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Robot Path Planning Performance Evaluation of a Dynamic Environment

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Abstract: *In the recent times, there are tremendous demands for application of robots in in military, industrial and academic communities. The aim of this research work is to bridge the gap to plan a trajectory and minimizing the path lengths and arrest the problems that has to do with collisions of a mobile robot with static and moveable obstacle in dynamic environment. In this work, an intelligent approach and user-friendly module for navigation of a mobile robot in dynamic environment with the use of particle swarm optimization (PSO) algorithm was realized and the path planning parameter performance used are MSE, RMSE and AAE. The design and implementation of PSO algorithm and computer simulations were done using MATLAB 2018a with hardware configuration of Intel(R) Core(TM) i5-2410M CPU @ 2.30GHz, 2301 Mhz, 2 Core(s), 4 Logical Processor(s). The main contribution of this research work is to produce an accurate, and fast planning performance evaluation model and convergence to optimize the path length, time taken and smart in response to static and dynamic obstacles. Overall, the developed simulator provided satisfactory results for various configurations of static and dynamic obstacles.*

Keywords: *MATLAB, Obstacle, PSO, Performance, Robot, Optimization*

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I. Introduction

The unprecedented development experienced in the field of Computational Intelligence (CI) with the onset of the various powerful optimization techniques /algorithms to solve complex, real-world optimization problems where conventional techniques failed or render limited usefulness. In recent years, path planning of robot has been widely applied to both civilians and military field of studies such as industrial, agricultural purposes for mapping, investigation, planning, coordination, surveillance to mention few [2]. A numerous of PSO research intelligent techniques or algorithms were formulated and employed to generate optimal or near-optimal path for robot path planning in which can be categorized into four namely intelligent algorithms [13-16], potential field-based algorithms [47], graph-based algorithms [ ] and heuristic search algorithms [18, 34].

II. Related Reviews

In other to solve the path planning issue of robot, researchers have proposed various methods that are different from the conventional techniques that involve a lot of calculations and limitations. Despite the recent development and wide acceptance of the PSO algorithm, it has drawn attention from different scholars in formulating improved algorithms to solve various problems and applications [13-15]. Due to reliability and simplicity in nature, principle and ease of implementation, PSO, is one of the frequently used intelligent algorithms, and its improved several variants proposed such as Global Best Particle Swarm Optimization (GBPSO), PSOPC [3, 6], QPSO [4], and CPSO [5], a novel Self-regulating and Self-Evolving Particle Swarm Optimization (SSPSO) [15], Dynamic Distributed Particle Swarm Optimization (DDPSO) [22], Dynamic Distributed Double Guided Particle Swarm Optimization (DDDGPSO) [22, 23] performed more than the original PSO [42].

In another shell, the hybridization of PSO with other computational intelligence techniques such as Neural Network (NN), Support Vector Machines (SVM), Genetic Algorithm (GA) and Ant Colony Algorithm (ACO) can increase the diversity of particles in the PSO algorithm, and the global search ability can be improved based on the other techniques. A novel research conducted by [19] to establish a coordinate system transformation through the map of an environment between the starting point and that of the target point (goal). In furtherance to [20] research which is similar to [19] techniques but with second-order oscillation using PSO to obtained a global optimal path. Also, the realization of danger degree map is developed using PSO with equidistant and non-equidistant distributions through weighted accumulation of the length of a path and its danger degree to obtain a globally optimal path [21].

The IPSO-DV was proposed and discussed by [43] which were hybridized improved variants of particle swarm optimization (IPSO) with differentially perturbed velocity (DV) algorithm for trajectory path planning of multiple robots in a static environment. In a research conducted by [25] GA was employed to increase the diversity of particles between the end of the iteration generation and the next generation in PSO in solving robot inverse kinematics. An optimal path planning algorithm that was employs an adaptive multi-objective PSO (AMOPSO) for five mobile robots to attain the shortest possible path was proposed and discussed by [44].

