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Smart element aware gate controller for intelligent wheeled robot navigation

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ABSTRACT

The directing of a wheeled robot in an unknown moving environment with physical barriers is a difficult proposition. In particular, having an optimal or near-optimal path that avoids obstacles is a major challenge. In this paper, a modified neuro-controller mechanism is proposed for controlling the movement of an indoor mobile robot. The proposed mechanism is based on the design of a modified Elman neural network (MENN) with an effective element aware gate (MEEG) as the neuro-controller. This controller is updated to overcome the rigid and dynamic barriers in the indoor area. The proposed controller is implemented with a mobile robot known as Khepera IV in a practical manner. The practical results demonstrate that the proposed mechanism is very efficient in terms of providing shortest distance to reach the goal with maximum velocity as compared with the MENN. Specifically, the MEEG is better than MENN in minimizing the error rate by 58.33%.

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1. INTRODUCTION

THE navigation of the mobile robot is very interesting area especially in the fields of healthcare, educations and services. Nowadays, intelligent mobile robot control system is developed to do a lot of applications [1–8]. The Non deterministic polynomial time (NP)-complete is one of the difficult problem in a navigation system, so the traditional methods to find an optimal solution is very hard with them. An intelligent methods which are based on artificial intelligent (AI) are most suitable and give a dramatically results to solve NP-complete problems. The aim of this paper is to develop the intelligent routing algorithm for the mobile robot navigation to control the movement of it from the start positing to target positing with overcome rigid and dynamic objects in the unknown area. Intact and efcient congregation navigation for mobile robot is a central yet challenging labor [2].

The use of artificial intelligent networks and machine learning with mobile robot navigation has now become a concern of researchers in recent. There are a lot of researchers focus on the use of many simulation and control strategies to control the mobile robot [9–12]. The use of AI as a controller to solve the problems of path planning of mobile robot in unknown environment are also considered by the researchers [13–16]. The powerful of the training algorithms for AI are very important issue to success the application that is designed for it.

This paper introduced neuro-controller mechanism to control the navigation of mobile robot. The proposed controller is utilized modified Elman neural network with element-aware attention gate (MEEG). This controller is able to estimate the trajectory of the movement and overcome rigid and dynamic barriers in an intelligent way. The main contributions of this paper can be outlined as:

– We propose a neuro-controller mechanism based on MEEG to control the navigating of the indoor mobile robot.
– We propose a modified architecture of Elman NN with intelligent element aware gate (MEEG) and modified training algorithm to learn MEEG.

The rest of this paper is presented as: Section 2 reviews related works. Section 3 presents the proposed system architecture and section 4 presents the proposed neuro-controller mechanism. Then, in section 5, the training algorithm of the proposed controller mechanism is explained. In section 6, data analysis is presented, in section 7, the practical implementation and the results are shown with discussed. Finally, the conclusion is provided in section 8.

2. RELATED RESEARCH WORK

This section introduces the most recent research relating to the use of AI in the field of mobile robot navigation. Chen *et al.* [3] presented an adaptive neural network (NN) control scheme for an uncertain wheeled mobile robot (WMR) with velocity constraints and non-holonomic constraints. Their simulation studied and practical experiments illustrated the effectiveness of the proposed control scheme.

Peng and Wang *et al.* [6] presented a design method for output feedback path-following control of under-actuated autonomous underwater vehicles. Two globally convergent recurrent neural networks called projection neural networks were used to solve the optimization problems in real-time. Simulation results substantiated the efcacy of the proposed method.

Dian *et al.* [17] established a mathematical model of a magnetic wheeled mobile robot (MWMR) with an intelligent discrete algorithm for trajectory tracking control to realize precise motion control of the robot. Simulations results were compared with those of neural network (NN) tracking control algorithm. Comparative analysis veried the effectiveness and advancement of their proposed method. Yudha *et al.* [14] presented the application of fuzzy logic control and NN in robot navigation and compared the performance in navigating the robot to the target. Their simulation results showed that NN application is more suitable confirmed by faster time in completing the task.

