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Fuzzy Neural Network based RFID Positioning and Navigation Method for Mobile Robots

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Abstract: This study proposes the Radio Frequency Identification (RFID) indoor positioning and navigation method based on fuzzy neural network. The proposed method is applied to a wheelchair home health care robot with wireless communication. One reader and four tags are used. Based on the Received Signal Strength Indication (RSSI) data, the position of the robot can be determined. Further, to overcome the measurement error problem due to environmental parameter variation, a Fuzzy Neural Network (FNN) is proposed to compensate the measurement data. The FNN automatically adjust the weight, the variance and the mean value to overcome effectively the environmental parameter variation. A back-propagation algorithm is developed to achieve self-learning. The successful experiment results show that the proposed system architecture and positioning system provide satisfactory accuracy and make home health care wheelchair robot positioning system available for navigation and guidance.

Keywords: Fuzzy neural network, indoor positioning, RFID, RSSI, wheelchair robot

INTRODUCTION

With the social and elderly population growth, human medical science and health care technology have gained much attention in recent years. The home care robot is particularly focused on the wheelchair robot for the aged people (Cooper *et al*., 2008). Consider an intelligent wheelchair robot that combines manipulation and mobility assistance with perception and decision-making. Some commonly used sensors include infrared sensors, ultrasonic sensors, gyroscopes, accelerometers, radio frequency identification systems, laser range finder, camera and so on Vachhani and Sridharan (2008), Misono *et al*. (2007), Celeste *et al*. (2008) and Ho *et al*. (2011). Many researchers have worked on automatic indoor positioning for years, for example, RFID indoor positioning system many researchers have worked on automatic indoor positioning for years, for example, the RFID indoor positioning systems (Ho *et al*., 2004).

Radio frequency identification indoor positioning system has been made significant progress. The hardware strategy is divided into active and passive. The application of passive RFID technology is extensive in various fields. Recently, the active RFID technology has been applied to develop indoor concerning the indoor positioning wheelchair robots. These robots need a number of sensors for positioning/navigation and result in complex system architectures.

In this study, an RFID indoor positioning technology for wheelchair home health care robots is proposed. Ultrasonic sensors are used to detect and avoid obstacles while navigating the wheelchair robot. With four tags and one reader, we measure the signal strength and calculate the position of the wheelchair robot. Further, to deal with the disturbed experimental RFID data leading to incorrect localization, we further develop the fuzzy neural network technology to compensate the measurement RSSI data. With the self-learning functions, the FNN technology can be applied to robotic applications.

Fig. 1: The prototype of the IRW

Our study intends to support an on-going research project in the Gerontechnology Research Center in Yuan Ze University, Taiwan in developing an Intelligent Robotic Wheelchair (IRW) as shown in Fig. 1. The goal of this project is to redefine the

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wheelchair as the center of mobility, everyday living and healthcare for the senior users. In this study, the proposed fuzzy neural network effectively overcomes the environmental parameter variation and compensates the uncertain RSSI value. Experimental result shows that the proposed system architecture and localization technique are indeed effective.

RFID INDOOR POSITIONING METHOD

The proposed positioning system consists of 2.4 GHz active RFID components which are four active tags and one active reader. The signals transmitted from four tags are collected by the reader setting on the wheelchair robot. They are further weighted and calculated in the world coordinates. Figure 2 shows the experimental floor on it every 50 cm of distance being one unit. The room size in experiment is 25 m^2. There are totally 81 measuring points.

