

Study of Localisation Methods of Mobile Users in Wireless Sensor Networks

Manoj Duhan¹, Satinder²

Profesor, ECE Department, DCRUST-Murthal, Sonipat, India¹

M.TECH Student in ECE Department, DCRUST-Murthal, Sonipat, India²

Abstract: To track the exact position of a mobile user is an important role for location services in an indoor environment. Low power, low cost and low complexity are the important characteristics of wireless sensor network. Indoor position system performance can be enhanced drastically with these properties. Diffraction, scattering and reflection has adverse effect on radio signal propagation, therefore the received signal strength requires good calibration method to provide accurate position. In this paper, grey prediction method is used in wireless sensor network and it makes use of wireless techniques (Zigbee/802.15.4). Received Signal Strength Indicator (RSSI) is predicted using the grey prediction, and Dynamic triangular (DTN) location method is also designed. For performance analysis, mean distant error of RSSI at offline stage on mobile user can be within 2.3m. In run time stage, grey prediction give more accurate predicted position and carries out mean distance error within 1.3 m.

Keywords: NLOS, Triangulation, RSSI, DTN and Grey Prediction.

I. INTRODUCTION

A wireless sensor network (wsn) is a distributed collection of nodes which are resource constrained and capable of operating with minimal user attendance. the nodes are distributed spatially to cooperatively monitor physical or environmental conditions, such as temperature, sound, motion, pressure, vibration or pollutants at different locations [1]. such nodes are usually embedded and report sensed data to a central base station. The base station (or gateway) can communicate with a number of wireless sensors via a radio link. Wireless sensor node collect, compressed, and transmitted the data to the central base station directly or, if required, uses other wireless sensor node to forward data to the gateway. the gateway connection then presents transmitted data to the system [1].

Localization is an inevitable challenge when dealing with wireless sensor nodes, and a problem which has been studied for many years. The localization problem has received considerable attention in the past, as many applications need to know where objects or persons are, and hence various location services have been created. Localization is usually carried out by measuring certain distance parameters of wireless radio link between the localization node and different localization base stations. There are many localization schemes for the localization of wireless sensor network. In this paper the main idea is comprise on approaches based on received signal strength indication (RSSI). The algorithm enables localization of moving wireless devices in an indoor setting. The algorithm used in this paper (grey prediction) provide low cost and low complexity, hence is most feasible.

II. LITERATURE REVIEW

A large number of researchers have worked in this field. In this paper we only focus on the indoor location system that exploits the RSSI to estimate location. The beginning

research was based on RARAR system for wireless LAN-based location estimation that record relationship from location and signal strength from each base station and establish the database at offline stage, in case of run time stage the base stations receive beacons that are transmitted from mobile user and find the most suitable match signal strength from k-nearest neighbours (KNN), and infer the location of mobile user. There are two methods based on RARAR for the estimation of location, one is use the empirical method and the other is signal propagation method [2].

The triangulation (TN) method is most widely used in location system such as GPS. The signal region circles that are generated from different base stations and there overlapped product is consider as the estimation of location in case of TN m method [6]. The other two different kind of wireless devices (IEEE802.11 and Bluetooth) has been utilized that provide overlapping coverage, and merge the signal strength data from multiple devices. For finding the location of mobile user they employ the smallest polygon algorithm. A candidate location set is estimated by each base station and SMP finds the smallest distinct vertex polygon from the candidate location set. The centroid of smallest polygon is assumed as the location of mobile user [6].

Another technique that is used at offline stage Learning Vector Quantization (LVQ) is a kind of neural network. This method uses the measured signal strength from several base stations at different locations to train the learning vector quantization. In this method a room is divided into several names of locations and a trained LVQ is used to determine names of the location where user present [5]. One more technique given by Gwon Y et al. Triangular (TIX) algorithm says that at least three Aps are required by TIX algorithm. TIX chooses the three base stations which measure highest three mobile user's RSSIs.

A triangle is formed by these base stations and finding the ratio of triangular sides which using measured RSSIs. The sides of triangle are used by TIX to estimate the final location of mobile user.