The excellent performance of behavioral cooperation of the robots was developed by [26] using differential evolution (DE) with a PSO to realized alternative local trajectories for collision avoidance among teammates. A work developed by [28] on hybridization technique with Hopfield Neural Net ((NN) and (GA) to solve the path finding problem. A maze-like environment unknown a priori with PSO-NAV algorithm was proposed and presented by [45] which focus on the possibility to drive a group of mobile robots from a starting zone to a final target. Also, [27] conducted a research and presented a path planning algorithm that uses a NN along with a skeletonizing technique.

III. Particle Swarm Optimization

Particle Swarm Optimization (PSO) is a meta-heuristic global optimization paradigm that has gained prominence and also of the numerous techniques widely used in solving ill-structured discrete /continuous, constrained as well as unconstrained function optimization problems [1]. A path is composed of either some straight lines parallel to the longitudinal axis of a Cartesian coordinate system [19 - 21] or a series of grids [35] or some polar radii and polar angles in a polar coordination system [36] or some vertexes of obstacles [37]. In recent times, PSO technique has received a significant growth which is applied to optimal pose selection in reducing friction during robotic machining [10], robotic arm movement [11], detumble and control of space robot [12], Robot path planning is one of the most important tasks in intelligent control [7] which finds application not only in robotic but in bioinformatics [9], medicine and virtual reality [8] and others fields of studies.

The fig. 1 depicts the obstacle avoidance of different shapes where the blue colour objects are mobile obstacles with velocity while the blue colours are static obstacles.

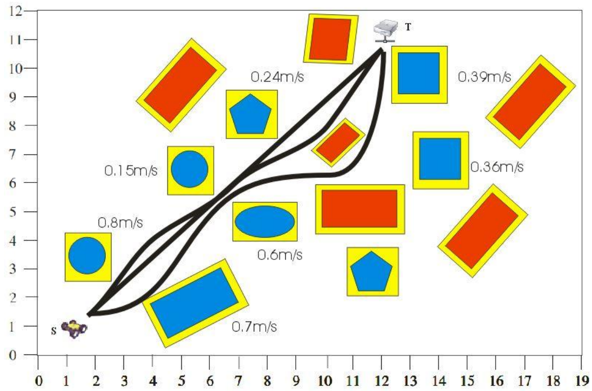

Fig.1: Obstacles (static and mobile) avoidance

The major goal of optimization model of path planning of robot is usually developed to fulfill two purposes namely the length and the danger degree of a path in which there are numerous techniques that can be used to model it such as Generalized Voronoi Diagrams (GVDs) [21, 38-41], Maklink graph [48] and so on.

PSO make sufficient use of probabilistic transition rules to make parallel searches of the solution hyperspace and the underlying physical model upon which the transition rules arise out of social interaction of schools of fish and flocks of birds. Unlike genetic algorithms (GA) that employ the likes of crossover and mutation, PSO uses optimization tool that is based on population, where each member is called a particle and each particle is a potential solution to the analyzed problem so as to implements the simulation of social behavior [46].

The basic concept of PSO algorithm is to accelerate the particles towards P_best and G_best as further itemized in the algorithm 1. Therefore, the current individual best position of the particle is denoted as P_best and the global best position is denoted as G_best. The position and velocity mechanisms of each particle are updated based on the previous position and its speed to the following mathematically equations in (1) and (2)

$$\overrightarrow{X_i^{d+1}} = \overrightarrow{X_i^d} + \overrightarrow{V_i^{d+1}} \quad (1)$$

$$\overrightarrow{V_i^{d+1}} = 2r_1\overrightarrow{V_i^d} + 2r_2\left(\overrightarrow{P_i^d} - \overrightarrow{X_i^d}\right) + 2r_3\left(\overrightarrow{G^d} - \overrightarrow{X_i^d}\right) \quad (2)$$

where,

r_1 and r_2 are independent and identically distributed random numbers in the range [0 1], V_i^{d+1} is the next velocity, $\overrightarrow{X_i^{d+1}}$ is the next position, $\overrightarrow{V_i^d}$ is the current velocity, X_i^d is the current position, $\overrightarrow{P_i^d}$ is the personal best solution, $\overrightarrow{G^d}$ is the global best solution, $\overrightarrow{P_i^d} - \overrightarrow{X_i^d}$ is the distance to the personal best, $\overrightarrow{G^d} - \overrightarrow{X_i^d}$ is the distance to the global best

