Performance Comparison of UWB-Fingerprinting Positioning with RBF Neural Network and k-Nearest Neighbor in an Indoor Environment

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ABSTRACT – In recent years, an indoor positioning system has been widely used in medical, industrial, public safety and transportation. In addition, its important requirement is high accuracy in dense multipath fading environments. This paper studies on indoor positioning using radial basis function (RBF) neural network and k-nearest-neighbor (k-NN) based on ultra wideband (UWB) signal. The channel transfer function was measured using vector network analyzer (VNA) at the frequency ranging from 3 GHz to 11 GHz. The path losses and the delay times of first three paths were investigated to build the fingerprints and signatures. The accuracy of this work is studied and shown in the term of cumulative distribution function (CDF). From the results, RBF neural network provides better accuracy than k-NN. Thus, RBF neural network is more suitable for an indoor positioning.

KEYWORDS -- ultra wideband (UWB); indoor positioning; radial basis function (RBF) neural network; k-nearest-neighbor (k-NN)

1. Introduction

Nowadays, the indoor positioning systems provide widely researched in many applications such as industrial sensors and equipments control [1], emergency services, people's position detection and many others. The positioning system is based on wireless technologies such as wireless local area network (WLAN), ZigBee, Bluetooth, ultrasonic, radio frequency identification (RFID) and ultra wideband (UWB). However, this system requires high accuracy and precision in an indoor environment. This leads the utilization of UWB for indoor positioning.

UWB is one of many technologies that are used widely in the indoor positioning because UWB has many characteristics such as low power, high data rate (high bandwidth) and robustness to multipath fading. There are many methods, which are used for the indoor positioning, such as received signal strength (RSS), time of arrival (TOA), time difference of arrival (TDOA), angle of arrival (AOA) and fingerprinting [2]. The fingerprinting technique is appropriate for indoor positioning because the indoor environment has more multipath fading. This technique can use the characteristics of multipath fading to build fingerprint stored in database and signature. The target signature will be compared with the fingerprint in database to estimate the position. Furthermore, there are some methods that are used to estimate position such as probabilistic method, interpolation, artificial neural network (ANN), k-nearest neighbor (k-NN) [3] and other methods.

The ANN is a method base on the human brain working that can be learned and adapted to the environment. Furthermore, the ANN has a strong structure. If some neurons are damaged, the remaining neurons are still able to run. Therefore, neural networks are used in many applications including pattern recognition, clustering, prediction, optimization, function approximation and so on [4]-[5].

The k-NN is an algorithm for classifying objects based on closest training examples in the feature space. It is amongst the simplest of all machine learning algorithms: an object is classified by a majority vote of its neighbors, with the object being assigned to the class most common amongst its k-NN (k is a positive integer, typically small).

In this paper, the biconical antennas with horizontal polarization are used as both transmitter (Tx) and receiver (Rx) antennas. The vector network analyzer (VNA) was used to measure channel transfer function with frequency ranging from 3 GHz to 11 GHz for covering the full band of UWB spectrum, which is specified by Federal Communications Commission (FCC). The path losses and delay times of first three paths were evaluated and used as both fingerprints and target signatures. Then, the positions were analyzed by using RBF neural network and k-NN. The comparison performance is shown in the term of cumulative distribution function (CDF).

The remainder of this paper is organized as follows. In Section 2, the positioning technique such as signal model, UWB fingerprint, RBF neural network and k-NN are described. Then, the measurement setup and results of this paper are explained in Sections 3 and 4, respectively. Finally, the conclusion is given in section 5.

