Turkish Journal of Science & Technology
16(2), 205-214, 2021
Research Paper

Analysis of The Performance According to Object Density in Static Environments of GA and PSO Algorithms Used in Mobile Robot Path Planning

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(Geliş/Received: 17/02/2021; Kabul/Accepted: 26/06/2021)

Abstract: In the movement of autonomous mobile robots in static or dynamic environments, one of the important issues sought for a solution is to reach the target with the shortest and safest path without collision. For this purpose, there are many algorithms. The solutions brought by these algorithms differ according to the dynamics of the environment. However, as is known, the real world environment is complex. As the environment gets more complex, more environment knowledge is required for the performance of the algorithms. Complex mobile robotic systems equipped with sensors are required to obtain environmental information. This causes more energy consumption, processing load and the formation of heavy structures. In order to solve these problems, there are algorithms that perform path planning without the need for all environment information. Two of these are the Genetic Algorithm (GA) and the Particle Swarm Optimization (PSO) algorithm. In the literature review, it is seen that these algorithms are effective in the selection and use of sensors according to the nature of the environment. However, in this respect, it was seen that their performances in static environments with different object densities were not analysed and compared. Therefore, in this study, the performance of both algorithms was compared according to the object density in the environment. Distance, time, curvature, and processing speed analyses were performed in MATLAB / Simulink environment according to different density environment scenarios.

Key words: Particle Swarm Optimization (PSO), Path Planning, Genetic Algorithm(GA), Object Detection.

Mobil Robot Yol Planlamasında Kullanılan GA ve PSO Algoritmalarının Statik Ortamlardaki Nesne Yoğunluğuna Göre Performansının Analizi

Öz: Otonom mobil robotların statik veya dinamik çevrelerdeki hareketinde çözüm aranan önemli konulardan biri de çarpışmadan hedefe en kısa ve en güvenli yol ile ulaşmasıdır. Bu amaçla birçok algoritma mevcuttur. Bu algoritmaların getirdiği çözümler ortamın dinamiklerine göre farklılıklar göstermektedir. Ancak bilindiği gibi gerçek dünya ortamı karmaşıktır. Ortam karmaşıklaştıkça algoritmaların performansının iyi olması için daha fazla ortam bilgisi gerekmektedir. Ortam bilgisini almak için ise sensörlerle donatılmış karmaşık mobil robot sistemler gerekmektedir. Bu da daha fazla enerji tüketimi, işlem yükü ve ağır yapıların oluşması sorunlarına neden olmaktadır. Bu sorunların çözümü için tüm ortam bilgisine ihtiyaç duymadan yol planlama gerçekleştiren algoritmalar mevcuttur. Bunlardan ikisi Genetik Algoritma (GA) ve Parçacık Sürü Optimizasyonu (PSO) algoritmasıdır. Literatür taramasında bu algoritmaların ortamın yapısına göre sensör seçimi ve kullanımında etkili olduğu görülmektedir. Fakat bu minvalde farklı nesne yoğunluklarına sahip statik ortamlardaki performanslarının analiz edilmediği ve karşılaştırılmadığı görülmüştür. Bu nedenle bu çalışmada her iki algoritmanın ortamdaki nesne yoğunluğuna göre performanslarının karşılaştırılması yapıldı. Farklı yoğunluktaki ortam senaryolarına göre mesafe, süre, kavis, işlem hızı analizleri MATLAB/Simulink ortamında gerçekleştirildi.

Anahtar kelimeler: Parçacık Sürü Optimizasyonu (PSO), Yol Planlama, Genetik Algoritma (GA), Nesne Tespiti

1. Introduction

One of the most important issues in the movement of autonomous mobile robots is to reach the target with the shortest and safest way without colliding. For this purpose, there are many path planning algorithms based on probabilistic, potential space and artificial intelligence [1-2]. The solutions provided by these algorithms differ according to the dynamics of the environment and the availability of environment information. Mobile robots move in environments with static or dynamic objects. Only the mobile robot is mobile in a static environment. In dynamic environment, it is present in moving objects together with the mobile robot. At the same time, according to the information of the movement environment, road planning is divided into two as general and local road planning. In general path planning, the mobile robot has knowledge about the motion environment before starting

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to move. Based on this information, a map and route planning is done offline. Then the action begins. There is no parameter that can disrupt the existing road plan during the movement. In local route planning, on the other hand, the mobile robot moves in an environment with little or no knowledge. The mobile robot detects objects in the environment and avoids them and obtains a dynamic route plan to the destination. Map information is updated according to the static or dynamism of the objects in the environment. Such algorithms are also called online path planning algorithms [3].