III. FRAMEWORK OF SYSTEM

The test-bed of our experiment is shown in fig.1. In our scenario when mobile user moves in building and locomotion of mobile user can be estimated by location system. Four CC2420BK Demonstration Board Kits labelled S1, S2, S3 and S4 is placed in our laboratory. The sensors nodes and mobile user equipped with a 2.4 GHz wireless interface (zigbee). The coordinate system is established by sensors node when mobile user moves around in blue colour zone in our laboratory. The system architecture is shown in fig.2. The predicted RSSIs can be computed by grey prediction when each sensor node receives RSSIs generated by mobile user. Predicted RSSIs can be used to estimate the location of mobile user from coordinate system. Different location algorithm such as SMP, KNN, DTN and TN those are used to estimate the location of mobile user are denoted by coordinate system. Here the algorithm describes in detail is DTN location method.

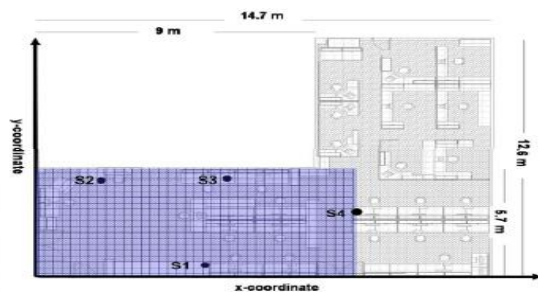


Figure 1 Test Bed

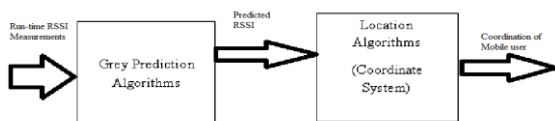


Figure2: Depicts location estimation system

A. RADIO PROPAGATION MODEL

The location of mobile user can be estimated in our laboratory by first determining the distance between the mobile user and sensor nodes. Then estimated distance is putted into different location algorithms (TN, SMP and DTN) to form the coordination of mobile user. The radio propagation model at off-line can be found by maximum likelihood (ML) method. Some phenomena such as reflections, diffraction and scattering induce the obstacles in a building during radio propagation. The NLOS (Non-Line-Of-Sight) and measuring errors contaminate the measurements of radio signal strength. With better SNR (signal to noise ratio) the measuring errors results from measuring process in a noisy channel, can be improved. NLOS errors depend on the multipath-dominated environments and vary from time to time.

The distances between the mobile user and sensor nodes and the RSSIs are recorded, and use the ML method is

used to find a propagation model for fading channel. The mean RSSI (d) that received from the mobile user is provided by radio propagation model and equation (1) states that. Here n is the path loss exponent and the RSSI (d) is the received signal strength in dB at a reference distance. The measured RSSI is calculated by the ML and find the parameter n and RSSI (d_0). The fit channel model for measured RSSI is obtained by using equation (1). \hat{d} is the estimated distance from equation (2), and X_σ is the random variable that denotes the estimation error with variance σ^2 from equation (3). We noted that random variable X_σ increase with distance between the mobile user and the sensor node in fig.3. Therefore at-least three sensor nodes are chosen by the proposed DTN to estimate the location of mobile user. The strongest RSSI is able to estimate distance with small distance error, so DTN improve the accuracy of location estimation.