Figure 3 is the schematic diagram of the RFID location sensing. According to the measured RSSI value from each tag to the reader, the distance between each tag to the reader can be estimated. There are four tags, so the distances are defined as the radii R_α, R_b, R_c, and R_d, respectively. Long dotted line, short dotted line, point long dotted line and point short dotted line represent respectively the converted distance of the four tags according to the measured RSSI values. Moreover, A-B intersections: W1 and W2, A-C intersection: P1 and P2, A-D intersection: Q1 and Q2, B-C intersection:

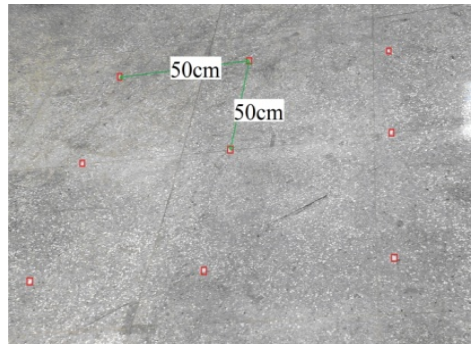


Fig. 2: The experimental environment (81 measuring points on the floor)

S1 and S2, B-D intersection: U1 and U2, C-D intersection: V1 and V2. These intersectional points can be calculated by the following formulas:

A-B intersection W:

$$\begin{cases} W(x_a, y_w) \Rightarrow \sqrt{(x_a - x_w)^2 + (y_a - y_w)^2} = R_a \\ W(x_b, y_w) \Rightarrow \sqrt{(x_b - x_w)^2 + (y_b - y_w)^2} = R_b \end{cases} \quad (1)$$

A-C intersection P:

$$\begin{cases} P(x_a, y_p) \Rightarrow \sqrt{(x_a - x_p)^2 + (y_a - y_p)^2} = R_a \\ P(x_c, y_p) \Rightarrow \sqrt{(x_c - x_p)^2 + (y_c - y_p)^2} = R_c \end{cases} \quad (2)$$

A-D intersection Q:

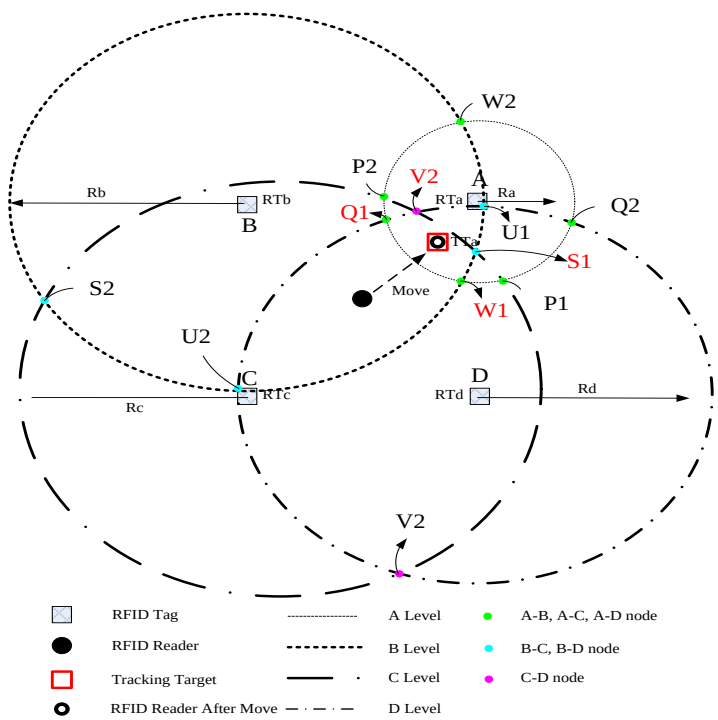


Fig. 3: Illustration of the operation of RFID localization

$$\begin{cases} Q(x_a, y_q) \Rightarrow \sqrt{(x_a - x_q)^2 + (y_a - y_q)^2} = R_a \\ Q(x_d, y_q) \Rightarrow \sqrt{(x_d - x_q)^2 + (y_d - y_q)^2} = R_d \end{cases} \quad (3)$$