$$\overrightarrow{V_i^{t+1}} = w\overrightarrow{V_i^t} + c_1r_1\left(\overrightarrow{P_i^t} - \overrightarrow{X_i^t}\right) + c_2r_2\left(\overrightarrow{G^t} - \overrightarrow{X_i^t}\right) \quad (3)$$

where,

w is the inertia weight factor, $c_1r_1\left(\overrightarrow{P_i^t} - \overrightarrow{X_i^t}\right)$ is the cognitive component, $c_2r_2\left(\overrightarrow{G^t} - \overrightarrow{X_i^t}\right)$ is the social component. The c_1 and c_2 are denominated cognitive and social components with positive constant values which is known as the acceleration constants, responsible for varying the particle speed towards *P_best* and *G_best* but not factors for determining the algorithm convergence.

In a situation where a high inertia weight is employed at the start of the algorithm making it decay to a low value through execution and form a globally search in the start of the search, and search locally at the end of the execution. By putting *MaxIter* into consideration, the maximum number of iterations of the algorithm and $iter$ the actual iteration; can be deduced through inertia weight strategy updated as shown in equation (4).

$$W = W_{max} - \frac{W_{max} - W_{min}}{Max_{iter}} \times iter \quad (4)$$

where

X_{min} and X_{max} are the initial and final values of the inertia weight, Max_{iter} is the maximum number of iterations. Meanwhile, position and velocity of each particle in the swarm is randomly initialized with uniform numbers from [X_{min} , X_{max}] and [V_{min} , V_{max}] are shown in equations (5) and (6)

$$x_i = X_{min} + \sigma_1(X_{max} - X_{min}) \quad (5)$$

$$v_i = V_{min} + \sigma_2(V_{max} - V_{min}) \quad (6)$$

where

σ_1 and σ_2 represent random numbers from 0 to 1.

Algorithm 1: Pseudo-code of PSO

Initialize the controlling parameters (N, c1, c2, Wmin, Wmax, Vmax and MaxIter)
Initialize the population of N particles
do
    for each particle
        calculate the objective of the particle
        update P_best if required
        update G_best if required
    end for
    update the inertia weight
    for each particle
        update the velocity (V)
        update the position (X)
    end for
while the end condition is not satisfied
Return G_best as the best estimation of the global optimum

IV. Experiment Simulations and Analysis

The designed and simulations of the improved PSO was carried out on MATLAB 2018a with system of hardware configuration of Intel(R) Core(TM) i5-2410M CPU @ 2.30GHz, 2301 MHZ, 2 Core(s), 4 Logical Processor(s). The following parameter settings are selected for the six trials: maximum number of iterations is set at 120, the minimum and maximum inertia weights are set to 0.4 and 0.9 respectively. The minimum and maximum velocities are 0 and 20 while the social learning factor, cognitive learning factor and number of waypoints are set to 1, 2 and 30 respectively. The σ_1 and σ_2 from 0 to 1, swarm size was set to 50 for the first three trials (1-3) and later increase to 60 for the last three trials (4-6). The MATLAB simulation results in dynamic and static environment are summarized in table 1 for different combinations of variable obstacles.