2. Positioning Technique

2.1 UWB Signal

For UWB signal, the rectangular passband waveform is used as the UWB transmitted waveform. The rectangular passband waveform in time domain and its spectral density function in frequency domain can be defined by

$$v_{\mathrm{t}}(t) = \frac{A}{f_{\mathrm{B}}}[f_{\mathrm{H}}\,\mathrm{sinc}(2f_{\mathrm{H}}t) - f_{\mathrm{L}}\,\mathrm{sinc}(2f_{\mathrm{L}}t)] \quad (1)$$

$$V_{\mathrm{t}}(f) = \begin{cases} \dfrac{A}{2f_{\mathrm{B}}} & \left||f| - f_{\mathrm{c}}\right| \le \dfrac{f_{\mathrm{B}}}{2} \\ 0 & \left||f| - f_{\mathrm{c}}\right| > \dfrac{f_{\mathrm{B}}}{2} \end{cases} \quad (2)$$

Where A is the maximum amplitude, f_B is the bandwidth, f_c is the center frequency, f_L and f_H are the lowest and highest frequencies, respectively.

Then, we can find the spectral density function of received signal $V_r(f)$ by using

$$V_{\mathrm{r}}(f) = V_{\mathrm{t}}(f)\cdot H_{\mathrm{c}}(f) \quad (3)$$

where $V_t(f)$ is transmitted signal in frequency domain and $H_c(f)$ is the frequency transfer function of channel obtained by using measurement scheme described in Section 3.

After that, the received signal in time domain $v_r(t)$ is evaluated by using inverse Fourier transform:

$$v_r(t) = \int_{-\infty}^{\infty} V_r(f) e^{j2\pi f t} df \quad (4)$$

2.2 Fingerprinting Technique

The fingerprinting positioning technique concept is based on the notion identifying a specified position by relying on some data that can represent this location. It has the same concept as human fingerprinting. In a given area, different information can be used to construct a fingerprint that can identify different parts of the area. This technique consists of two phases. First comprises the choice of the appropriate data to build a fingerprint and collect this information to database. The second phase consists of using the already built database in order to find locations by comparing a target signature with the database content (fingerprint). Theoretically, any information can be used to perform unique fingerprints. Here, the path losses and the delay times of first three paths of received power are comprised to build the fingerprint and signature of each specific position. The received power $p_r(t)$ in decibel is presented by

$$p_r(t)[dB] = -20\log|v_r(t)| \quad (5)$$

Figure 1 shows the consideration of path losses and delay times from received power. These parameters were used to build the fingerprints and signatures. From this figure, path losses of first, second and third paths are PL_1 = $-P_1$, PL_2 = $-P_2$ and PL_3 = $-P_3$.

Similarly, the delay times of the first, the second and the third paths are t_1, t_2 and t_3 respectively.

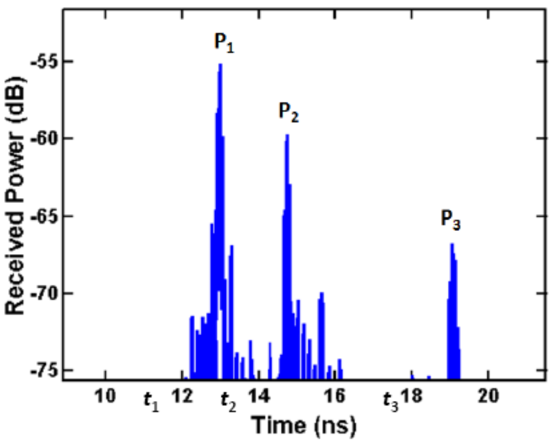

Figure 1. Received power waveform.

2.3 RBF Neural Network

The RBF neural network is a class of feed-forward neural networks that consists of one input layer, one hidden layer and one output layer, the kind of activation functions at hidden layer is nonlinear whereas at output layer is linear. The RBF structure is shown in Figure 2.