B-C intersection S:

$$\begin{cases} S(x_b, y_s) \Rightarrow \sqrt{(x_b - x_s)^2 + (y_b - y_s)^2} = R_b \\ S(x_c, y_s) \Rightarrow \sqrt{(x_c - x_s)^2 + (y_c - y_s)^2} = R_c \end{cases} \quad (4)$$

B-D intersection U:

$$\begin{cases} U(x_b, y_u) \Rightarrow \sqrt{(x_b - x_u)^2 + (y_b - y_u)^2} = R_b \\ U(x_d, y_u) \Rightarrow \sqrt{(x_d - x_u)^2 + (y_d - y_u)^2} = R_d \end{cases} \quad (5)$$

C-D intersection V:

$$\begin{cases} V(x_c, y_v) \Rightarrow \sqrt{(x_c - x_v)^2 + (y_c - y_v)^2} = R_c \\ V(x_d, y_v) \Rightarrow \sqrt{(x_d - x_v)^2 + (y_d - y_v)^2} = R_d \end{cases} \quad (6)$$

Consequently, W (x_W, y_W), P (x_P, y_P), Q (x_Q, y_Q), S (x_S, y_S), U (x_U, y_U), and V (x_V, y_V), are obtained. Applying the above algorithm, the exact location of the wheelchair robot can be obtained.

The definition of coordinates for the RFID tag is Tag_A (A_x, A_y). Each measured RSSI value recorded from the reader to the associated tag is expressed as Tag R_i, i = 1, 2, …, 4,. Due to varying RSSI values in the experimental environment considering the multi-path fading and the shadowing effect that lead to measurement error. The maximum and minimum RSSI values read by the reader are defined as R_{max} and R_{min} and its scope is defined as:

$$R_{scope} = R_{\max} - R_{\min} \quad (7)$$

Let w_i be the weight between the reader and Tag i, i.e.:

$$w_i = \frac{R_{scope}}{R_{\max} - Reader R_i} \quad (8)$$

$$Reader_A = (A_x, A_y) = \left(\frac{\sum_{i=1}^{n} R_{i\_x} \cdot w_i^2}{\sum_{i=1}^{n} w_i^2}, \frac{\sum_{i=1}^{n} R_{i\_y} \cdot w_i^2}{\sum_{i=1}^{n} w_i^2} \right) \quad (9)$$

where, R_{i_x} and R_{i_y} are the X and Y coordinates of ith tag, w_i is the weighting value between i^{th} tag and the reader. Suppose the target coordinates is e = ($Target_x$, $Target_y$) and the error is Error = $Target_A$-Tag_A. Then:

$$Error = (e_x, e_y) = (Target_x - A_x, Target_y - A_y) \quad (10)$$

In short, (8) and (9) are computed to get (10). The FNN on-line tunes the weighting values iteratively. The calculated coordinates are sent to the Field Programmable Gate Array (FPGA). Then the FPGA