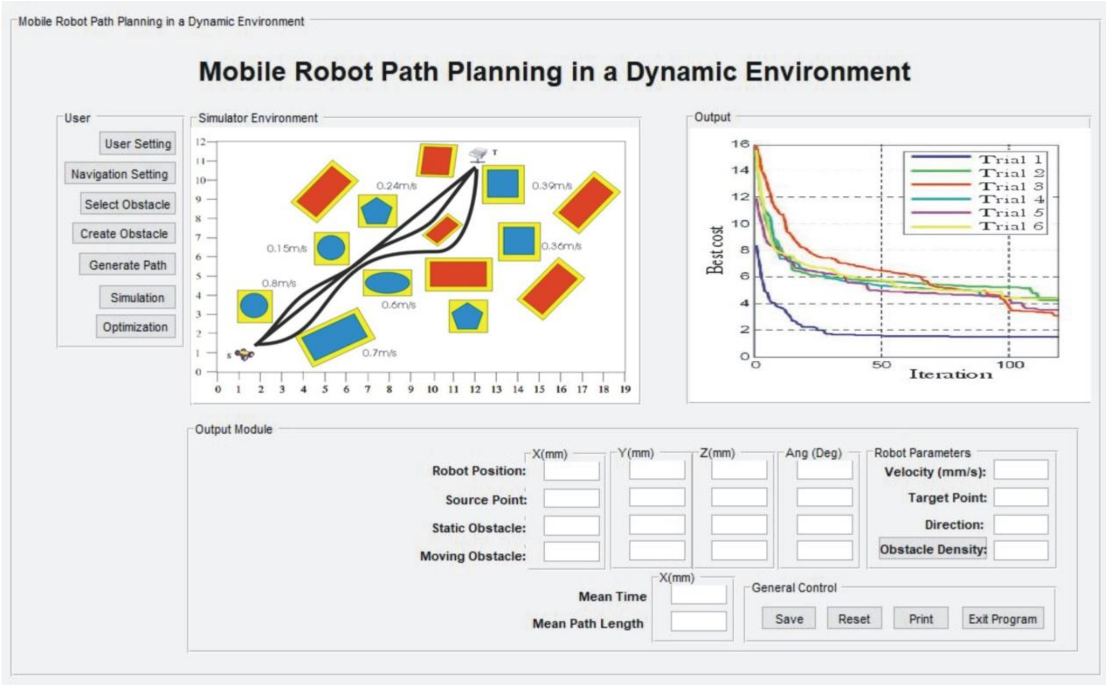

Fig 2: Path Planning Graphic User Interface Window

Table 1: Performance comparison for variations of static and dynamic obstacles

Trial Num	Obstacle Num	Dynamic Obstacle	Static Obstacle	Swarm Num	Goal Target	Path Length	Path Planning Parameter Performance			Optimal solution (cm)	Conv. Rate (Iteration)	Time (S)
							MSE	RMSE	AAE			
1	4	0	4	50	1	32.27	0.2043	0.45	0.33	525.14	33	87
2	4	2	2	50	1	35.11	0.1321	0.36	0.27	577.34	11	96
3	8	8	0	50	1	33.66	0.0932	0.31	0.26	616.08	72	115
4	8	4	4	60	1	34.64	0.1069	0.33	0.26	812.11	81	137
5	12	6	6	60	1	40.03	0.5362	0.77	0.51	913.94	116	122
6	12	12	0	60	1	43.12	0.0443	0.21	0.16	968.02	96	201

The experimental results show that the 6 trials on improved-PSO algorithm with variance of static and dynamic obstacles have relatively least costs and invariably excellent in performance as depicted in Fig 3. The path planning parameter performance that showcased the mean square error (MSE), root means square error (RMSE) and average absolute error (AAE) are depicted in Fig. 4 through Fig 9.