$$RSSI(d) = RSS(d_0) - 10 \log \left(\frac{d}{d_0} \right) \quad (1)$$

$$\hat{d} = d_0 * 10^{\left(\frac{RSSI(d) - RSSI(d_0)}{10n} \right)} \quad (2)$$

$$\hat{d} = d + X_\sigma \quad (3)$$

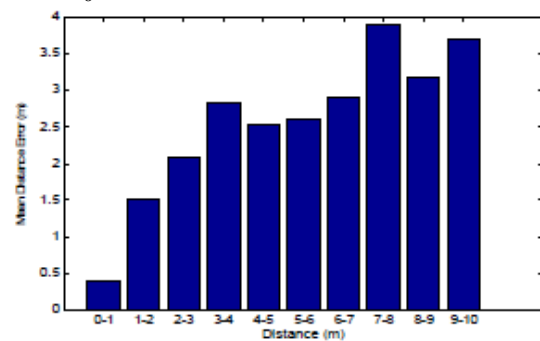


Figure 3: Represents estimation distance error

B. Local Coordination System

Local coordination system is introduced in this section, this system keeps the scalability if as number of nodes increases, and estimates user location in high density of sensor network. It is assumed that each sensor node knows its location, and a small set of total sensor nodes in a room is established by local coordination system. This set contained at-least three sensor nodes. In the following discussion, we talk about the formation of local estimation and its communication protocol. Beacons are sends to its adjacent nodes periodically by mobile user when moves in an office. Sensor nodes broadcast the RSSIs that receive from the mobile user, and the sensor node which receives the strongest RSSI declares itself as master node. Then master node send a message to each sensor node to establishes as master, message including the master node ID, mobile node ID and time slot. Local coordination synchronization is achieved by time slot. The other nodes those receives the message call the slave nodes. The RSSI of the mobile user is forwarded by the slave nodes to the master node, message including the mobile node ID, master node ID, RSSI of mobile node and time slot. The master node receives the message and then estimates the location of mobile node. At-last the master node send the coordinate of the mobile user to the master node and location server. The coordinates and the mobile node ID

are composed in location message. The location server and mobile node knows its location from this coordination system. The sensor nodes are equipped with different location algorithms such as KNN, SMP, DTN and TN.

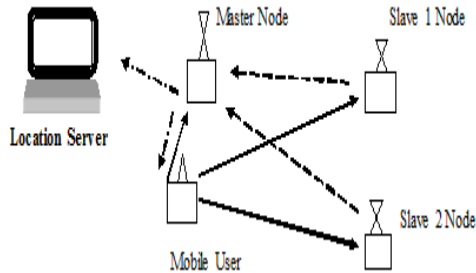





Figure 4: The location estimation system

- (1)  Mobile node sends beacons to the adjacent sensor nodes periodically
- (2)  Mobile node broadcasts the message to establish location estimation system
- (3)  Master node sends the location of the mobile user to the location server & the mobile user

C. Dynamic Triangular Algorithm

At-least three sensor nodes are required by DTN to estimate the location of mobile user. We use four sensor nodes in our experiment. Worst RSSI measured by a sensor node will be discarded by DTN and other sensor nodes are used to estimate the location. A node which receives the strongest RSSI is chosen by DTN and taken as master node, and assume the mobile user's location in mapping circle of master node. The mapping circle is the estimation distance d_1 between the master node and mobile user. DTN finds the angle θ on mapping circle by using a cost function to pick one that best matches the observed distance. Following steps are comprised in DTN:

1. To generate the mapping circle: best possible location of mobile user $(x_1+d_1\cos\theta, y_1+d_1\sin\theta)$ found by DTN on the mapping circle by using the possible distances ($d_2\theta, d_3\theta$) between the mobile user and slave nodes.
2. The distance of mobile user estimation: A error between the estimation distances (d_2 and d_3) and possible distances ($d_2\theta, d_3\theta$) is found by the DTN.
3. The coordinate of mobile approximation: A cost function at each angle θ is calculated by DTN and θ increase one degree at each time. DTN search the minimum cost function, and θ of minimum cost function is estimation angle on mapping circle. The angle θ on the mapping circle is the estimation location \hat{D} of mobile user. Figure5 describes the procedure of DTN location algorithm. At-last we shift the local coordinate \hat{D} and find the global coordinate of mobile user $(x_1+d_1\cos\theta, y_1+d_1\sin\theta)$.

We compare our location method with other algorithms (KNN, TN and SMP) and employ 'mean distance error' metric to analyse performance of different algorithms at offline stage. Mean distance error is computed by equation (4), N denotes the number of estimation locations, (\hat{x}, \hat{y}) means the estimation coordinate, and (x, y) denotes the true location of grid in our laboratory.

