IOP Conference Series: Materials Science and Engineering

PAPER • OPEN ACCESS

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To cite this article: R J Musridho *et al* 2019 *IOP Conf. Ser.: Mater. Sci. Eng.* **551** 012053

IOP Conf. Series: Materials Science and Engineering **551** (2019) 012053 doi:10.1088/1757-899X/551/1/012053

uFA-FastSLAM: The New Hybrid of Firefly Algorithm and FastSLAM Algorithm

R J Musridho[1], H Hasan[1,2] and H Haron[1,2]

[1]Department of Computer Science, School of Computing, Faculty of Engineering, Universiti Teknologi Malaysia, Johor Bahru, Johor, Malaysia
[2]Applied Industrial Analytics Research Group, Johor Bahru, Johor, Malaysia

rajajoko@gmail.com

Abstract. Simultaneous Localization and Mapping (SLAM) is a challenging and fundamental issue in autonomous mobile robots. One of two main solutions of SLAM problem is FastSLAM. In terms of accuracy, FastSLAM is known to degenerate over time. This work hybridized Firefly Algorithm (FA) and FastSLAM to optimize FastSLAM. But in FA, there is a ranking process which ranked the fireflies based on their light intensity. It caused the output needed by particles in FastSLAM came in different sequence. Thus, the FA in this work is modified before it is applied to FastSLAM, the ranking process is deleted. The result has shown that the modified FA, that is unranked Firefly Algorithm (uFA) has been successfully hybridized with FastSLAM.

1. Introduction

Simultaneous Localization and Mapping (SLAM) is a challenging and fundamental issue in autonomous mobile robots. The problem of SLAM is state estimation, which is the robot and landmarks position estimation. Two main solutions to the SLAM problem are extended Kalman filter based SLAM (EKF-SLAM) and particle filter based SLAM (FastSLAM) [1].

In FastSLAM, robot position is estimated by the particle filter and landmarks position is estimated by EKF. Each particle represents the estimation of the robot position, where in each of it the estimations of the detected landmarks are saved. So decisions of data association is made on each particle. Therefore, different particles have different landmarks estimation, this is the key advantage of FastSLAM [2].

However, FastSLAM is known to have some shortcomings. It produces optimistic estimation of uncertainty in long-term [3], causing production of inconsistent estimation [2]. This happens because low weighted particles are replaced at the resampling phase. Meanwhile each particle carries their own collection of landmarks that represents the environment. So, the entire hypothesis of the environment in those replaced particles are lost, causing information depletion [4].

There are many algorithms [4–6] that have been proposed overcome the problem of information depletion. In [5], FastSLAM is optimized by using Particle Swarm Optimization (PSO). In [6], FastSLAM is optimized by using Genetic Algorithm (GA). And in [4], both GA and PSO are used to optimize FastSLAM.

In this work, FastSLAM is hybridized with a swarm algorithm, i.e. Firefly Algorithm (FA). It is used to update the estimation of robot and landmarks position estimation before the resampling phase in FastSLAM. However, there is a ranking process in FA that caused the values processed by FA go to different particles. Thus, this work proposed a modified FA without the ranking process for its hybridization with FastSLAM.

The next section is methodology which explains about FastSLAM, FA and reason of ranking process deletion, and the proposed hybrid. Section 3 presents the results and discussion. Section 4 as the last section provides the conclusion of this work.

2. Methodology

2.1. FastSLAM
FastSLAM is one of two main solutions to the SLAM problem [1]. In FastSLAM, path is sampled by Particle Filter. In each particle, all detected landmarks which represent the map is stored [6]. The steps of FastSLAM algorithm can be described as follows [4]:
1. A new robot pose is drawn.
2. Update the map by Extended Kalman Filter (EKF) that associates observed landmarks in each particle with new detected landmarks.
3. Calculate the importance weight of each particle.
4. Draw a new particle set from the weighted particle set by resampling.

2.2. Firefly Algorithm (FA) and Reason of Ranking Process Deletion
Firefly's flashing behavior inspired [7] to develop an algorithm at Cambridge University in 2007. Three main rules in FA:
1. All fireflies are attracted to each other because they are unisex;
2. Attractiveness of the fireflies is related to their brightness, the brighter one attracts the less bright fireflies. And the attractiveness is inversely proportional to the distance between them. And if the brightness is the same for all fireflies, they will move randomly;
3. The brightness is determined by the objective function's landscape.

Objective function of FA is related to the brightness of the firefly. And FA is appropriate for multimodal optimization problems because they can divide themselves into smaller groups and those groups swarm around local models, this is due to their attractiveness [8].

In FA, there is a ranking process which ranked the fireflies based on their light intensity. It caused the output to be in different sequence. Meanwhile, the particles in FastSLAM need to use them. If the sequence of output (light intensity) from FA is different from output (weight of particles) that FastSLAM has previously sent to FA, it would cause the new values go to different particles. Thus, the FA in this work is modified, the ranking process is deleted and then it is called unranked Firefly Algorithm (uFA). The pseudocode of uFA can be seen in figure 1.

```
Objective function f(x), x = (x_1, ..., x_d)^T
Generate initial population of fireflies x_i (i = 1,2, ..., n)
Light intensity I_i at x_i is determined by f(x_i)
Define light absorption coefficient γ and randomization parameter α
while (t ≤ MaxGeneration)
        for i = 1:n all n fireflies
                for j = 1:n all n fireflies (inner loop)
                        if (I_i < I_j), Move firefly i towards j; end if
                        Vary attractiveness with distance r via exp[−γr]
                        Evalute new solutions and update light intensity
                end for j
        end for i
end while
Postprocess results
```

Figure 1. Pseudocode of uFA, based on FA by [9] without the ranking process

2.3. The Proposed unranked Firefly Algorithm FastSLAM (uFA-FastSLAM)

The proposed uFA-FastSLAM is an optimized FastSLAM which has been hybridized with FA without the ranking process, which then is called uFA. The uFA is added into FastSLAM before the resampling phase to optimize the robot and landmarks position estimation. Weight of the particles from FastSLAM is the objective function, because the weight represents quality of the estimation [10]. Figure 2 shows the pseudocode of uFA-FastSLAM.