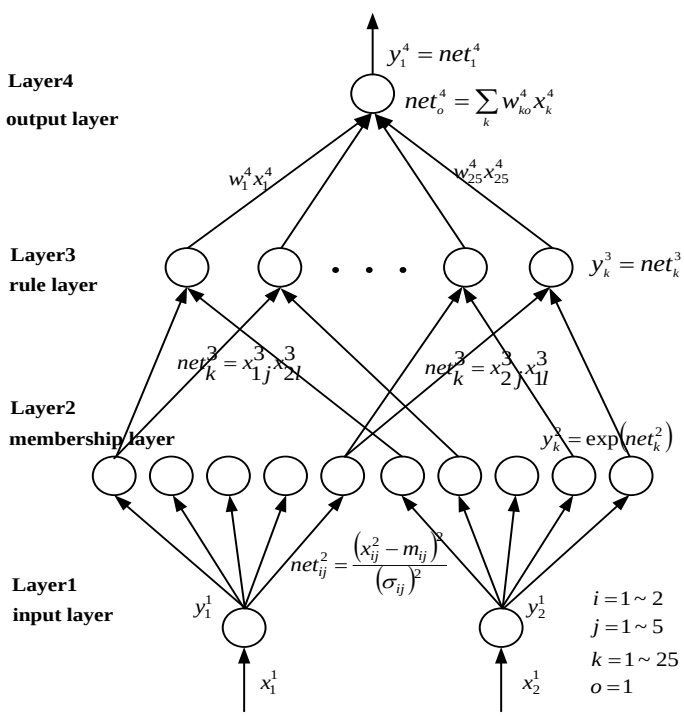


Fig. 4: The structure of the fuzzy neural network

determines the necessary control commands for the navigation and obstacle avoidance of the wheelchair robot.

FUZZY NEURAL NETWORK

The structure of the FNN is shown in Fig. 4. The purpose here is to improve the accuracy of the localization[9]. Define Layer 1, 2, 3 and 4 be the input layer, the membership layer, the rule layer and the output layer, respectively. Let the number of neurons be f (x) = x. Define the X-axis error be e_x and Y-axis error be e_y. The error difference $\dot{e}_x$ and $\dot{e}_y$ are selected to be input variables. For every neuron in the input layer, the net input and the net output can be represented as:

$$x_1^1 = e_c,\ \ x_2^1 = \dot{e}_c,\ c = x, y \tag{11}$$

$$y_i^1 = f_i^1\left(net_i^1\right) = x_i^1,\ i = 1, 2 \tag{12}$$

In the membership layer, each neuron performs a membership function. The Gaussian function is adopted to be the membership function. The net outputs are:

$$net_{ij}^2 = \frac{\left(x_i^2 - m_{ij}\right)^2}{\left(\sigma_{ij}\right)^2}\quad i = 1, 2,\ j = 1,\ldots,5 \tag{13}$$

$$y_{ij}^2 = f_{ij}^2\left(net_{ij}^2\right) = \exp\left(net_{ij}^2\right),\ i = 1, 2,\ \ j = 1,\ldots,5, \tag{14}$$

where, m_{ij} and σ_{ij} are the mean and the standard deviation of the Gaussian function, respectively.

In the rule layer, each neuron multiplies the input signals and sends out the product, i.e.:

$$net_k^3 = x_{1j}^3 x_{2l}^3,\ \ j, l = 1,...,5,\ k = 1,...,25 \tag{15}$$

$$y_k^3 = f_k^3\left(net_k^3\right) = net_k^3,\ \ k = 1,...,25 \tag{16}$$

where,
x^3_{lj} : The jth input to the neuron of Layer 3
x^3_{2l} : The lth input to the neuron of Layer 3

The overall output is the summation of all incoming signals, i.e.:

$$net_o^4 = \sum_k w_{ko}^4 x_k^4,\ \ k = 1,...,25,\ \ o = 1, \tag{17}$$

$$y_o^4 = f_o^4\left(net_o^4\right) = net_o^4,\ \ o = 1, \tag{18}$$

where,
x^4_k : The kth input to the neuron of Layer 4 and the connecting weight
x^4_{ko} : The output action strength of the oth output associated with the kth rule.

Next, to determine whether the FNN finishes learning, define a cost function E as:

$$E = \frac{1}{2}\left(Y_i - y_i^4\right)^2 \tag{19}$$

where,
Y_i = The target
y_i = The output of FNN controller

In order to minimize the cost function, the gradient decent method is adopted to tune those parameters and weights. The learning rate affects the variation of the parameters and the weights. The learning algorithm based on the back-propagation method is represented below. The error term to be propagated is given by:

$$\delta_1^4 = -\left(\frac{\partial E}{\partial y_1^4}\frac{\partial y_1^4}{\partial net_1^4}\right) = \left(Y_1 - y_1^4\right) \tag{20}$$

$$\Delta w_k = \eta_w\left(Y_1 - y_1^4\right)x_k^4 \tag{21}$$

where,
w_k = The weight between the rule layer and the output layer
η_w = The learning rate of the connected weight