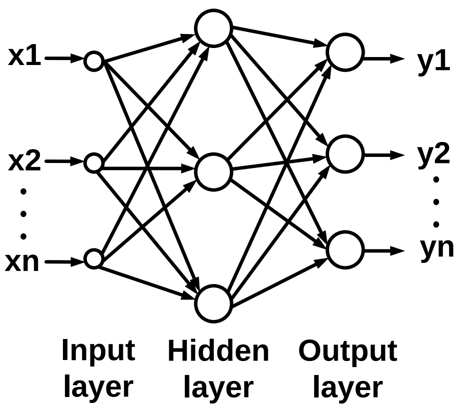

Figure 2. The structure of the RBF neural network

The RBF neural network has properties of the approximation and less time of training. The most important of structure is the hidden layer; the hidden layer outputs are found from activation functions then will be calculated with inputs from the input layer. Finally, neural network outputs are found from addition of weights and the hidden layer outputs. The neural network outputs can be written as

$$y_i = \sum_{k=1}^{s} w_{ik}\phi_k(\|p - c_k\|) \quad (6)$$

where s is number of neurons in the hidden layer, w_{ik} is value of the neural weight from the neurons k, $\varphi_k(\,.\,)$ is the activation functions, $\| p - c_k \|$ is the distance from the point of the input (p) to the center of the activation functions (c_k) at neurons k as is shown by norm, y_i is the output of the network.

The activation function, which is used in this paper, is a Gaussian activation function, which is the most popular of the RBF neural network. This Gaussian activation function can be expressed as

$$\phi(p) = \exp\left(\frac{-p^2}{\sigma^2}\right) \quad (7)$$

where σ is spread of the RBF neural networks as it is determined to width of the Gaussian activation function.

The RBF neural network training based on solve of equation. From the RBF neural network output can be written in matrix form as

$$\begin{bmatrix} \tilde{y}_1 \\ . \\ . \\ . \\ \tilde{y}_Q \end{bmatrix} = \begin{bmatrix} \phi(p_1, c_1)\cdots\phi(p_1, c_s) \\ . \qquad\qquad . \\ . \qquad\qquad . \\ . \qquad\qquad . \\ \phi(p_Q, c_1)\cdots\phi(p_Q, c_s) \end{bmatrix} \begin{bmatrix} w_1 \\ . \\ . \\ . \\ w_s \end{bmatrix} \quad (8)$$

Thus, the simple equation of RBF neural network output can be written as

$$\tilde{y} = \Phi w \quad (9)$$

The objective function is defined as

$$J(w) = 0.5\sum_{q=1}^{Q}\left[\hat{y}_q - \tilde{y}_q\right]^2 \quad (10)$$

This equation can be written in the simple form as

$$J(w) = \frac{1}{2}(\hat{y} - \Phi w)^T(\hat{y} - \Phi w) \quad (11)$$

Finally, the weight can be adjusted by find the least objective function from that shows in equation (12) – (14)

$$\frac{\partial J(w)}{\partial w} = 0 \tag{12}$$

$$-\Phi^T \hat{y} + \Phi^T \Phi w = 0 \tag{13}$$

$$w = \left(\Phi^T \Phi\right)^{-1} \Phi^T \hat{y} = \Phi^{-1} \Phi^T \hat{y} \tag{14}$$

Where $\hat{y}_q$ is the target, $\tilde{y}_q$ is the output from neural network and Q is number of output.

The weight is occurred as RBF neural network training. It shows about ability of learning and approximation the data which unknown.

2.4 k-Nearest Neighbor

The estimated position is considered from the position that has minimum difference between its signature and fingerprint. The fingerprint error at (x, y) position $e_f(x, y)$ is defined as

$$e_f(x,y) = \sqrt{\sum_{i=1}^{3} \left\{ \frac{[PL_i(x,y) - PL_{si}]^2}{\sigma^2_{PL_i}} + \frac{[t_i(x,y) - t_{si}]^2}{\sigma^2_{t_i}} \right\}} \tag{15}$$

where $PL_i(x, y)$ and $t_i(x, y)$ are the path losse and delay time of fingerprint at (x, y) position of path i^{th}, $PL_{si}(x, y)$ and $t_{si}(x, y)$ are the path loss and delay time of signature of path i^{th}, σ_{PLi} and σ_{ti} are the standard deviation of path loss and delay time of fingerprint of path i^{th}.