Al-Jamali and Shihab [18] proposed a modified algorithm for feedforward spike neural network (FSNN) for (Khepera IV) robot. The authors practically implemented the algorithm in two indoor environments, which have static and dynamic obstacles. The experimental results showed that,the proposed algorithm is more efficient than the other algorithms in terms of minimizing the distance and maximizing the speed for reaching to target. There are a lot of algorithms that are proposed by the researchers to empower the ability of AI to fast train with high quality of adaptation in variety applications [19–23] .

3. SYSTEM ARCHITECTURE

Figure 1, shows the proposed system architecture. The robotic platform of this work is the K-team Khepera IV. This is a cylindrical two-wheel robot with a 14 cm diameter and a 6 cm height. It has five infrared sensors as shown in Figure 1. These sensors have capability to emit and receive an infrared light with a range of measuring from (2 to 250 mm). The detached angle is $45°$ from the sensor neighbor of each sensor. More importantly, each Khepera IV is a full-fledged Linux computer running on a 800 MHz ARM Cortex-A8 Processor with 512 MB of RAM. The robot model lies on the assumptions that, i) robots have a limited communication range, ii) they can only perceive information in their local coordinate systems, and iii) they can exploit the "situated communication" model. In Figure 1, the inputs to the neuro-controller mechanism are the left space (LS), the right space (RS), and the front space (FS), which is collected from the infrared sensors. The RS variable represents the maximum value of right and front_ right sensors, the LS variable represents the maximization of left and front_left sensors, and FS variable represents the reading values of Front sensor. The variable TR represents the desired angle error to reach. In Figure 1, there are two controllers, one of them is for barriers avoidance and the other is for reaching to the desired. The mobile robot can switches to the barriers avoidance controller if (FS or LS or RS) is lower than a specific value (γ), otherwise, the wheeled robot will move to the desired unless the barrier shows. The neuro-controller mechanism has two identical models, each model has a modified structure of Elman NN with element aware attention gate (MEEG) one for controlling the right velocity and the other for controlling the left velocity. The flowchart of the proposed controller for navigation of the wheeled is illustrated in Figure 2.

