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# 통신기지국과 모바일장치간의 수신신호강도를 기반으로 하는 신경망과 푸쉬-풀 평가를 이용한 위치추정

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## 요 약

글로벌 포지셔닝 시스템(GPS)의 기술이 점점 발전하고 있으나, 그 정확성은 건물의 내부나 지하도로에서의 위치인식이 아닌, 실외에서의 위치인식에서만 적합하다. 건물의 내부나 지하도로에 대한 위치 인식의 응용분야에 대하여, 글로벌 포지셔닝 시스템은 빌딩의 내부나 지하도로에서 정확한 위치인식을 요구 받을 경우, 건축구조물들로 인하여 정확성을 달성할 수 없다. 왜냐하면 사람이 필요로 하는 공간은 건물의 내부나 지하도로에서 수 평방미터에 불과한 매우 작은 공간이기 때문이다.

위치추정에 기반을 둔 수신신호강도(RSS)는 거의 모든 건물과 지하도로에서 수신이 가능한 무선 근거리통신망, IEEE 802.11, WiFi 전파신호 위치추정을 이용한 방안으로서, 특별히, 매우 좋은 선택이 될 수 있다. 이와 같은 위치추정시스템들의 근본적인 필요성은 특정 위치에서 수신신호강도를 이용하여 통신기지국으로부터 모바일장치에 이르는 위치의 평가를 가능하도록 하는 것이다. 이와 같은 과정에서 발생하는 다중 경로 페이딩 현상들은 위치추정에서 불확실성의 원인으로서, 수신신호강도를 예측하기 어렵게 만든다. 이와 같은 문제들을 해결하기 위하여, 신경망과 푸시-풀 평가 방법의 결합은 건물의 내부나 지하도로에서 모바일장치들을 이용하여 위치의 결정을 학습하고, 결정할 수 있도록 적용된다.

**키워드 : 통신기지국(AP), 위치추정, 수신신호강도(RSS), 푸시-풀 평가, 신경망**

# Localization using Neural Networks and Push-Pull Estimation based on RSS from AP to Mobile Device

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## ABSTRACT

Although the development of Global Positioning System (GPS) are more and more mature, its accuracy is just acceptable for outdoor positioning, not positioning for the indoor of building and the underpass. For the positioning application area for the indoor of building and the underpass, GPS even cannot achieve that accuracy because of the construction materials while the requirement for accurate positioning in the indoor of building and the underpass, because a space, a person is necessary, may be very small space with several square meters in the indoor of building and the underpass. The Received Signal Strength (RSS) based localization is becoming a good choice especially for the indoor of building and the underpass scenarios where the WiFi signals of IEEE 802.11, Wireless LAN, are available in almost every indoor of building and the underpass. The fundamental requirement of such localization system is to estimate location from Access Point (AP) to mobile device using RSS at a specific location. The Multi-path fading effects in this process make RSS to fluctuate unpredictably, causing uncertainty in localization. To deal with this problem, the combination for the method of Neural Networks and Push-Pull Estimation is applied so that the carried along the devices can learn and make the decision of position using mobile device where it is in the indoor of building and the underpass.

**Keywords : Access Point(AP), Localization, Received Signal Strength(RSS), Push-Pull Estimation, Neural Networks**

## 1. Introduction

Locating electronics devices gains more and more attention for the purpose of management and for the need of locating the people who carry the devices. For indoor localization, Global Positioning System (GPS) devices provide poor accuracy because of the serious signal