Start Algorithm
1) Sample new robot pose (Predict mobile robot's pose by the motion model)
2) Update the map by EKF with observed landmarks in each particle
3) Calculate the weight of each particle
4) Optimize robot and landmarks position estimation using uFA
    Objective function is the weight of the particles
    Define light absorption coefficient γ and randomization parameter α
4.1) Robot Position Estimation
    Initial population of fireflies is the current position of robot position estimation
    Light intensity I_i at x_i is determined by the weight of the particles
    while ($t \leq MaxGeneration$)
        for $i = 1{:}\,n$ all n fireflies
            for $j = 1{:}\,n$ all n fireflies (inner loop)
                if ($I_i < I_j$), Move firefly i towards j; **end if**
                Vary attractiveness with distance r via $\exp[-\gamma r]$
                Evalute new solutions and update light intensity
            end for j
        end for i
    end while
    Update robot position estimation
4.2) Landmarks Position Estimation
    for $p = 1{:}\,dlm$ all detected landmarks
        Initial population of fireflies is the current position of landmarks position estimation
        Light intensity I_i at x_i is determined by the weight of the particles
        while ($t \leq MaxGeneration$)
            for $i = 1{:}\,n$ all n fireflies
                for $j = 1{:}\,n$ all n fireflies (inner loop)
                    if ($I_i < I_j$), Move firefly i towards j; **end if**
                    Vary attractiveness with distance r via $\exp[-\gamma r]$
                    Evalute new solutions and update light intensity
                end for j
            end for i
        end while
    end for
    Update landmarks position estimation
5) Draw a new particle set by resampling

Figure 2. Pseudo code of the uFA-FastSLAM.

3. Experiment Setup

The experiment is done in MATLAB, using the FastSLAM in the toolbox provided by [11] along with the environment which can be seen in figure 3. Appropriate setting of parameters is necessary to make sure that the experiment is done properly. The setup of parameters can be seen in table 1.

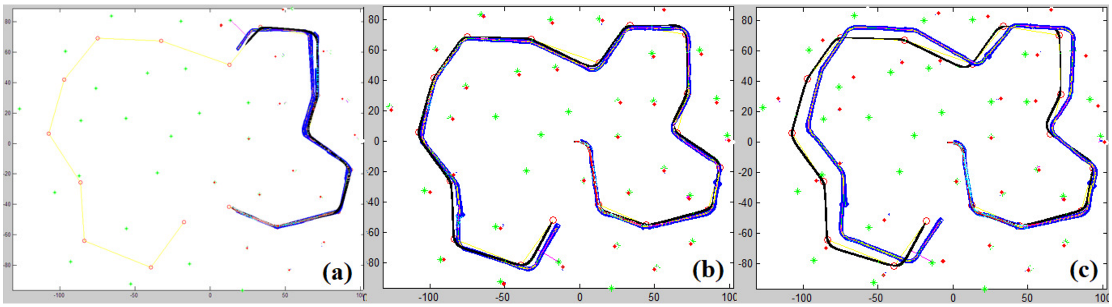

Figure 3. An Incomplete Run (a) and Two Samples of Different Run Results of uFA-FastSLAM (b and c).

Table 1. Setup of parameters.

No	Parameter	Value	Unit
1	Total of simulation	50	run
2	Velocity of the robot	3	m/s (meter per second)
3	Wheelbase size of the robot	4:2	m (meter)
4	Time interval (control signal)	0.05	s (second)
5	Time interval (observations)	0.2	s (second)
6	Number of particles	100	particles
7	Number of loops	1	loop
8	Max Generation	100	times
9	Population of firefly	100	fireflies

4. Results and Discussion

Proof that uFA is worked when hybridized with FastSLAM can be seen in figure 3. It has been proven to work successfully because there was no error happened in the simulations. The circles in figure 3 are the waypoints which connected by lines, this is the reason of showing a picture of an incomplete run, figure 3(a). The stars are true landmarks while landmarks estimations represented by the dots around them. The true robot is path is the thick line with sharper edge than the estimated robot path which is the line next to the true robot path. The sensor detection is represented by the line near the end of the true robot path.

5. Conclusion

This work explained the hybridization of FA and FastSLAM. But in FA there is a ranking process that caused the output for FastSLAM to be rearranged based on the light intensity. Thus, the FA in this work is modified, the ranking process is deleted and then it is called uFA. The goal is to successfully hybridize uFA with FastSLAM. A selected toolbox and an environment map are used for the experiment. The new proposed hybrid, uFA-FastSLAM, is proven to be successfully hybridized.

This work was supported by Tier 1 under grant number Q.J130000.2528.18H65 funded by Research University Grant for Universiti Teknologi Malaysia (UTM).

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