After the weights are updated, the means and variances of the Gaussian functions in the membership layer will be tuned with the outputs of the rule layer. The error term to be propagated is given by:

$$\delta_k^3 = -\frac{\partial E}{\partial net_k^3} = \delta_1^4 w_k \tag{22}$$

$$\delta_{1j}^2 = -\frac{\partial E}{\partial net_j^2} = \sum_j \delta_k^3 y_{1j}^3 \tag{23}$$

$$\delta_{2j}^2 = -\frac{\partial E}{\partial net_j^2} = \sum_j \delta_k^3 y_{2j}^3 \tag{24}$$

$$\Delta m_{ij} = -\eta_m \frac{\partial E}{\partial m_{ij}} = \eta_m \delta_{ij}^2 \frac{2\left(x_i^2 - m_{ij}\right)}{\left(\sigma_{ij}\right)^2} \tag{25}$$

$$\Delta \sigma_{ij} = -\eta_\sigma \frac{\partial E}{\partial \sigma_{ij}} = \eta_\sigma \delta_{ij}^2 \frac{2\left(x_i^2 - m_{ij}\right)^2}{\left(\sigma_{ij}\right)^3} \tag{26}$$

where,
m_{ij} = The mean of the Gaussian function in the membership layer
σ_{ij} = The variance of the Gaussian function in the membership layer

η_m = The learning rate of the mean
η_σ = The learning rate of the variance

Every weight, mean and variance is updated as:

$$w_k = w_k + \Delta w_k \tag{27}$$

$$m_{ij} = m_{ij} + \Delta m_{ij} \tag{28}$$

$$\sigma_{ij} = \sigma_{ij} + \Delta \sigma_{ij} \tag{29}$$

Note that FNN off-line learns the environment. Then the updated parameters are used for the indoor localization.

EXPERIMENTAL RESULTS

In the experiment, the RFID components include one 2.4 GHz active reader and four tags. The reader is setup on the wheelchair robot. The space size of the experiment is 5 m in length and width. Indoor signal transmission quality affects positioning precision. In fact, indoor signals could be easily interfered by signal reflection, scattering, diffraction, multi-path fading and shadowing effect. The weighting algorithm is used for the calculation to get the real measurement data and display them on the map coordinate. The measurement of RSSI values in 81 test points from Tag 1, 2, 3 and 4 is shown in Fig. 5.

The angle of the RFID Tag placement affects the accuracy remarkably. Hence, we add bar antenna on RFID tags to reduce the directional influence. After adding the antenna, the average measurement error reduces to below 0.7 m, while it was 1 to 1.5 m without using the antenna. Then, the Fuzzy neural network is applied to further reduce positioning errors. The adjusted weight, variance and the mean are shown in Fig. 6.