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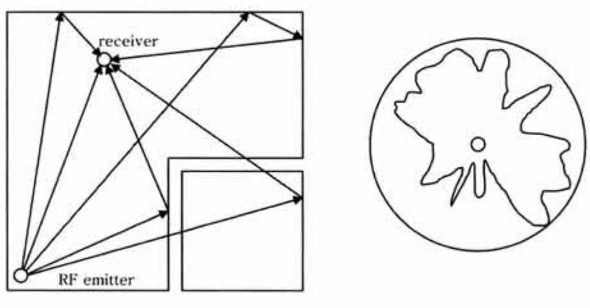
attenuation due to the construction materials, and the unstable signals due to multipath fading effect. The requirement of accuracy is critical because several meters of error can cause serious error if a person is detected to be in a living room instead of to be actually in the bedroom. This kind of serious error cannot be tolerated for supporting living especially for health-care system. There may be some other approaches that can provide information of a device's location. The input data can be image, video stream, ultra sound signal, radio frequency signals, etc. However, RF signal is the most convenient scheme to be used for personal monitoring because of following reasons [1, 2, 3, 4]. Current recognition techniques based on image and video stream are still limited in terms of accuracy. Identifying someone requires lots of face image data and complicated learning face. That is difficult for the scenarios when a person entering a building without looking at a camera closely, not to mention the low speed and low quality of digital cameras. It is even more difficult to use the choices of input channels like images, videos, sounds or ultrasounds to identify and locate people in the crowded area. Besides, both TOA and TDOA schemes need the RF channel for signaling the start of measuring (wake up signaling) to avoid continuous sampling at the receivers, which causes much energy consumption. In addition, RF signal has an important property, which is the ability of going through most of objects [5, 6]. This gives RF the advantages over other input data schemes like images and sounds because the mobile device can be anywhere along with the person without being view blocked. Moreover, monitoring a person or a patient's activity must respect his or her privacy. Image and sound signals would be too sensitive, for example: when he or she is being in the bathroom, toilet, bedroom, etc. For wireless devices, RF signal is now available with the pervasive adoption of IEEE 802.11 (a/b/g) wireless Local Area Network (LAN, WiFi). Since the signal strength is measured over time by the wireless network devices for the purpose of evaluating the health of the connection, location estimation based on RSS of wireless LAN is easy to implement. Therefore, the RF signal is the best channel to give the monitor system this identification, to compare with other channels like images, videos, voices, etc.

RF signal has many advantages to be chosen for the scheme of collecting input data. However, it has the properties of electromagnetic waves: RF has the ability to go though most of objects, but suffers from different attenuation rates depending on object material. Moreover, RF signal also reflects when hitting a surface, causing multipath propagations besides the line-of-sight to the receiver as illustrated in (Figure 1(a)). One more thing, the RF emitters never radiates the signal with the same energy at every direction as illustrated in (Figure 1(b)). The fluctuation does not only happen in the change of the angle view to the emitters but also in any direction over time. Those phenomena make the RF signal strength fluctuate in wide range. That means the measurements are not stable especially for indoor settings where there are walls and objects. Even when the position does not change, measurements of the RF signal strength are unstable, not to mention when the mobile devices are rotated in some way, or change the positions a little bit. Since the measurements depend much on the building structures and the errors suffer from uncertainty properties, the best way to recognize a location within an indoor setting is to use machine learning techniques to learn relations between the locations and the ranges of RF signal strength values. After the training phase, the knowledge can be stored in the mobile devices and the location can be recognized by the knowledge of those relations. In this paper, we introduce an RF based method that utilizes machine learning to estimate the relationship between RSS vector and the distance vector, and then the Push-Pull Estimation is used to infer the locations of the devices.

## 2. Related works

There are three major location sensing techniques based on the RSS [7, 8, 19]. They are Proximity, Triangulation, and Scene Analysis which are listed as following. Proximity method tries to find the strongest RSS reading from a specific AP and determines the location to be the region covered by this AP. This method only gives a very rough position estimate but it is easy to be implemented.




(a) (b)

(Figure 1) (a) RF signal's ability of going through some obstacles and RF signal's multipath fading phenomenon. (b) RF emitter never emits the same energy at all directions or the magnitude gain is too bad to be considered as isotropic.

For Triangulation, the RSS value can be converted into distance from the particular AP according to a theoretical or empirical signal propagation model (path loss, shadowing, wall reflection models, etc.). Then, with distance measurements from at least three APs whose positions are known, lateration will be performed to estimate the locations. This kind of approaches does not give accurate estimate, because the indoor radio propagation channel is highly unpredictable and thus the use of the propagation model is not reliable.

Meanwhile, Scene Analysis method first collects RSS readings at known positions, which are referred to as fingerprints, in the area of interest. Then, it estimates the locations by comparing the online measurements with the fingerprints through pattern recognition techniques. This method is used by most WLAN positioning systems, as it is able to compute accurate location estimates. It is the approach used by the positioning and tracking system proposed in this paper [16].

The key problem for the indoor RSS-based positioning systems is to identify the RSS position relationship, so that the user's location can be estimated based on the RSS collected at that location. There are two approaches in dealing with this relationship [9]. the uses of signal propagation models [10, 11] and the location fingerprinting methods [12, 13, 14].