Mobile robots receive environmental information through sensors such as cameras, LIDAR, ultrasonic sensors, laser, GPS mounted on them. This causes mobile robots to become complex and heavy systems. However, as is known, the real world environment is complex. As the environment gets more complex, more environment knowledge is required for the performance of algorithms to be better [4]. This causes more energy consumption, processing load and the formation of heavy structures. In order to solve these problems, algorithms that perform path planning with limited environment information are required without the need for all environment information. Generally, such path planning is performed by artificial intelligence-based algorithms. In this way, the ability to make decisions like a human is gained. For this purpose, meta-heuristic algorithms, inspired by the behaviour of living things in nature, have been developed. Two of these are the Genetic Algorithm (GA) and the Particle Swarm Optimization (PSO) algorithm [2-5]. GA performs operations by taking samples in very complex environments. This ensures high processing speed. The PSO algorithm, on the other hand, performs meta-heuristic progress according to the information of the particles randomly distributed in the environment. The optimum results are not always obtained from these algorithms. However, the most ideal result can be achieved. In particular, optimization features based on incomplete data have spread their hybrid use with other algorithms [6].

There are many studies on PSO and GA. Ibraheem et al. (2018), with PSO and improved bat algorithm, Hassani et al. (2018) presented a hybrid path planning algorithm with PSO and firefly algorithm [7, 8]. Li et al. (2010) proposed an improved PSO path planning algorithm by increasing the capacity of the PSO algorithm to get out of local minimums [9]. Davoodi et al. (2015) tested problems such as distance and time in route planning with the energy-oriented PSO algorithm [10]. Das et al. (2016) proposed an improved PSO algorithm based on robot rotation and time, focused on reducing energy consumption [11]. Purcaru et al. (2013) presented a hybrid path planning algorithm for static environments from PSO and Gravitational Search Algorithm (GSA) [12]. Roberge et al. (2013) developed a GA and PSO-based hybrid path planning algorithm for autonomous movement in real environment in unmanned aerial vehicles [13]. Shivgan et al. (2020) developed energy optimized path planning to reduce the number of turns of the drone using a genetic algorithm. Souza et al. (2020) developed a hybrid path planning algorithm for unmanned aerial vehicles consisting of GA and Ray Casting algorithm [14]. Tao et al. (2020) developed a path planning and obstacle avoidance algorithm for unmanned aerial vehicles based on an advanced genetic algorithm [15]. Abhishek et al. (2020) presented a hybrid algorithm consisting of PSO and GA for 3D path planning in drones [16]. Yan et al. (2019) developed a hybrid multipurpose route planning model consisting of PSO and waypoint guidance in real-time applications in unmanned water vehicles [17]. Jianwei Ma et al. (2020) developed a hybrid path planning algorithm for a straighter path formation based on GA with Bezier optimization [1].

As can be seen in the studies examined, PSO and GA are among the algorithms widely used in path planning, especially due to their adaptation to the environment and optimization properties. Defining the properties of these algorithms well provide the correct approaches in planning the task and action. At the same time, it enables the mobile robot to make the sensor planning more accurately according to the structure of the environment. This will enable us to obtain mobile robot motion planning that responds faster and prevents the use of unnecessary sensors. At this point, the density of the obstacles in the environment in road planning is one of the factors that significantly affect the performance. Because the curves, lengths and degrees of safety of the roads they put forward will differ [1, 18, 19].