The estimated position of k-NN (x_e, y_e) is considered as the position with minimum estimated error divide by k which k is 1,2,…,n, and can be written as

$$(x_e, y_e)_k = \frac{\sum_{j=1}^{k} (\arg\min e_f(x,y))_j}{k} \tag{16}$$

Finally, the accuracy of UWB fingerprinting is considered in the term of distance error. The distance error e_d can be defined as

$$e_d = \sqrt{(x_c - x_e)^2 + (y_c - y_e)^2} \tag{17}$$

where (x_e, y_e) is the correct position.

3. Measurements

The measurements were done at the corridor of 12th floor, E-Building, Faculty of Engineering, King Monkut's Institute of Technology Ladkrabang. VNA was used to measure the UWB channel at the frequencies ranging from 3 GHz to 11 GHz, which cover the full band of UWB spectrum specified by Federal Communications Commission (FCC) [8]. The biconical antennas were used with horizontal polarization as both Tx and Rx antennas. The geometry and dimension of the biconical antenna are shown in Figure 3. The positions models were divided 2 models. The first model was reference data measurement that is the database content in fingerprinting technique and the second model was testing data measurement that is the target signature in fingerprinting technique.

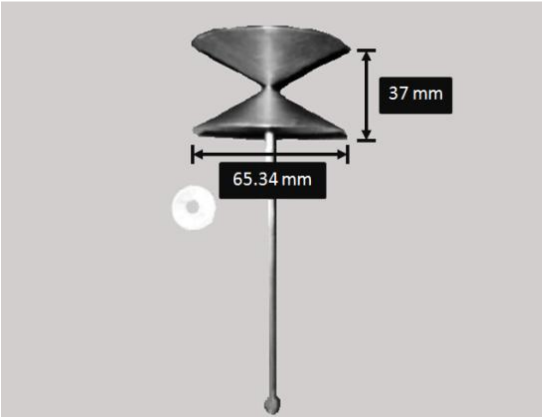

Figure 3. The geometry and dimension of the UWB biconical antenna

The measurement model for reference data is shown in Figure 4. It has 18 data points with 1 m space between each data points. The obtained data are fingerprints, which are stored in database. The same process of reference data measurement was done, but changed the measurement model as shown in Figure

5. The data points are changed from 18 to 55 with space reduced to 0.5 m.

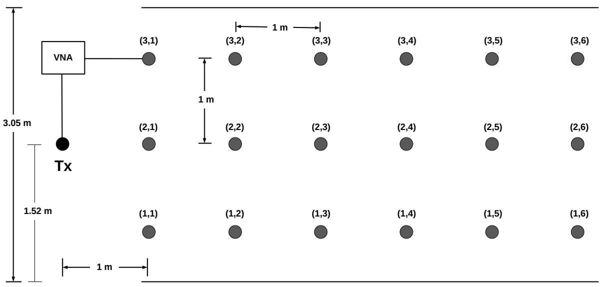

Figure 4. Measurement model for reference data.

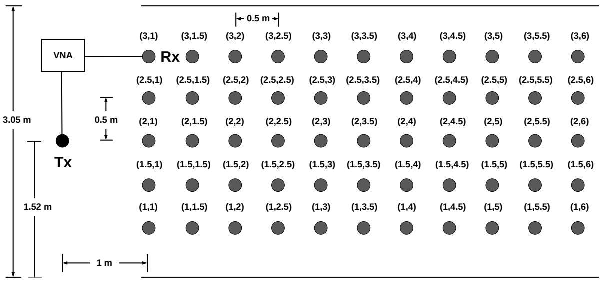

Figure 5. Measurement model for testing data.

4. Experimental Results

After obtained all data from the measurements, the RBF neural network and the k-NN are used for analyzing the position.

4.1. RBF Neural Network Result

For the best results, the RBF neural network spread is 12.5 with 10 neurons in hidden layer. The CDF of distance error is shown in Figure 6. The average distance error is 0.48 m, and the maximum distance error is 1.27 m.