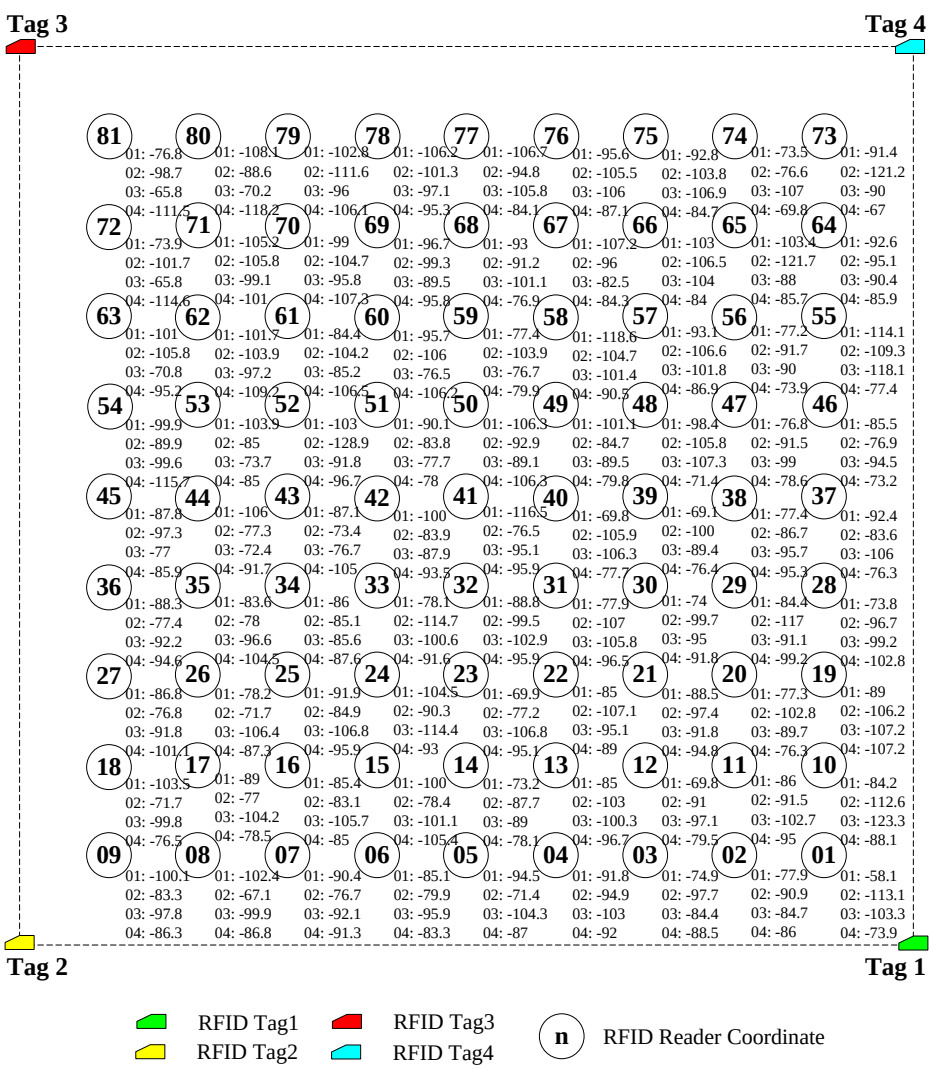
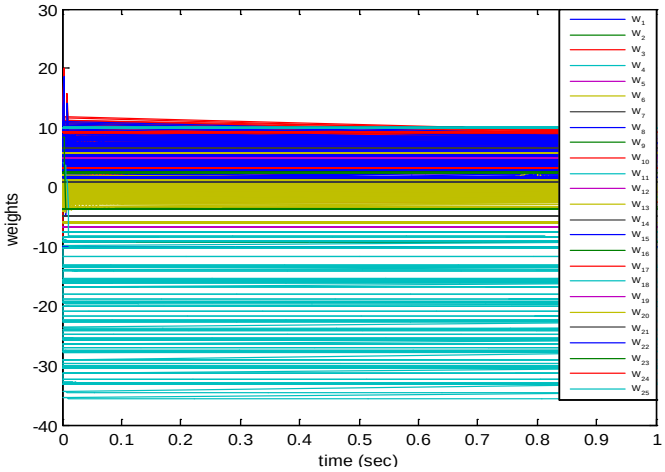
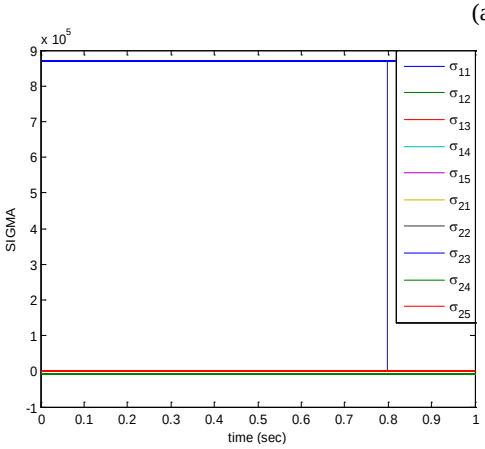