For signal propagation modeling, two main models are the combined model of path loss and shadowing and Wall Attenuation Factor model. The former [15] combines the simplified path-loss model with the effect of shadowing, multipath fading as depicted in (Figure 1(a)). Therefore the model is assumed to present a log-normal random process or Gaussian random variable is used to model the noise on logarithm domain. The later [17] includes the effects of obstacles or walls between the transmitter and receiver. The more obstacles or walls in the environment cause higher attenuation. These two models are both empirical and need the calibration of the parameters, such as the path loss exponent, which change depending on different environments. Calibration usually requires a comprehensive survey of the RSS distributions over the environment, which takes much time. Moreover, the models assume that the RSS is distributed isotropically from the transmitter. This is often not the case for indoor environments because of the presence of obstacles. The orientation of the antenna of the mobile device also affects the RSS [18], but it is not reflected in the two models (see Figure 2(b)). All of these make the models unsuitable to present the RSS-position relationship in real situation.

Location fingerprinting methods are more preferred than the radio propagating model, because they give better estimations for the user's locations for indoor settings [19]. This kind of method is categorized into two phases: training phase and estimating phase. During the training phase, or so called offline phase, the RSS readings from different APs are collected by the WLAN-integrated mobile device at known positions, which are referred to as the reference points to create a fingerprint database, a.k.a. the radio map. The mobile device, which is carried by the user, records RSS readings from different APs at an unknown position. Then, these RSS online measurements are compared to the fingerprint database to estimate the user's location by using different methods. Most of these methods are based on machine learning techniques in order to construct the data base and use the data base for later estimating. The dominant works can be found are K-nearest neighbors (KNN) Localization [19,20], K-nearest neighbors (KNN) Localization [21], Support Vector Machine (SVM) [22] Localization, etc.

Our proposed method is actually a combination of learning method and localization method. The learning and inference engine, which is the Neural Network tool, is not used to construct the direct relationship between the input RSS vector and the location. In fact, the engine is for learning about the relationship between the input RSS vector and the estimated distances. This could avoid difficulties of the propagation models and the calibration. After that, with the inferred distance vector, PPE is used to calculate the device's position.

## 3. Neural Network and PPE based Localization

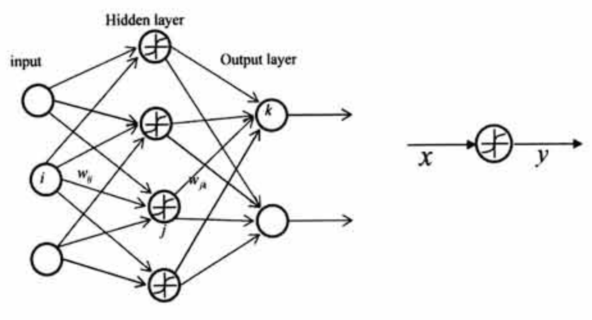
This part aims at improving our previous work of Modular Multi-Layer Perceptron based Localization [20], in which the positions used in the experiments are just sparse reference points, both for training and testing phase. In this work, we try to locate the exact position of the mobile device, not just some specific positions.

### 3.1 Neural Network overview [23]

A typical artificial Neural Network (ANN) has three layer. input layer, hidden layer and output layer. Input data is driven by the weights $W_{ij}$, then they are summed up before being fed into each cell of the hidden layer, then again the output data of the hidden layer is driven by the weights $W_{jk}$ to reveal the output data. Hidden layer has a set of "neurons" which do transformations, or mappings from the input to the output of the "neurons" (see Figure 2(a)). The function for mappings is usually a continuous and derivable function. The common choice for this mapping function is (see Figure 2(b)):

$$y = \sigma(x) = \frac{1}{1+\exp(-x)} \tag{1}$$

The key idea can be expressed like this: Given input data and coded output data (all is call training data set), the training phase tries to update the weight set $W_{ij}$ and the weight set $W_{jk}$ so that the errors between calculated output and given output are as small as possible.

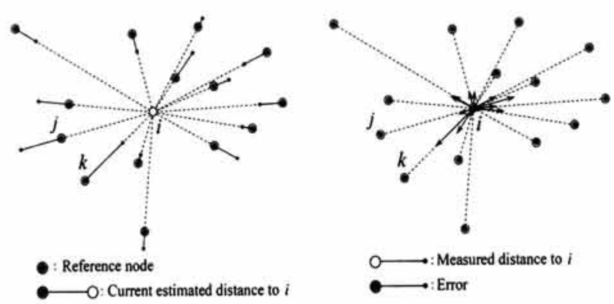



(a) (b)
(Figure 2) An example of an Artificial Neural Network (ANN) structure

Given a trained network with assigned weights, an input will be translated into coded output. This is called the decision phase. The idea of putting ANN in to localization can be seen as a labeling task. Input APs' readings and a set of related positions (reference points) is used to train the NN. Later, input APs' readings and NN are used to infer the estimated distance.