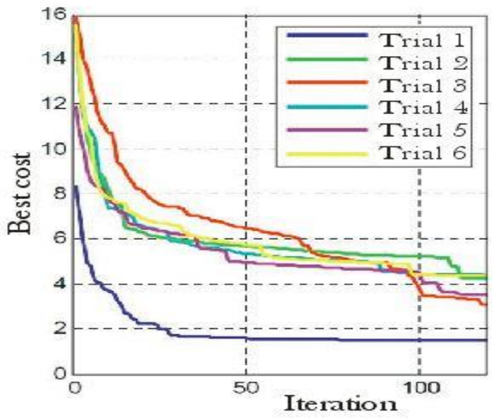

Fig 3: The convergence curves for the 6 different trials of iPSO

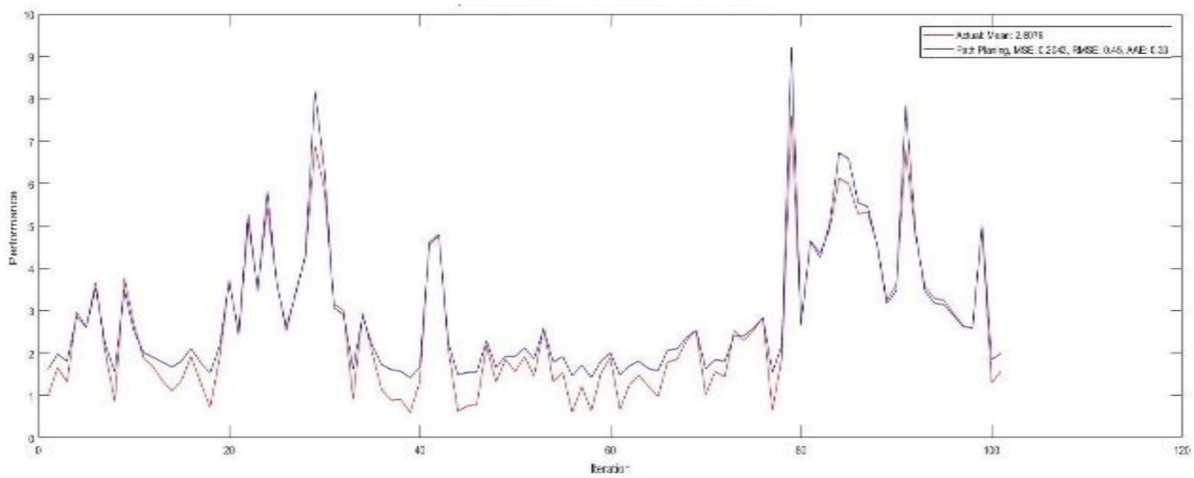

Fig. 4: Path planning performance generated for the working environment using iPSO of 50 swarm size and a goal with only four (4) static obstacles, zero (0) dynamic obstacles.

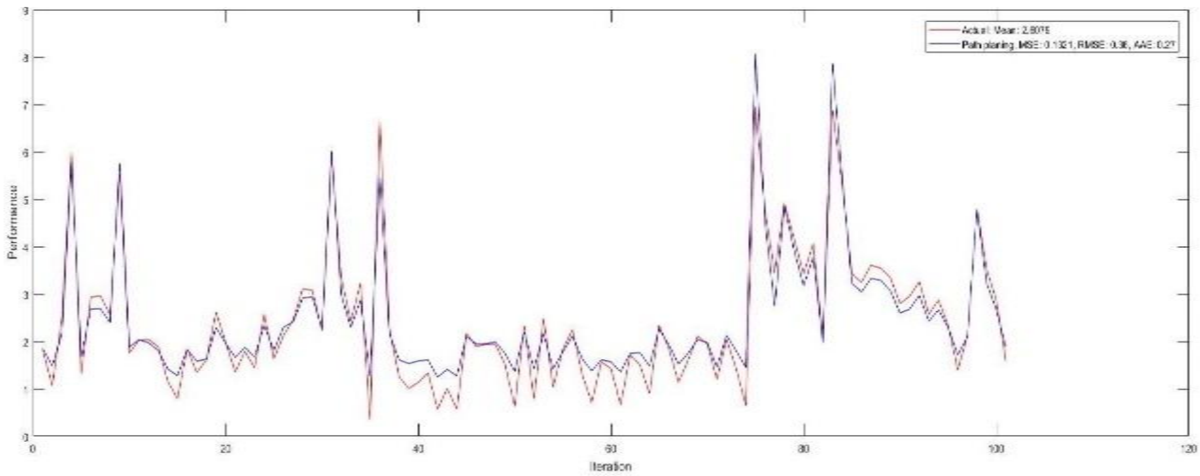

Fig. 5: Path planning performance generated for the working environment using iPSO of 50 swarm size and a goal with only two (2) static obstacles, two (2) dynamic obstacles.