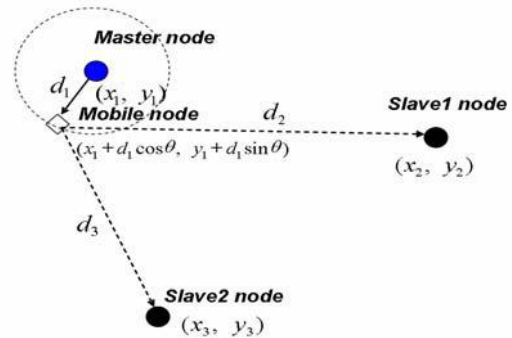


Figure 5: Generation of mapping circle

Figure 6 depicts the distance of different location algorithms using four sensor nodes at offline stage. KNN performs better than TN, SMP and DTN, because our sensor nodes deploy at high density (13.68m/n) and KNN only search for 417 locations in total area of 54.7 m space, and mean distance error of DTN is 2.3 m, and DTN is comparable of other classical algorithms. We describe that Grey Prediction integrate with different location methods in the section IV.

$$MSE = \frac{1}{N} \sum_{i=0}^N \sqrt{(x - \hat{x})^2 + (y - \hat{y})^2} \quad (4)$$

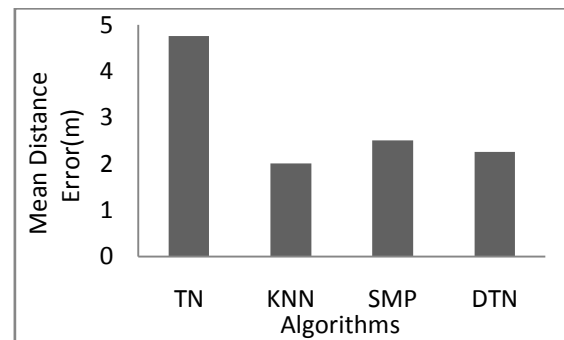


Figure 6: Performance analysis of different algorithms

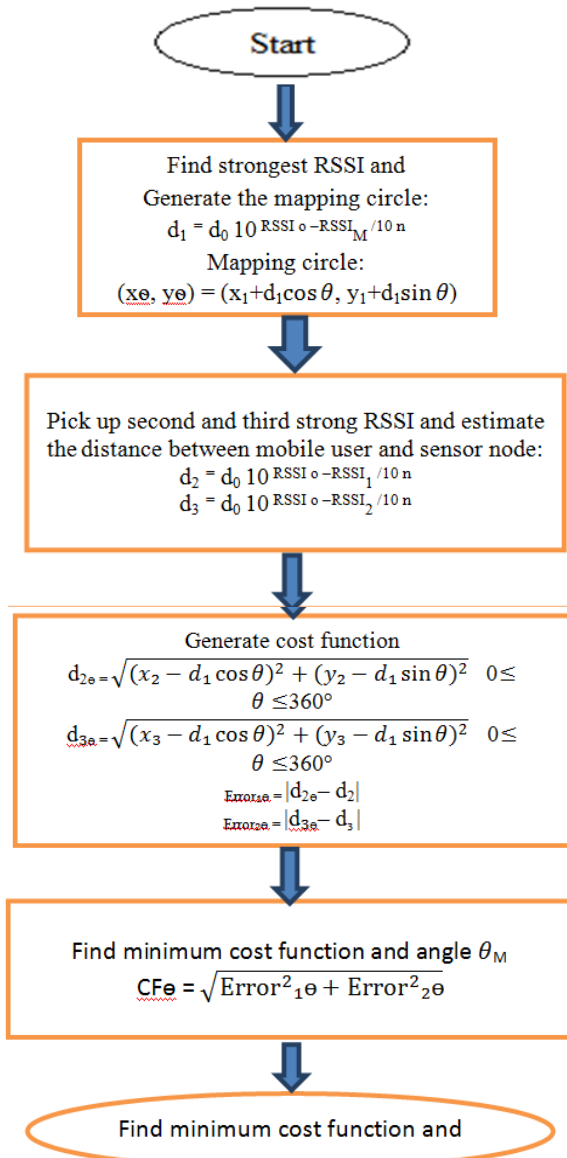


Figure 7: Procedure of DTN algorithm

IV. GREY PREDICTION MODEL

To improve the accuracy of mobile user's location we use the RSSI predictive based model. For tracking mobile user, the proposed grey prediction approach [8] utilizes the grey system to predict RSSI. We model the dynamic RSSI of x using first order ordinary differential equations as follow:

$$\frac{dX^{(1)}}{dt} + a X^{(1)} = b \quad \dots\dots(5)$$

$X^{(1)}$ is the accumulated generating operation that can be obtained by

$$X^{(1)} = (x^{(1)}(1), x^{(1)}(2), x^{(1)}(3), \dots, x^{(1)}(n)) \dots(6)$$

where

$$x^{(1)}(k) = \sum_{m=1}^k x^{(0)}(m), \quad k \in \{1, \dots, n\} \quad (7)$$

$X^{(0)} = (x^{(0)}(1), x^{(0)}(2), x^{(0)}(3), \dots, x^{(0)}(n))$ is the original data sequence, where $x^{(0)}(k)$ represents RSSI at time t . Equation (5) is called "white descriptor" for modelling a white system and its parameters (a, b) can be found directly from the observed RSSI. By solving the differential equation (5), prediction equation (8) is obtained.