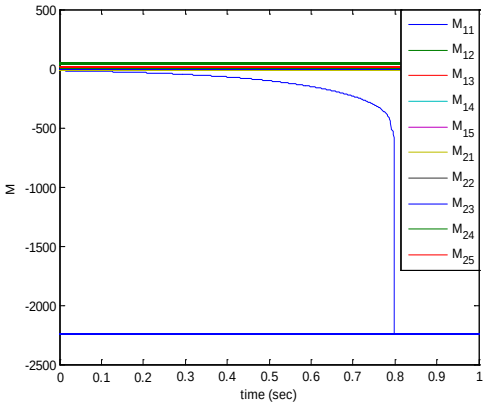
Fig. 5: The measured RSSI values and the testing points



(a)



(b)



(c)

Fig. 6: The weight, variance and mean diagram of the FNN

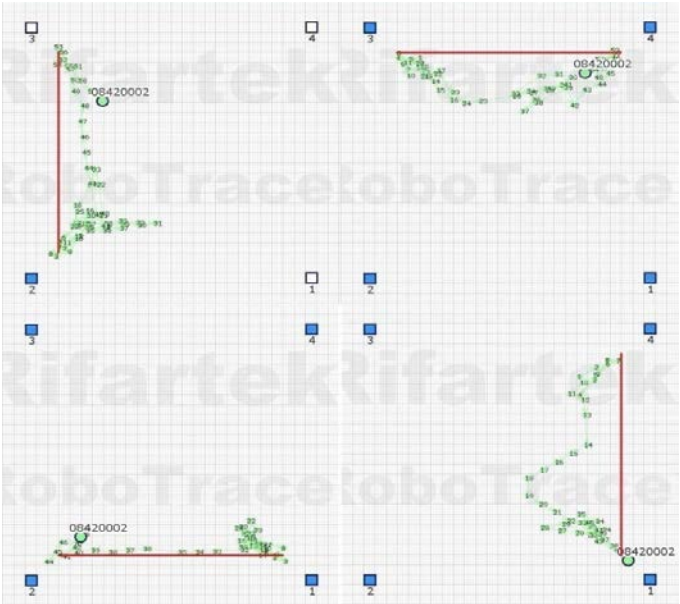


Fig. 7: The tracks of the wheelchair robot

Next, the wheelchair robot is driven to move forward. The tracking error between the actual distance and the measured distance is larger than while the wheelchair robot stands still. With the parameter adjustment by using the proposed FNN, the average error is reduced. It is also found that when the wheelchair robot moves faster, the error becomes larger. A worst case typical experimental result is shown in Fig. 7, where the track of the wheelchair robot can be determined by applying the proposed method. The red lines are the actual tracks of the robot and the continuous green dots are the locations obtained through FNN positioning. Experimental result shows that the localization error can be smaller than 2 m as long as the moving speed of the robots is not more than 20 m/min. In short, the proposed system is realized and verified to have relatively accurate indoor localization. The use of FNN further increases the accuracy on the real measurement.

CONCLUSION

In this study, an RFID technology with the use of fuzzy neural network for indoor positioning of wheelchair home health care robots is proposed. The proposed RFID positioning system includes one 2.4 GHz RFID reader and four tags. The computational algorithm is somewhat similar to that with four readers and one tag. Yet the cost is much lower. Further, the FNN technology for adjusting the positioning system parameters increases the environmental adaptability and positioning accuracy. Experimental result shows that the localization error can be smaller than 2 m as long as the moving speed of the robots is not more than 20 m/min. The successful result can be applied to most of the wheelchair robots. Therefore, the method is indeed practical in many applications.

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