In this study, the performance of PSO and GA in static environments was compared according to object density in the environment. Objects in the environment were detected according to the image information. Distance, time, curvature, processing speed and safe path analyses were performed in MATLAB/Simulink environment according to different intensity environment scenarios.

When we look at the other parts of the article, in the second part, there is the material and method part that contains information about PSO, GA and mobile robot system used in the study. In the third part, simulation results in environments with different barrier density are analysed.

2. Materials and Methods

2.1 Genetic algorithm (GA)

It is an optimization algorithm based on population, genetic and random selection, presented by John Holland in 1975. In particular, it provides the most ideal solution for difficult and complex situations. It has the goal of reaching the best solution by mutation. The processing speed is high by sampling the data it uses. Whether it is ideal or not, it always produces a solution. All solutions are available on chromosomes. The process begins with the formation of the chromosome population. The proper value of each chromosome is determined. Then, according to this fitness value, cross-over, mutation of genes and selection steps are performed. This process is carried out recursively as shown in Figure 1. Meanwhile, the solution definition is expressed as the fitness value. With each iteration, this value is replaced by the value of the best fitting chromosome. Thus, orientation towards the best result is achieved. Chromosomes are randomly selected during the selection phase. Next generation is produced by crossing the chromosomes belonging to the best solution. It realizes the definition of the solution obtained by crossover by the sequence of bits or the exchange of genes [5, 13-15, 20].

In the study, the orbits produced for the path are randomly generated as the first population. Then the suitability values are determined. The sample set suitable for these values is selected. From the chosen coordinate parents, the solution suitable for the fitness function is obtained from the parents of children. Child solutions are mutated by adding, deleting and changing the new waypoint. This process is repeated for each point to be reached until the target is reached.

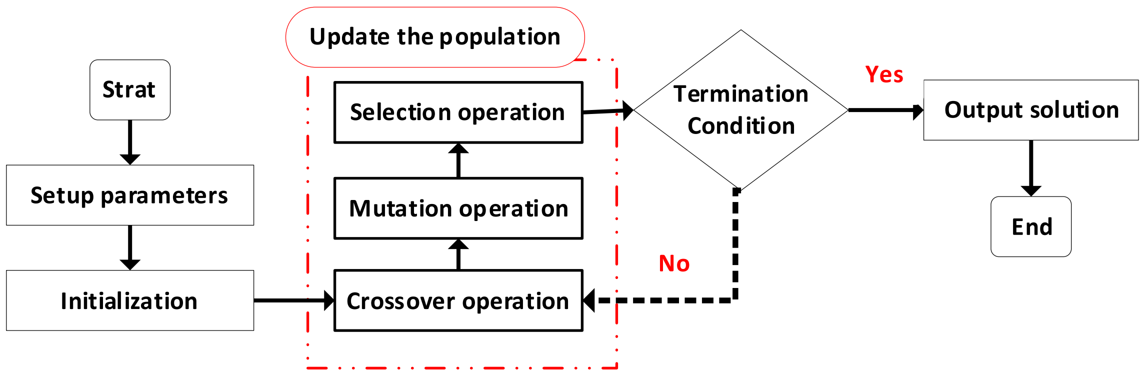


Figure 1. The flowchart of Genetic Algorithm (GA).

2.2 Particle swarm optimization (PSO)

Particle driver optimization (PSO) is a meta heuristic algorithm proposed by Eberhart and James Kennedy in 1995, inspired by the swarm behavior of birds and fish. Generates solutions from randomly generated individuals like GA. Especially, individuals' communication with each other reduces the processing burden. Uses the fitness function for the solution. First, the random particle swarm is created. Every particle has its speed and position. The best solutions (p_{best}) of the particles and the best solutions (q_{best}) of all particles are determined. The best value parameter is updated each time. Points are created with the best solutions until the goal is reached. The algorithm is mathematically expressed as follows.

$$V_{t+1} = w.V_t + crand(p_{best} - X_t) + crand(q_{best} - X_{t)} \quad (1)$$

V_t particle velocity, X_t particle position, best solution of p_{best} particle, best solution in q_{best} group, rand random variable, c constant [13, 19, 22-24].

