the

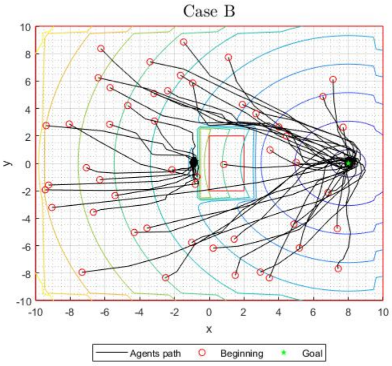

Fig. 8: Agents trajectories in case B simulation with Choset model in additive behaviour

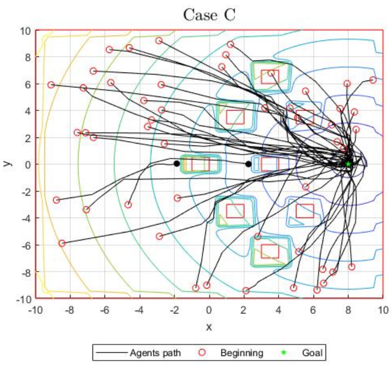

Fig. 9: Agents trajectories in case C simulation with Choset model in additive behaviour

TABLE I: Percentage of successful agents

		CM AB[a]	***CM MB***[b]	***KM AB***[c]	***KM MB***[d]
Case A	Average	67.44	66.32	68.16	67.44
	Std. Dev	8.66	5.98	6.74	5.97
Case B	Average	75.84	77.6	73.68	73.72
	Std. Dev	5.71	3.75	5.95	7.29
Case C	Average	92.16	92.56	88.88	88.72
	Std. Dev	3.66	3.73	5.28	5.24

[a]Choset Model in additive behaviour
[b]Choset Model in multiplicative behaviour
[c]Kim, Wang and Shin Model in multiplicative behaviour
[d]Kim Wang and Shin Model in multiplicative behaviour

PSO algorithm. However, it can be seen in Table 1 that the majority of the swarm system converges towards d=the global minimum.

Of all the cases, the one that presented the least convergence was case A, since it presented a major obstacle to overcome by the agents. As expected, case B presented greater convergence compared to case A, since the size of the obstacle was reduced, and case C proved to be the case with greater convergence of agents to the target. In case C, despite presenting a greater number of obstacles, these were smaller and presented less difficulty for the agents to avoid them.

TABLE II: Number of iterations for convergence of agents

		CM AB[a]	***CM MB***[b]	***KM AB***[c]	***KM MB***[d]
Case A	Average	13.08	12.00	13.92	10.20
	Std. Dev	9.00	3.89	5.86	3.49
Case B	Average	15.28	16.92	16.60	17.32
	Std. Dev	5.20	4.31	5.08	4.23
Case C	Average	27.32	34.88	30.60	31.28
	Std. Dev	8.06	10.04	6.12	8.54

[a]Choset Model in additive behaviour
[b]Choset Model in multiplicative behaviour
[c]Kim, Wang and Shin Model in multiplicative behaviour
[d]Kim Wang and Shin Model in multiplicative behaviour

From the results obtained in Table 1, it can be seen that the Choset model with multiplicative behavior shows a higher average of agent convergence in cases B and C, with one of the lowest standard deviations in any case.

Regarding the number of iterations that it takes for the models proposed with the PSO algorithm to achieve that the agents converge to the goal, it can be observed that the model of Kim, Wang and Shin with multiplicative behavior is the fastest for case A, while that the applied Choset model with additive behavior is the fastest in cases B and C.

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