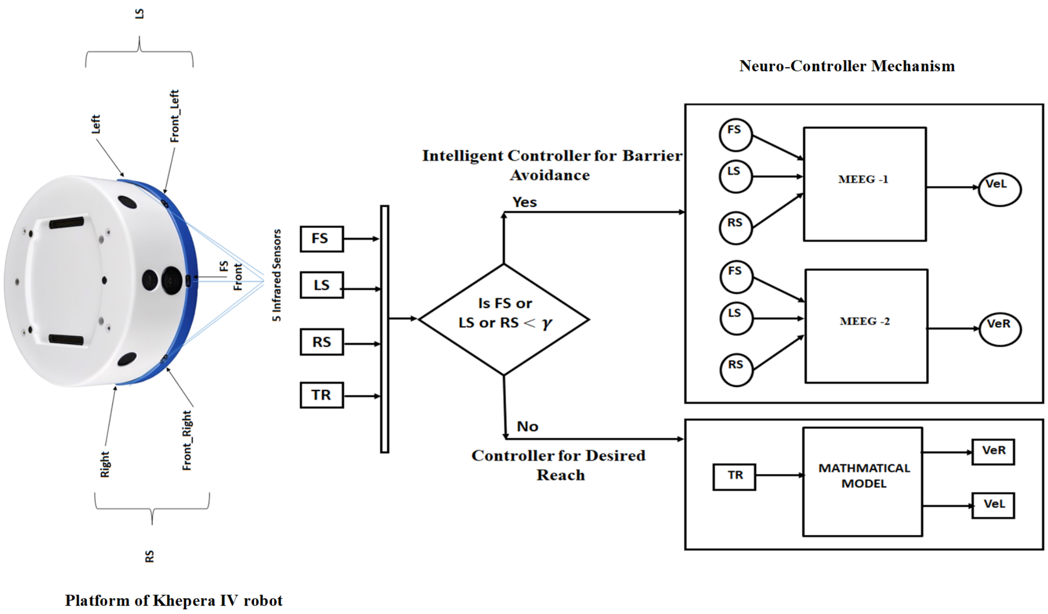

Figure 1. Proposed mobile robot navigation system

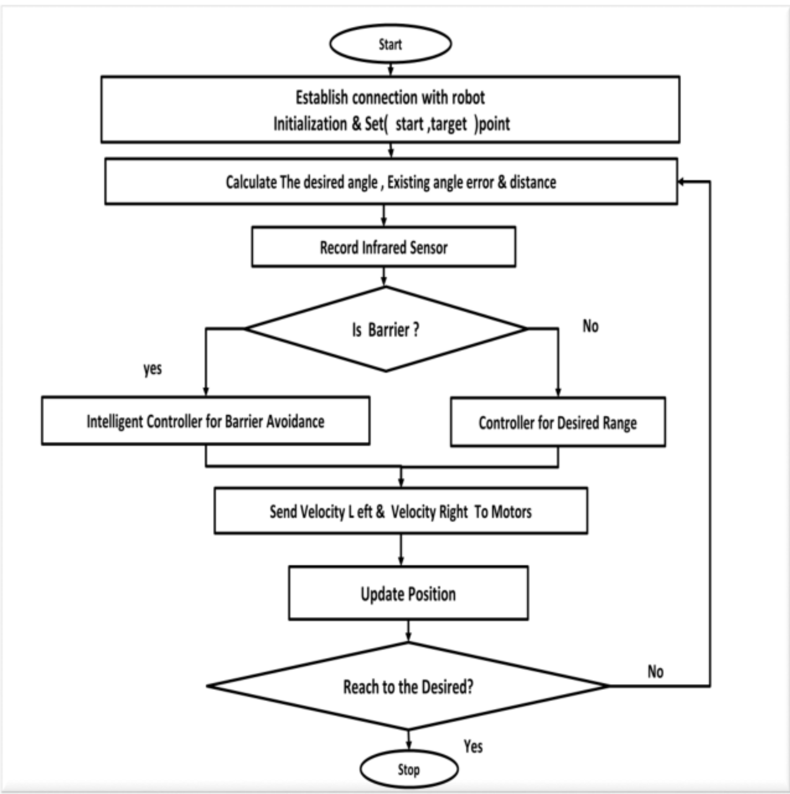

Figure 2. Flowchart of the proposed mobile robot navigation

4. THE PROPOSED NEURO-CONTROLLER MECHANISM

In this section, we describe the proposed neuro-controller. This controller is based on two type of controller, one of them is known as modified Elman with element aware attention gate as an intelligent controller for barriers overcome, while the other is based on mathematical model for controlling the desired range. We describe both of them as:

4.1. The controller for desired range

The wheeled robot is accessed to the desired point depended on the Ve_R and Ve_L which can be computed according to (1), (2):

$$Ve_R = \frac{2Ve}{r} + \frac{TR}{T_s \times r} \tag{1}$$

$$Ve_L = \frac{2Ve}{r} + \frac{TR}{T_s \times r} \tag{2}$$

Where Ve_R and Ve_L represent the right and left velocity respectively, r is the radius of the wheel of the robot with a sampling time Ts, Ve is the centroid linear velocity of the robot. TR is calculated as (3).

$$TR = \frac{\sin(\theta_D - \theta_e)}{\cos(\theta_D - \theta_e)}. \tag{3}$$

where θ_D is the desired angle and θ_e is the existing angle. The θ_D is calculated as:

$$\begin{aligned} \theta_D &= \frac{Y_{DD}}{X_{DD}} \\ Y_{DD} &= Y_D - Y \\ X_{DD} &= X_D - X \end{aligned} \tag{4}$$

X and Y are the Cartesian position of the robot, Y_D and X_D are the Cartesian of the desired point