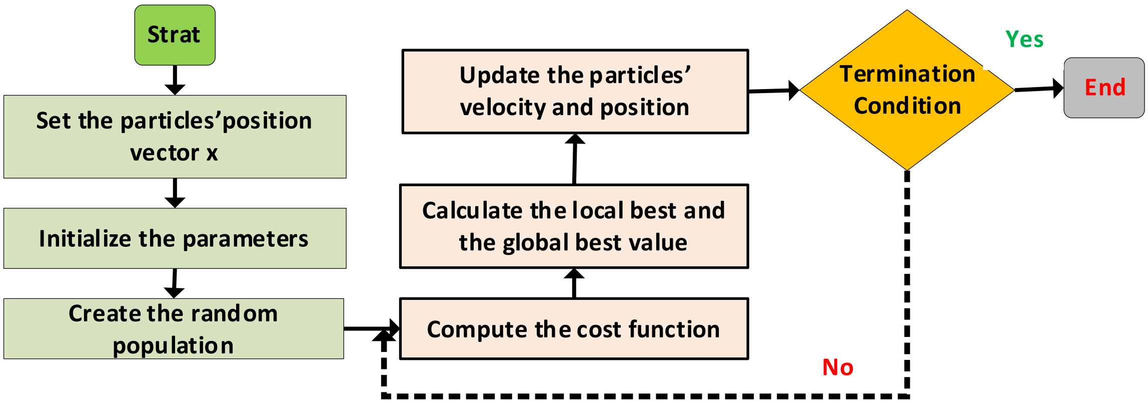


Figure 2. The flowchart of Particle Swarm Optimization (PSO).

2.3 Mobile robot system model

The mobile robot system generally consists of kinematics, dynamic analysis, path planning, speed and position control components. PSO and GA were used for road planning in line with the goal of our article. In this study, a study was carried out according to the object density in the static environment. In this article, the purpose of establishing the mobile robot system model is to determine the safe travels at certain speeds and transportation times of the routes obtained by road planning algorithms in a simulation environment. For this purpose, predetermined environment maps were used.

Kinematic analysis allows us to obtain the position and orientation information of the mobile robot in the environment. Thus, the information about where it is and where it will go is obtained. A mobile robot needs to meet the following coordinate information according to linear velocity V and orientation angle (θ). With kinematic modeling, general, local position information and orientation angle are obtained according to the signals measured from incremental encoders connected to the motor. The encoders generate a digital PWM signal based on the amount of rotation on the wheels of the robots. The obtained position information is compared with the reference motion waypoints and the deviation rate is obtained and necessary signal generation is obtained from the controllers (PID, Fuzzy, etc.). According to the control laws, the movement of the mobile robot is realized by PID speed control. PID gains were obtained by Ziegler-Nichols method for high stability [25].

$$\begin{aligned} V &= V_x = \frac{(V_R + V_L)}{2} = \frac{(r.w_R + r.w_L)}{2} \\ \dot{x} &= v.\cos\theta \\ \dot{y} &= v.\sin\theta \end{aligned} \tag{2}$$

Dynamic analysis is a mathematical model of the mobile robot system. Since the motion is realized by DC motors, it is usually sufficient to create a DC motor model. The mathematical model of the DC motor is obtained as a transfer function according to Kirchoff's and Newton's laws.
According to Kirchoff's laws;

$$\sum V = V_{in} - V_R - V_L - EMF = 0 \tag{3}$$

According to Newton's law;

$$T_m = T_L + T_s + T_a$$

Transfer function;

$$G_s(s) = \frac{w(s)}{V(s)} = \frac{K}{(Ls+R_a)(J_m s+b_m)+K^2} \tag{4}$$

Ra is armature resistance, K_t inductance constant, L armature inductance, T_L load torque, J_m motor inertia, and bm motor internal friction [25, 26].