$$\hat{x}^{(1)}(k+1) = (x^{(0)}(1) - \frac{b}{a})e^{-ak} + \frac{b}{a} \quad \dots(8)$$

For the case of $k \geq 2$ ordinary minimum least square estimation can be employed with a linear model $yn = B \hat{a}$. By minimizing the least square error term using the matrix equation (10), the optimal solution can be obtained by using following equation (9).

$$\hat{a} = \begin{bmatrix} a \\ b \end{bmatrix} (BTB)^{-1}BTy_n \quad \dots(9)$$

where

$$B = \begin{bmatrix} -\frac{1}{2}(x^{(1)}(1) + x^{(1)}(2)) & 1 \\ -\frac{1}{2}(x^{(1)}(2) + x^{(1)}(3)) & 1 \\ -\frac{1}{2}(x^{(1)}(3) + x^{(1)}(4)) & 1 \\ \dots & \dots \\ -\frac{1}{2}(x^{(1)}(n-1) + x^{(1)}(n)) & 1 \end{bmatrix} \quad (10)$$

$$y_n = [x^{(0)}(2), x^{(0)}(3), x^{(0)}(4), \dots, x^{(0)}(n)]^T \quad \dots(11)$$

Finally, the prediction result \hat{x} of the moving object at $t = k + 1$ can be obtained by equation (10). Figure 8 depicts the all procedure of grey prediction.

$$\hat{x}^{(0)}(k+1) = \hat{x}^{(1)}(k+1) - \hat{x}^{(1)}(k) \quad \dots(12)$$

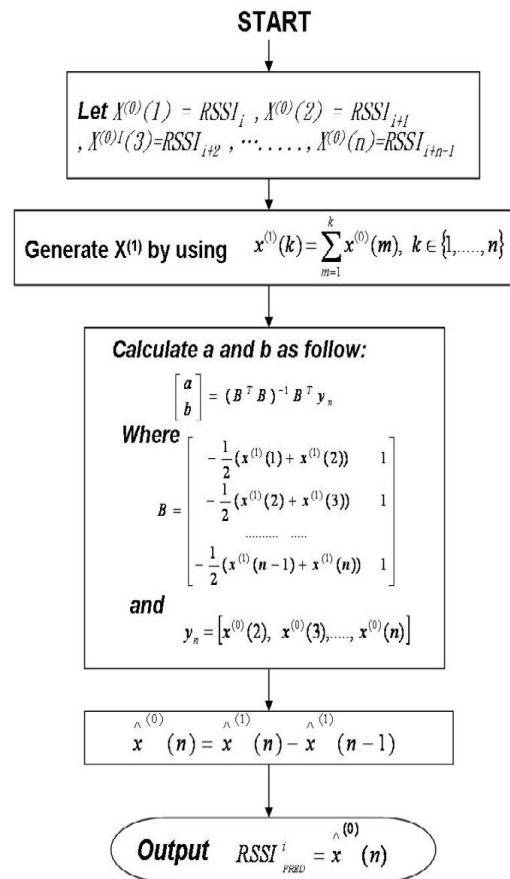


Figure8. Grey prediction system

The mean square error (MSE) is used to determine the performance of grey prediction system, and at the Run-time stage we put the measured RSSIs which generated from mobile user to the grey prediction system, and then get the predicted RSSI. We compare two methods of grey

prediction, one is original grey prediction output, the other is grey prediction with weight method, from equation (12) weight method is used to obtain RSSI, w_1 and w_2 denote the weighting of original RSSI and predicted RSSI. The MSE1 and MSE2 are used to evaluate the accuracy of RSSIpred1 and RSSIpred2 from the Equation (13) and (14), n is the path loss exponent. We measured four different independent sets of RSSIs when mobile user moved away from the same sensor node, and each set of RSSI was measured at different time a day, because signal strength fluctuates from time to time. The number of original RSSI and predicted RSSI are the same 300 and the mobile user move the same distance (6m). The RSSI pred1 is determined by using the grey prediction process that show in the Figure 9 and Figure 10 respectively for predicted and weighted predicted.