4.2. Intelligent controller for barrier avoidance

The intelligent controller for barrier avoidance is designing based on modified Elman element aware attention gate (MEEG). Figure 3 explained the structure of the MEEG. In this Figure, the MEEG consists of three nodes in the input layer. Six nodes in the hidden layer with six nodes as the context layer, and one node in the output layer to control the right velocity Ve_R of the robot. The inputs to the context layer are the prior values of the hidden layer so that the count of nodes in the context layer is equal to the count of nodes in the hidden layer [24]. The input to the MEEG are FS, LS, and RS as shown in Figure 3(a). The structure also has a self-recurrent in the context layer to increase the short term memory of the NN. Each node in the context layer is represented as node with element aware attention gate. The internal structure of element aware attention gate is shown in Figure 3(b). This structure is the updated one from the structure that was proposed by [25]. The dynamic equations of the MEEG are described by (5), (6), (7):

$$G_t = \Omega(W_{LG}L_t + W_{HG}H_t) \tag{5}$$

$$H_t^c = \rho(H_{t-1}^c) + W_{HG}G_{t-1} \tag{6}$$

$$L_t^{\sim} = G_t \odot L_t \tag{7}$$

Where, Ω represents the activation function, $\odot$ represents the element aware product. W_{LG} and W_{HG} are the weight matrices. When the response of gate function is near to zero, the hidden layer state H_t^c with its self-recurrent is prompted to neglect the previous hidden state and shift with the current input individually. Figure 4 shows the internal structure of MEEG. The computations of the MEEG block are as (8):

$$
\begin{aligned}
R_1 &= \Omega(W_{LR}L_t^{\sim} + \rho W_{HR}H_{t-1}^{c}),\\
O_t &= \Phi(W_{LO}I_t^{\sim} + \rho W_{HO}H_{t-1}^{c}),\\
H^{c\sim}_{t} &= \tan(W_{LH}L_t^{\sim} + \rho W_{HH}(R_1 \odot \rho H_{t-1}^{c})),\\
H_t^{c} &= (1 - O_t) \odot \rho H_{t-1}^{c} + (O_t \odot H_t^{c\sim}).
\end{aligned} \tag{8}
$$

Where, W_{LR}, W_{HR},W_{LO},W_{HO},W_{LH} and W_{HH} are the weigh matrices in the internal element aware gate structure. The same structure is used for controlling the velocity left. The element aware gate empowers the structure of MEEN to control the navigation of the wheeled robot. So the wheeled robot will be able to avoid the obstacles and to access the desired point with shortest distance and high velocity. The back-propagation training algorithm in modified form is implemented for weights updated in the training mode.