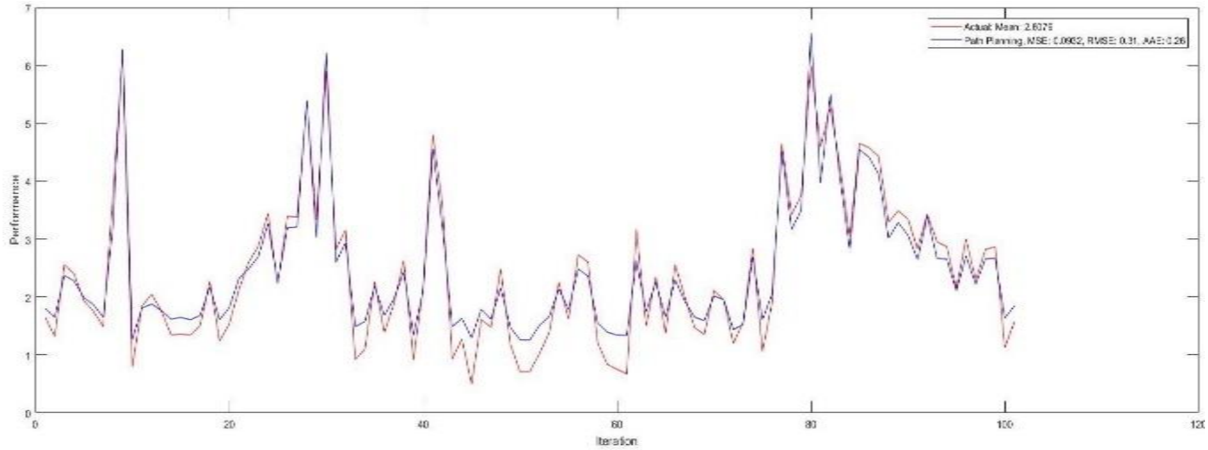

Fig. 6: Path planning performance generated for the working environment using iPSO of 50 swarm size and a goal with nil static obstacles, eight (8) dynamic obstacles.

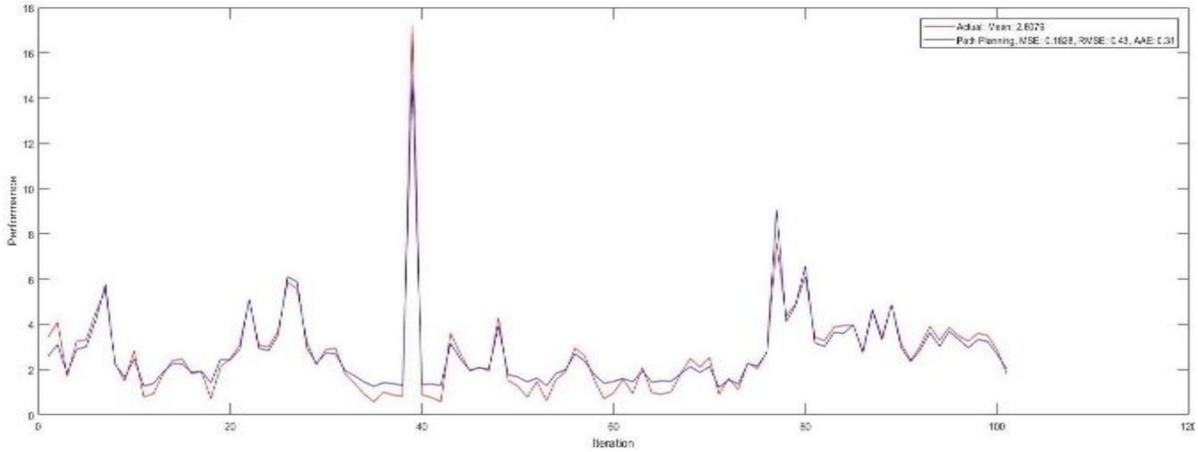

Fig. 7: Path planning performance generated for the working environment using iPSO of 60 swarm size and a goal with only four (4) static obstacles, four (4) dynamic obstacles.