$$RSSI_{pred2} = w_1 \times RSSI_{pred1} + w_2 \times RSSI_{i-1}$$

$$MSE_1 = \frac{1}{n} \sum_{i=0}^n \sqrt{RSSI_{pred1} + RSSI_i}^2$$

$$MSE_2 = \frac{1}{n} \sum_{i=0}^n \sqrt{RSSI_{pred2} + RSSI_i}^2$$

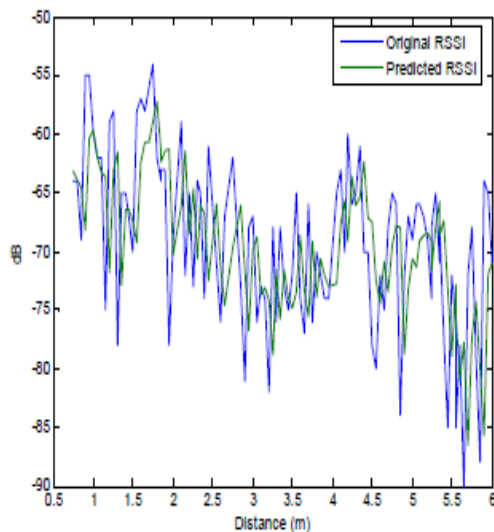


Figure9. Plot of predicted RSSI

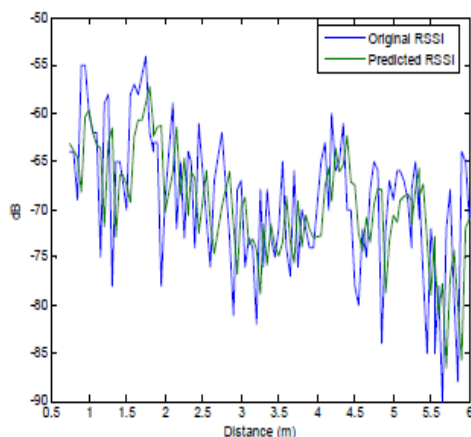


Figure10. Plot of weighted Predicted RSSI

Grey Prediction with other Location Methods:
There are several location algorithms such as TN, KNN, SMP and DTN which can be integrated with grey

prediction methods. Figure 11 we show experimental problem and four sensor nodes in the laboratory. The mobile user moves in the direction pointed out by the arrow heads and broadcast the beacons every 50ms. The velocity of mobile user is 0.15m/s. The sensor node again beacons and views RSSIs result to grey prediction algorithm. Now we will compare various approaches. First is the grey prediction method itself and another method is grey prediction with weight. Now these predicted RSSIs are used to estimate the location of mobile user with the true location and the estimated location of mobile user. The true location and the estimated location are recorded when the mobile user is traversing through various nodes. MDE (mean distance error) is used to evaluate the location of the mobile user.

Grey Prediction can reduce errors arising from non-line of sight and predict the tendency of RSSI when mobile user is moving. Thus results predicted with location algorithms are used to predict mobile user location and origination. We change the number of grey prediction inputs and analyse the change which affects the accuracy of mobile user position. The figure 12 shows the mean distance error of several location algorithms which incorporation with grey prediction demonstrates the various variations with grey prediction. KNN and SMP have greater mean distance error than the rest two algorithms in case of less than 100 grey prediction inputs. The mean distance error is smaller in case of DTN. Now when the number grows beyond the limit then the best evaluated error value is 1.3m for DTN. The figure 13 also depicts mean distance by using weight method also.