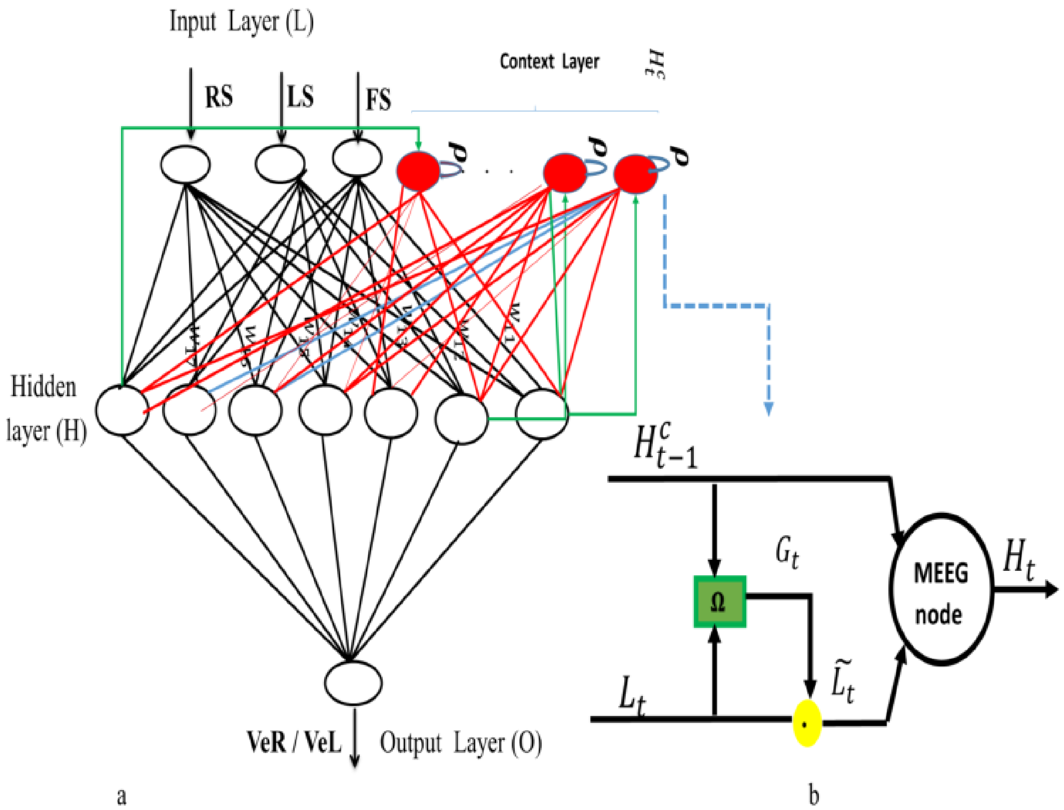

Figure 3. Strcture of modified Elman element wise gate

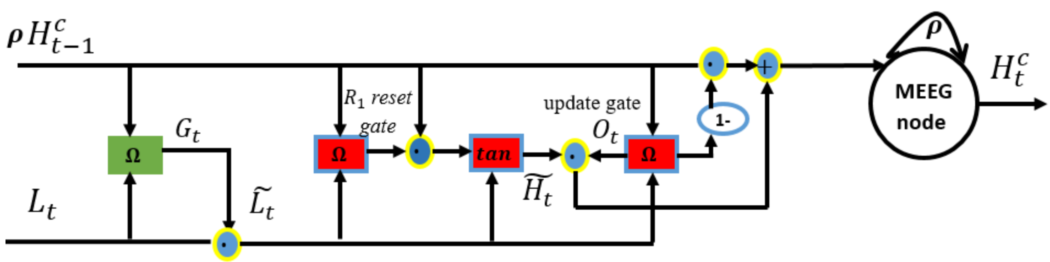

Figure 4. The internal structure of the element aware gate. Each line represents a vector, the self-recurrent ρ has a constant value between (0.21), the red boxes represent the modified EA with the output vector, the blue circles represent element wise operation (vector product or vector addition)

5. TRAINING ALGORITHM FOR MEEG

The modified training algorithm for MEEG is described in this section. The weights of the MEEG is updated through the training phase with offline and online stages. The activation function $\Omega(R_1)$ is defined as:

$$\Omega(R_1) = \tan\frac{(R_1)}{\tau} \tag{9}$$

For simplicity, we defined the function $\Phi(R_1)$ as y_H and $\Phi(O_t)$ as y_i. The error E represents the different between the desired and actual velocity is calculated as:

$$E = (VeR_d - VeR_a) \tag{10}$$

the weights of the hidden layer and output layer will be updated according to (11-16).

$$W_{LR}(t+1) = W_{LR}(t) - \Delta W_{LR}(t) \tag{11}$$

where

$$\Delta W_{LR}(t) = \eta.\delta_j.y_H \tag{12}$$

$$\delta_j = \frac{E}{\sum_{(i=1)}^{NH} W_{LR}\frac{\partial y_i}{\partial t}} \tag{13}$$

$$\delta_i = \frac{\sum_{(h=1)}^{(NH)} \delta_j W_{LR}\frac{\partial y_i}{\partial t}}{\sum_{(I=1)}^{NI} w_{LO}\frac{\partial y_h}{\partial t}} \tag{14}$$

$$W_{LO}(t+1) = W_{LO}(t) - \Delta W_{LO}(t) \tag{15}$$

where

$$\Delta W_{LO}(t) = \eta.\delta_i.y_i \tag{16}$$

The other weights W_{HR},W_{HO},W_{LH} and W_{HH} are updated by the same way.η is the learning rate and τ is the time constant

6. DATA ANALYSIS

At the beginning, The measurements of the sensors (MS) are weighted and normalized into values (0-1) before applying to the controller. This will improved the training process in terms of speeding up the training phase, and decreasing the probability of falling into local minimum during it. The normalization of the measurements of the sensors are described by (17).