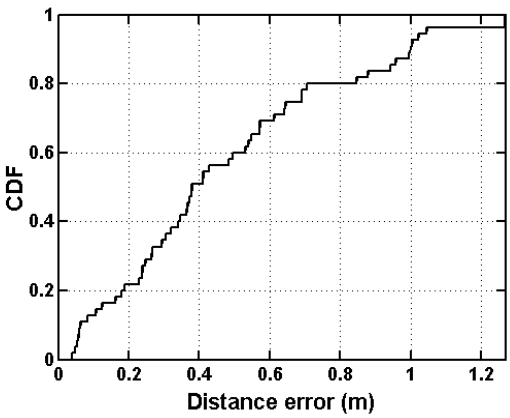

Figure 6. CDF of distance error for RBF neural network.

4.2. k-Nearest Neighbor Results

The CDFs of distance error for k-NN with k equal to 1, 2 and 3 are shown in Figures 7, 8 and 9, respectively. The maximum distance errors for k-NN with k equal to 1, 2 and 3 are 2.06 m, 1.50 m and 1.43 m., respectively. The case of 3-NN has the lowest of the maximum distance error. Furthermore, the average distance errors for k-NN with k equal to 1, 2 and 3 are 0.54 m, 0.58 m and 0.63 m, respectively. The case of 1-NN has the lowest of the average distance error. Generally, the distance error of each case of k-NN is not much different. However, k-NN with k equal to 1 is chosen to be the best case of k-NN by considering the average distance error.

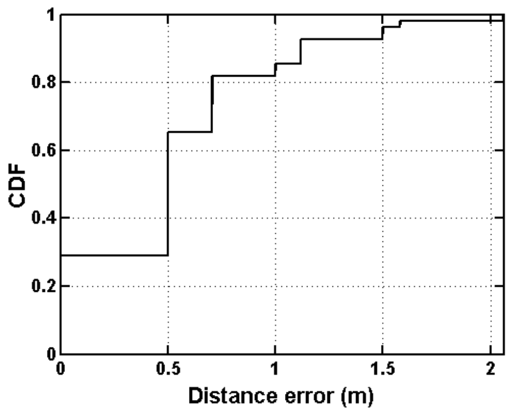

Figure 7. CDF of distance error for k-NN with k equal to 1.

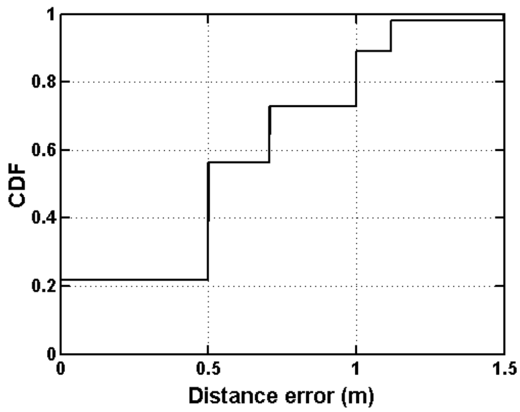

Figure 8. CDF of distance error for k-NN with k equal to 2.

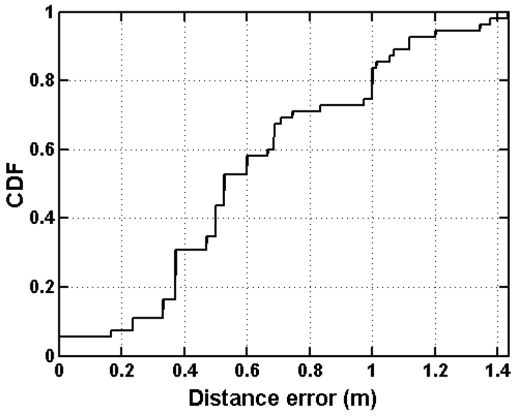

Figure 9. CDF of distance error for k-NN with k equal to 3.

4.3. Comparison Result

The comparison between CDFs of distance error for RBF neural network and k-NN with k equal to 1, 2 and 3 are shown in Figure 10. The RBF neural network has lower average, median and maximum distance errors than all cases of k-NN.