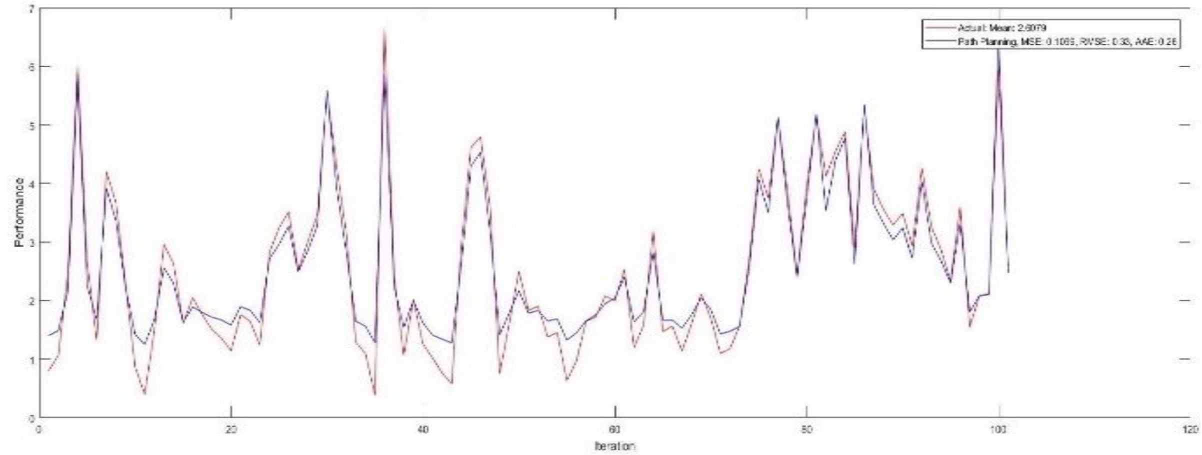

Fig. 8: Path planning performance generated for the working environment using iPSO of 60 swarm size and a goal with only six (6) static obstacles, six (6) dynamic obstacles.

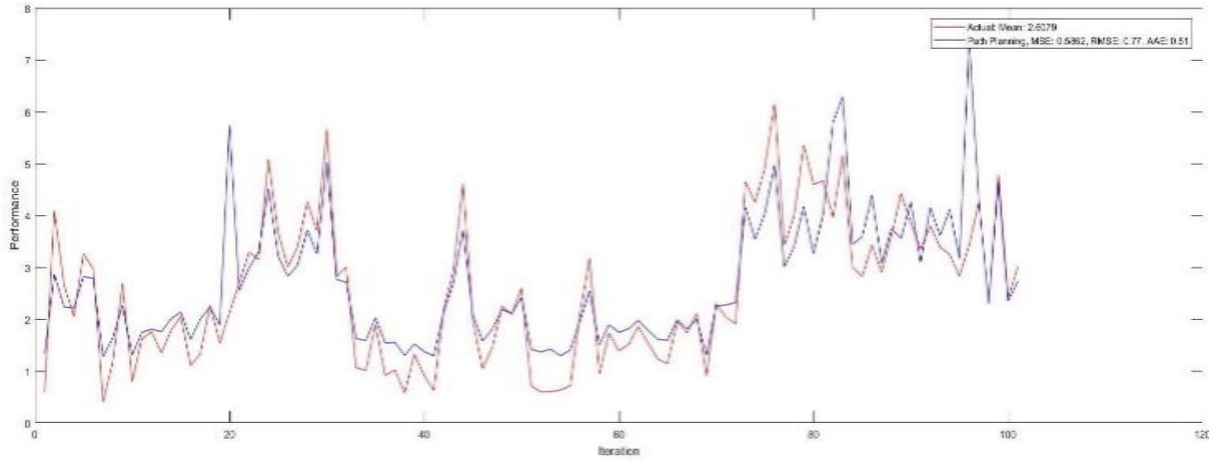

Fig. 9: Path planning performance generated for the working environment using iPSO of 50 swarm size and a goal with nil static obstacles, twelve (12) dynamic obstacles.

V. Conclusion

In this study, path planning performance for mobile robot was investigated using improved PSO techniques in which the performance can deal simultaneously with both global and local planning requirements. The method is easy to implement, fast and can be deployed in all types of environments without restrictions in any form of the obstacles. MATLAB 2018a environment was used to generate the graphic user interface window and simulate the processes that lead to optimal path planning performance. The end results of experiments demonstrate the proposed algorithm is effective, better performance in convergence speed and dynamic convergence and optimization result.

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