$$MN_s = max(min(\frac{max_M - MS}{max_M - min_M}, 1), 0) \tag{17}$$

where max_M, min_M are the maximum and minimum values of measurements sensors respectively. The ranges of the measurements sensors are (0 to 1022 A.). The sensor records the value 1022; when the barrier is very near and 0.1 when the barrier is far. Because the difficulties that is faced in the training process when use this big values of the range, this range will be mapped into (0-1). This means that the record value 1 represents that there is no barrier in the way of robot and the record value 0 represents that the barrier is very near. To speed up the training process, the pattern that is used to train MEEG is re-scaled to new record as (0.1, 0.5, 0.9). Each value represents near, average, and out of the way barriers respectively. The output is the velocity which is weighted to (-2.5, -1.5, 1.5, 2.5) to represents reverse quick, reverse slow, progress slow, progress quick respectively. The velocity weight parameter is selected in such away that increases the speed gradually and then quit for a maximum speed that the wheeled robot can be accessed without collide with barrier. For simplicity we explain some of examples for these patterns as:

If RS=0.85,LS=0.45,and FS=0.25 then VeL=2 and VeR=-2
If RS=0.85, LS=0.85, and FS=0.85 then VeL=2 and VeR=
If RS=0.25, LS=0.85, and FS=0.85 then VeL=1 and VeR=2
If RS=0.85, LS=0.25, and FS=0.85 then VeL=2 and VeR=1
If RS=0.25, LS=0.85, and FS=0.85 then VeL=1 and VeR=2

7. PRACTICAL SETUP AND EVALUATION

We implement two experiments based on the proposed mechanism with the environment size is (280×190). The start point is (0.1,0.1) and the desired point is (260.0). The connection between Khepera IV robot and the laptop is setup via Bluetooth and the Tera Term emulator is used to communicate between the wheeled robot and laptop. The sampling time is 0.08 sec. for the two scenarios. The comparison is done between the proposed mechanism and that one based on MENN. Figure 5 shows the rate of error through offline training as a comparison between the MEEG and MENN. It is clear form Figure 5 that the performance of MEEG is better than the performance of MENN in terms of minimizing the error rate with minimum number of epochs. The practical results are shown in Table 1 and the working environments have a number of static obstacles and number of dynamic obstacles It is clear from the results in Table 1 that the MEEG is more efficient than MENN in terms of shortest distance with high speed to reach the target. Figures 6 and 7 represent the performance of Khepera IV robot with static and dynamic obstacles in the environment. The size of the enviroment is (100×100). The start point is (48.12) and the desired point is (94.92). The dashed red line represents the robot's path when MENN is used while the soild blue line represents the robot's path when MEEG is used. It is clear that the performance of robot based on MEEG is better than that one based on MENN, in terms of accurate reaching to the target point and avoiding the obstacles as well. it is clear from Figure 7 that the Khepera IV robot response very quickly and avoids the obstacles in the environment and this reaction is appeared very clearly when using the MEEG as neuro-controller as compared with the performance of the robot with MENN The performance of the robot is also very good in dynamic obstacle environment as shown in Figure 7 in terms of fast adaptive with all types of obstacles in the area as compared with the performance of robot when MENN is used as obstacles avoidance controller.