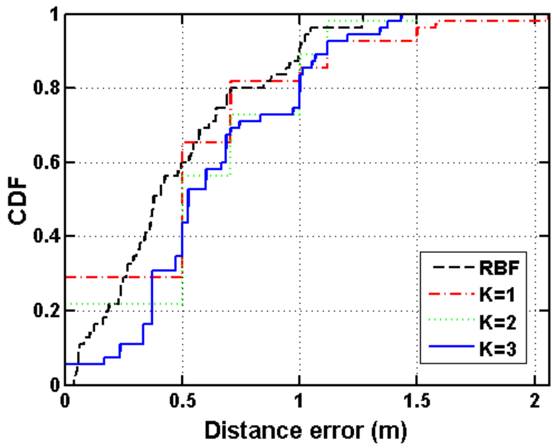

Figure 10. CDFs for RBF neural network and k-NN.

Table 1. Distance errors of RBF neural network and k-NN.

Distance Error	RBF Neural Network (m)	1-NN (m)	2-NN (m)	3-NN (m)
Maximum	1.27	2.06	1.50	1.43
Median	0.38	0.50	0.50	0.53
Average	0.48	0.54	0.58	0.63

4.4. Analysis of Result Error

The distance errors of RBF neural network and k-NN are listed in Table 1. The distance errors of RBF neural network are significantly lower than k-NN. Thus, RBF neural network is chosen to analyze the distance errors in this section.

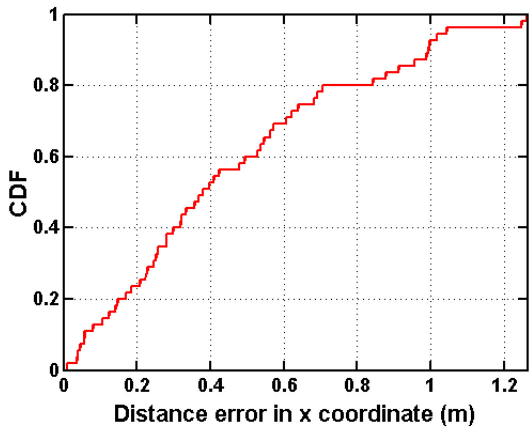

Figure 11. CDF of distance error in x coordinate

The CDF of distance error in x coordinate is shown in Figure 11. The maximum distance error is 1.29 m and the average distance error is 0.54 m.

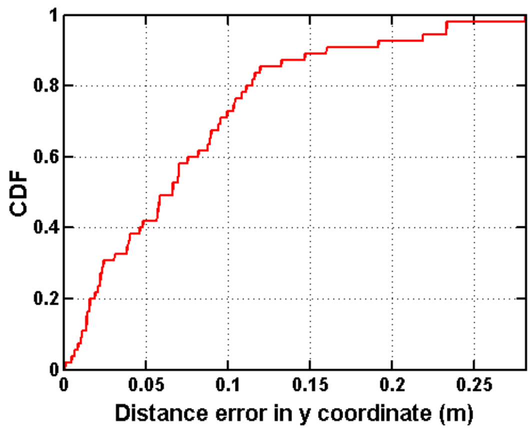

Figure 12. CDF of distance error in y coordinate

Figure 12 shows the CDF of distance error in y coordinate. The distance error in y coordinate has 1.29 m maximum distance error and 0.54 m average distance error.

Moreover, the distance error in y coordinate is lower than that in x coordinate. The distance error of x coordinate is higher because of symmetry. The Tx antenna is at the center of x coordinate. Therefore, the reference data at right and left sides of x coordinate are almost the same.

5. Conclusion

This paper is studies on indoor positioning using RBF neural network and k-NN based on UWB signal. From the results, the most distance error is in x coordinate. The RBF neural network has the average distance error between the target and approximate positions of 0.48 m and the maximum distance error is 1.27 m., while the k-NN with k equal to 1, the best case of k-NN, has average distance error of 0.54 m. and the maximum distance error of 2.06 m. That shows the accuracy of the RBF neural network is better than that of the k-NN. Therefore, the RBF neural network is more suitable to identify the position.

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