In order for the mobile robot to proceed without deviating from the road, a position control algorithm is required. It provides speed-based control by taking into account the difference between the current position and the target position. Pure Pursuit, Kalman, Kinematic Model, Markov etc. position algorithms are available [25].

The speed control algorithm is required to realize the speed that the position control algorithm obtains for the advance. For this, PID, Fuzzy, Fuzzy-PID, visual based etc. controllers are used. The aim is to bring the speed of the mobile robot closer to the speed required for the desired position. It does this by taking into account the targeted speed difference achieved during the movement.

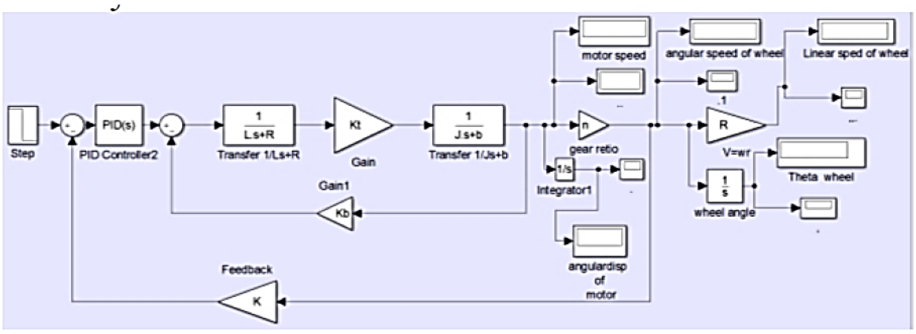


Figure 3. Mobile robot DC motor model [26].

3. Experimental Result and Discussion

Required DC motor parameters for simulation K_t= 0,062 Nm/A, K_e= 0,062 Vs/rad, J_m = 0,0551 Kg/m^2, b_m = 0,188 Nms/rad, R_a,= 0.56 Ohm, L_a=0,97 mH, b_z=0,7 Nms/rad, K_{tac} =1,8 Volt.s/rad [26]. PID was used for speed control in the mobile robot simulation model. PID gain values were determined as Kp = 20, Ki = 5 and Kd = 25. Mobile robot dimensions are width = 0.1 m, length = 0.1 m.

Pure Pursuit algorithm was used to follow the obtained path. The parameters required for the algorithm were determined as look ahead distance (m) -0.2, maximum angular velocity (rad / s) -3, linear velocity (m / s) -0.6.

PSO parameters: Number of handle points = 5, maximum number of iterations = 100, population size (swarm size) = 150, inertia weight damping ratio = 0.98, personal learning coefficient c1 = 1.5, global learning coefficient c2 = 1.57

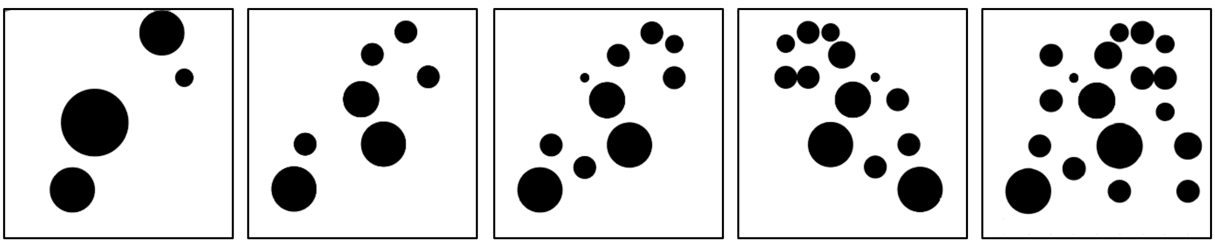
GA parameters: No of points that represent a candidate path, excluding the source =3, minimum generation size= 10, swarm size =150.

Starting and target points were determined as [x, y] = [0.5 0.1] and [x, y] = [4 4.9].

In order to be used in road planning, 5 object-dense environment maps in Figure 4 were used. Algorithms were run 5 times.

In this study, for a successful comparison of both algorithms, the mobile robot model and parameters, environment structure, maps and object densities, population numbers, position control algorithms, speed control structure and gains are taken common.