### 3.2 Push-Pull Estimation (PPE) introduction [23]

Push-Pull Estimation (PPE) is a method we originally developed for minimizing the virtual force-vectors modeled from differences of the current location estimation and the distance measurement. Our proposed algorithm [24] is based on geometry in which the errors of measurements are modeled into pushing and pulling forces. The effect of these forces drags a node to the balanced point where the errors are minimized via the averaging mechanism. The algorithm is called the Push-pull Estimation according to this concept. PPE fulfills the basic requirement that if the range measurement is shorter than the calculated distance between two nodes, these two nodes pull each other, and vice versa. In addition, the force magnitude should be a monotone function of the discrepancy between the measured and the calculated distances in order for PPE to work and converge. The bigger is the discrepancy, the higher is the influence it gives to reduce itself. This idea is demonstrated in (Figure 3) where node $i$ needs to update its coordinates to the balanced position. Node $j$ causes a pushing force on $i$ because the range measurement between $i$ and $j$ is longer than the current calculated distance between them, and contrarily, node $k$ exerts a pulling force on $i$. It should be noted that in the concept of this model, we give normal nodes the moving ability and consider location updating as a process in which normal nodes move under the influence of forces caused by their neighbors. When a normal node attempts to locate its balanced position, it considers the other nodes to be still. The calculation is basically performed with following two equations.



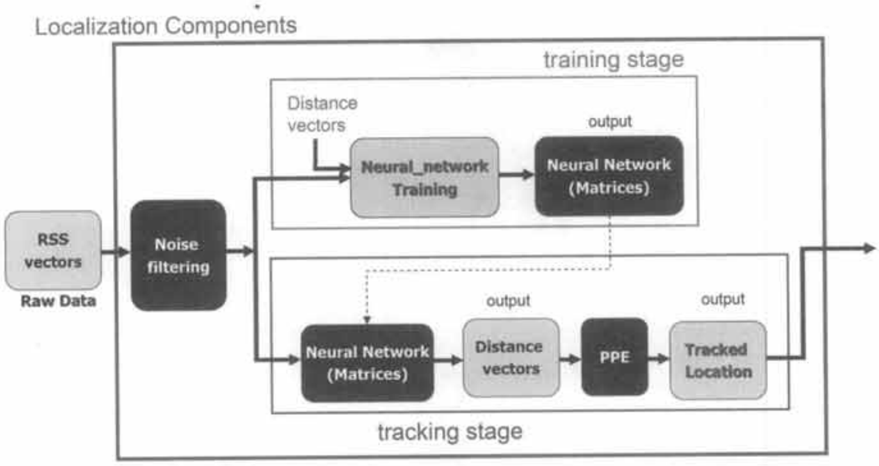

(a) (b)
(Figure 3) (a) Node $i$ and measurement errors from $i$ to its reference nodes. (b) The errors are modeled as pull-push forces[23]

$$\overrightarrow{f_{ij}} = \left(\tilde{d}_{ij} - \delta_{ij}\right)\overrightarrow{e_{ij}} \tag{2}$$

$$\overrightarrow{F_i} = \frac{1}{M_i^{(p)}}\sum \overrightarrow{f_{ij}} \tag{3}$$

$$\tilde{x}_i \leftarrow \tilde{x}_i + \alpha \overrightarrow{F_i}. \tag{4}$$

where $\tilde{d}_{ij}$ is the current estimated distance from node $i$ to the reference node $j$ and $\delta_{ij}$is the measured distance from node $i$ to the reference node $j$. Meanwhile, $\alpha$ in (4) is the rate of moving and $\overrightarrow{F_i}$ is the mean force caused by a set of $M_i$ related nodes or reference nodes. There are actually several phases of PPE but in the focus of this paper, only the first phase of PPE is used. PPE is guaranteed to provide robust and convergent estimation. Further analysis can be found in [24].




(Figure 4) Details of the design for "ANN and PPE based Localization" method. RSS is a vector whose entries are the measured received signal strength values. Neural Network is including matrices which play the role of transforming input vectors to higher dimensions, linear multiplying and compensate the offset. PPE is the Push-Pull Estimation block that gives the estimation of location based on the input distance vector

### 3.3 Neural Network and PPE based Localization

This is the main part of the proposed method where the combination of ANN and PPE is used to calculate the device's position.