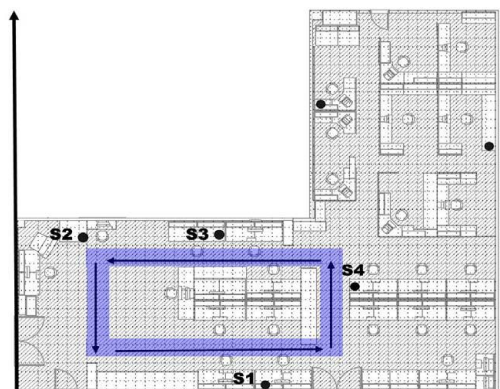


Figure 11. Showing Experimental Problem

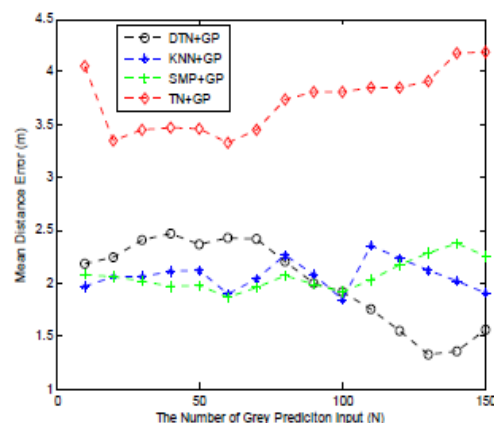


Figure12. The Grey Prediction Experimental results

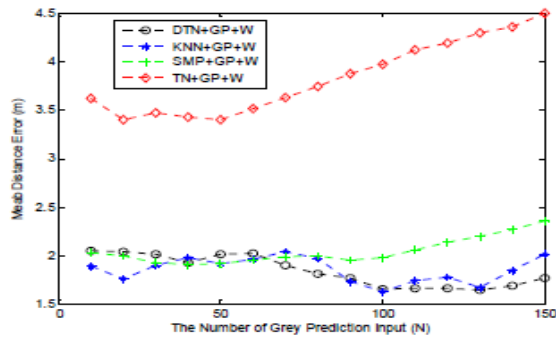


Figure13. The Grey Prediction experiment with weight method

V. CONCLUSION

We presented the study of various location algorithms with respect DTN location algorithm for the wireless sensor network along with the employment of grey prediction to improve the accuracy with respect to the others. We have used grey prediction to predict the tendency of RSSI and we reduced the fluctuation of RSSI when mobile user is moving.

REFERENCES

- [1] Y. Gwon, and R. Jain, "Error Characteristics and Calibration-free Techniques for Wireless LAN-based Location Estimation," In Proceedings of MobiWac, section 1 pp. 2-9, Oct. 1, 2004
- [2] P. Bahl, V. N. Padmannabhan, "RADAR: A In-Building RF-Based User Location and Tracking System," In Proceedings of the IEEE Conference on Computer Communications (INFOCOM '00), vol.2, pp. 775 – 784, March 2000
- [3] Patwari, N.; Hero, A.O., III; Perkins, M.; Correal, N.S.; O'Dea, R.J., "Relative location estimation in wireless sensor networks," IEEE Trans. Signal Processing, vol. 51 , pp. 2137 - 2148, Aug. 2003
- [4] P.-C. Chen, "A non-line-of-sight error mitigation algorithm in location estimation," In Proceedings of IEEE Conference WCNC (Wireless Communications and Networking, vol.1, pp. 316 – 320, Sept. 1999
- [5] T. Ogawa, S. Yoshino, M. Shimizu, H. Suda," A new in-door location detection method adopting learning algorithms," In Proceedings of IEEE Conference Pervasive Computing and Communications(PerCom 2003), pp. 525 – 530, March 2003
- [6] D. Pandya, R. Jain, and E. K Lupu, "Indoor Location Using Multiple Wireless Technologies," In Proceedings of the IEEE Personal, Indoor and Mobile Radio Communications, vol.3, pp. 2208 – 2212, Sep. 2003.
- [7] Y. Gwon; R. Jain, T Kawahara, "Robust indoor location estimation of stationary and mobile users" In Proceedings of the IEEE Computer and Communications Societies (INFOCOM), vol. 2, pp. 1032 – 1043, March 2004.
- [8] C. H. Lee, and C. J. Yu, "An intelligent handoff algorithm for wireless communication systems using grey prediction and fuzzy decision system," In proceedings of IEEE Networking, Sensing and Control Conference, vol. 1, pp. 541 – 546, March 2004.