Best results used in this article:



a) b) c) d) e)

Figure 4. Five different object density maps: Towards more objects from less objects a) Map 1, b) Map 2, c) Map 3, d) Map 4, e) Map 5

Path planning created with PSO:

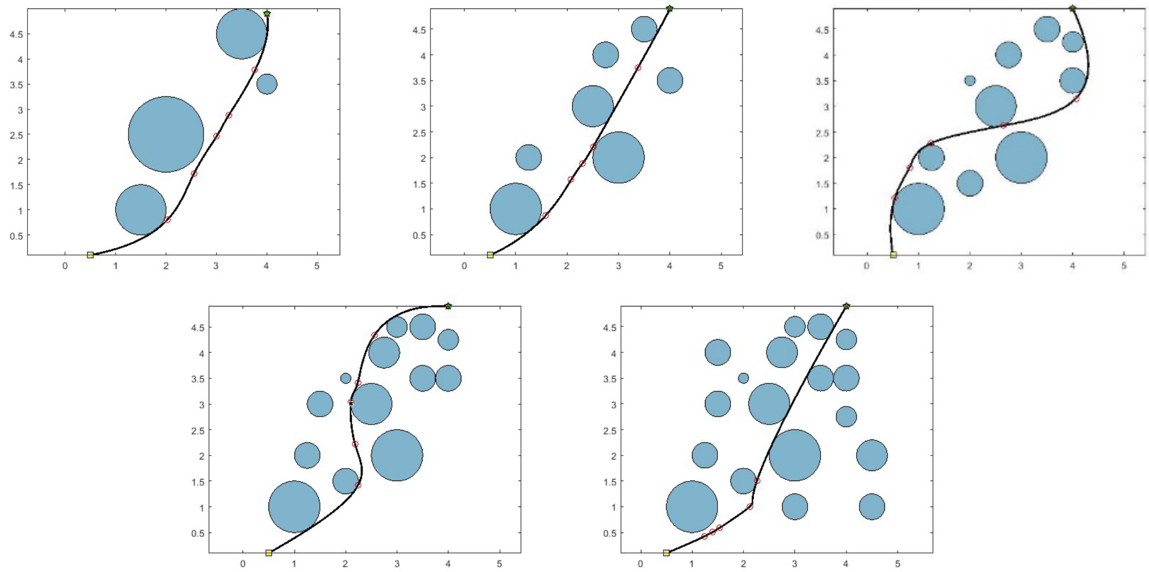


Figure 5. Path planning according to object density by PSO

Path planning created with GA:

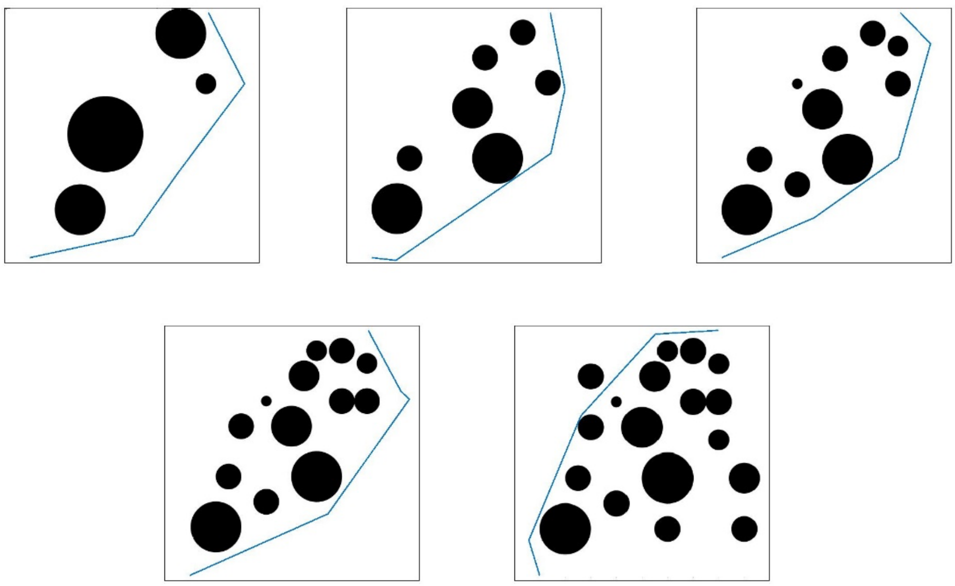
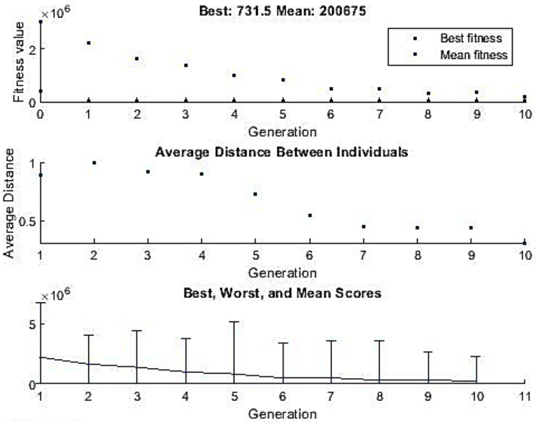
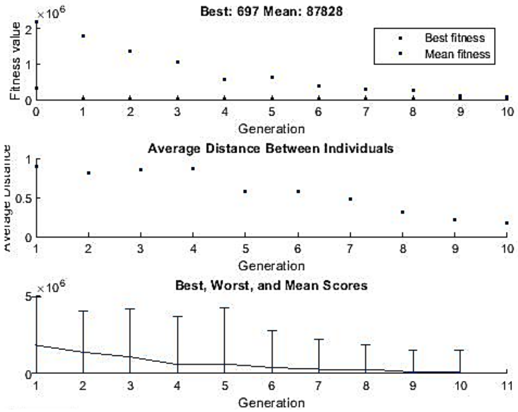


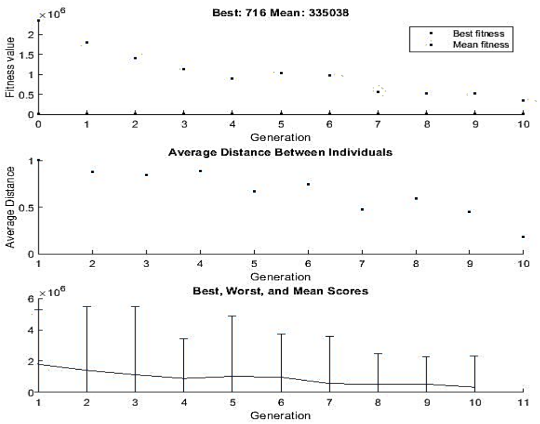
Figure 6. Path planning according to object density by GA



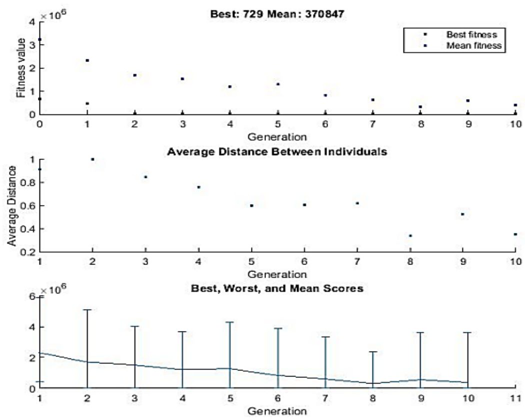
a)



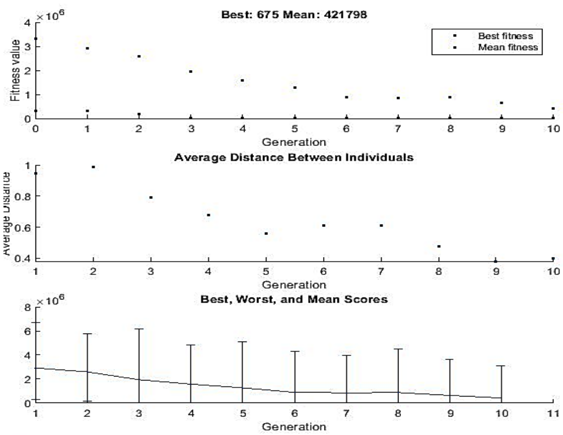
b)



c)



d)



e)