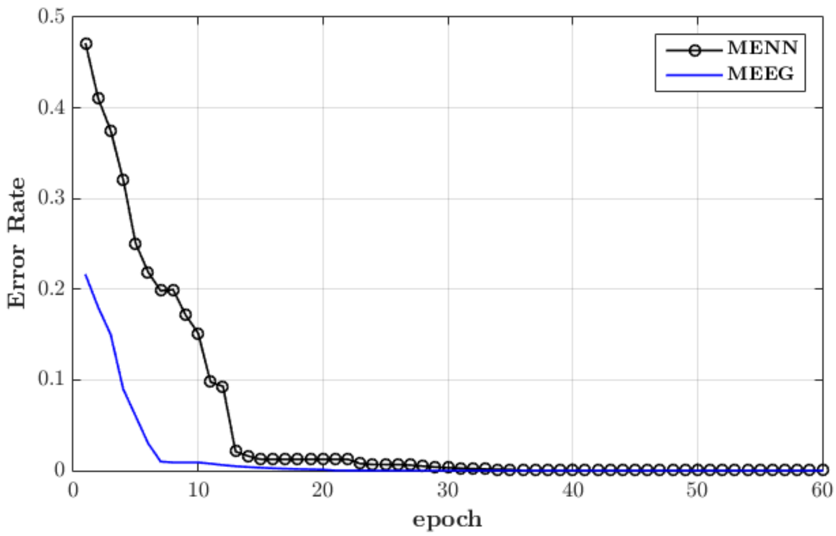

Figure 5. The error rate minimization during offline mode

Table 1. Practical result of the areas

Area	Type of Controller	Distance (cm)	Time (sec.)	Speed
1	MEEG	160.6	13.18	12.18
1	MENN	165.3	15.19	10.88
2	MEEG	183.9	17.85	10.30
2	MENN	188.6	19.54	9.65

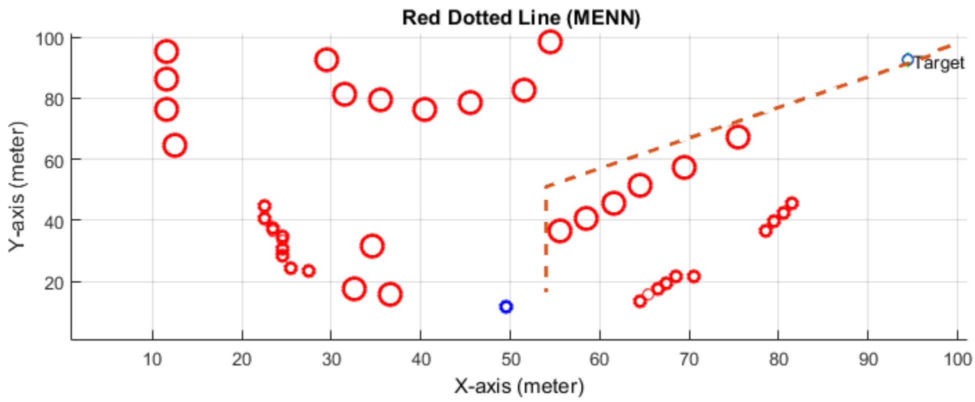

Figure 6. The simulation environment, the scattered red circle represent the fixed barriers whilst the close interconnected ones represent the mobile barriers

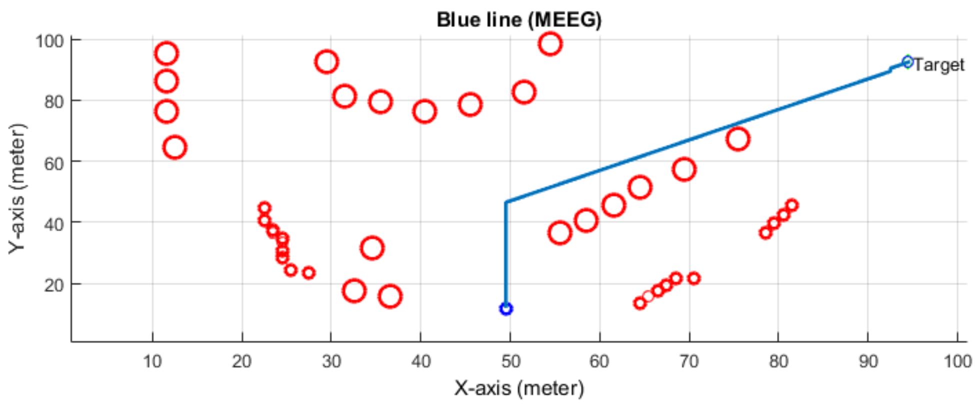

Figure 7. The simulation environment, the scattered red circle represent the fixed barriers whilst the close interconnected ones represent the mobile barriers

8. CONCLUSION

This paper presented the modified structure with the modified training algorithm for MEEG to overcome the barriers in indoor area. The wheeled robot (Khepera IV) robot is used for practical experiments. Two experiments are implemented with rigid and dynamic barriers areas. The practical results show that the proposed controller has reached the goal with high speed and shortest distance as compared with MENN controller. The MEEG reaches to the error goal during training algorithm at epochs 25 as compared with MENN (at epochs 60), so the MEEG is better than MENN is minimizing the error rate by 58.33%.

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