Figure 7. Optimization process in GA-based path planning: a) For Map 1, b) For Map 2, c) For Map 3, d) For Map 4, e) For Map 5

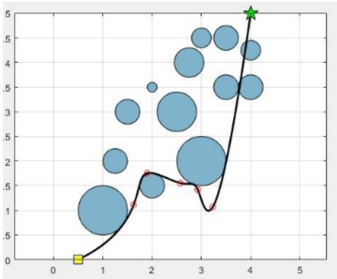
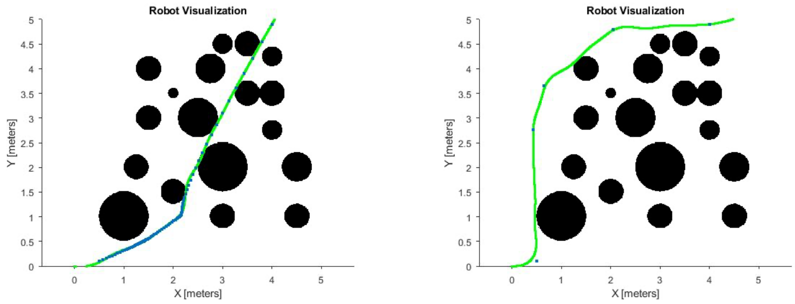


Figure 8. PSO algorithm's obstacle conflict



a) b)

Figure 9. Real time simulation experiment. a) PSO b) GA

Table 1. Comparison of GA and PSO algorithms in object density

	PSO				GA			
	Distance	Time	Curvature	Processing Speed	Distance	Time	Curvature	Processing Speed
1. Case	6.3273	123.2	~3	50.7748	7.3150	144.8	2	34.6343
2. Case	6.0448	109.1	~1	57.3396	6.9700	132.1	3	25.7731
3. Case	7.2769	130.2	~2	58.4811	7.1600	139.3	3	27.6668
4. Case	6.8704	127.1	~3	67.9069	7.2900	140.1	2	27.2910
5. Case	6.2153	113.2	1	69.4000	6.7500	132.6	3	24.8320

Path plans were obtained from GA and PSO algorithms for the environment consisting of 5 different maps. PSO algorithm has found soft paths. GA found a faster solution compared to the PSO algorithm. However, as the environment got more complex, the search times of both algorithms increased. PSO struggled to produce solutions in complex environments. Even in a very complex environment, in cases where the number of iterations was not enough, it also produced solutions by ignoring the obstacles as in Figure 8. However, GA continued to seek conclusions at high transaction times. Although GA spent a lot of time in an environment considered to be unsolvable, it was able to offer limited solutions. The PSO algorithm generated different road routes each time. However, GA produced the same or very close paths for the same environment. It can be seen in Table 1 that GA searches for safer roads and causes longer distances. As seen in Figure 8, it was observed that in real-time applications, path smoothing algorithms are required for GA, curved paths increase deviations from the road and the distance increases even more due to oscillations. Since the processing times of the algorithms are very high, they cannot respond to instant changes in real-time applications. Therefore, they are generally used in offline static environments. In online road planning, they are used as a hybrid in optimization according to advanced road information.

4. Results

In this paper, the performance of meta-heuristic PSO and GA algorithms in object density in static environments was analysed. As a result of the analysis, they produced very successful results offline in static environments. Optimization successes revealed the prevalence of hybrid usage with other algorithms. Choosing the appropriate algorithm for the density of objects in the environment ensures more successful task and motion planning. With the selection of sensors suitable for the nature of the environment, less processing load, energy consumption and unnecessary movements are avoided. In the next study, it is aimed to measure the performance of GA and PSO algorithms in different object density in dynamic environments

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