There are 2 stages for this proposed method, training stage and localizing stage as illustrated in (Figure 4) in which RSS is the input vector whose entries are the measured received signal strength values, it has the form. $\mathrm{RSS} = [RSS_1, RSS_2, ..., RSS_K]^T$. Raw data is filtered to eliminate the noise before being used in both stage of training and tracking. Given the position of the device and the RSS reading values, the distance vector, whose entries are the distances from the APs to the mobile device, can be calculated and used as the prior information input for training the NN. Block "Neural_network Training" is used to learn the knowledge of the relation between the RSS vector and the real distances. This knowledge is stored under the form of Matrices (the block "Neural Network (Matrices)" in (Figure 4)) and an offset vector (not displayed in the (figure 4)). That means the result of this stage is the NN which has the knowledge of the relationship between the distance vector and the RSS reading vector. After training phase finishes, tracking stage then is performed for location estimating. This stage can be considered as being composed of two sub-stages that are distance inference and positioning. Now given the AP reading vector and the knowledge of its relation to distances, the distances from the mobile device to the APs are calculated and then PPE is applied to estimate the device's final position.

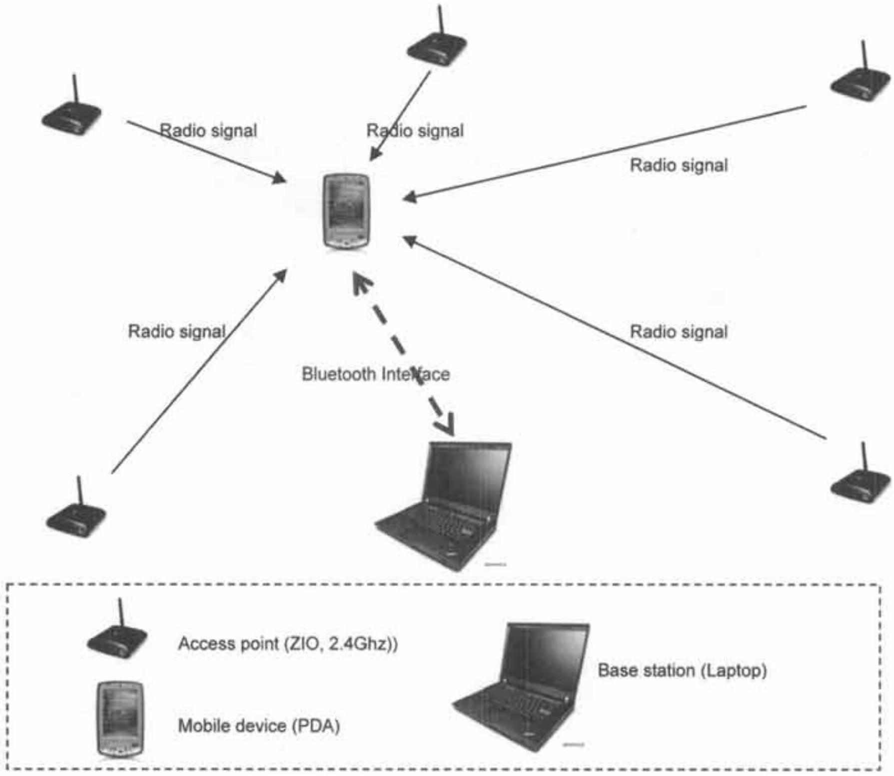
Note that since PPE needs unbiased distance estimation, calibration on measurement, which is difficult due to high fluctuation of the input values, is necessary. With the training phase, the relationship between the RSS vector and distance vector is constructed. In the tracking stage, the distance can be calculated unbiasedly and therefore the complex calibration can be avoided with the replacement of training stage.

## 4. Experiments and discussions

We conduct the experiment of locating a mobile device in the 4$^{th}$ floor of a building, the area is [7m x 12m] with three rooms and one hallway (see Figure 4). The experiment needs two missions to be fulfilled: first, recording the signal strength values from the RF (radio frequency) sources, or the access points (APs), and then calculating the distances to these RF sources and estimate the current position of the object in the setting. The experiment is set up with the framework described in (Figure 5). A PDA is used as the mobile device which can get AP readings and send the data to the base where both learning and tracking tasks are performed.

### 4.1 Data collecting methodology

As in most of the schemes that use RSS values for localization, for collecting RSS of the RF signals emitted by the access points (APs), we have intervened and modify a program which can access to the output data of the WiFi driver of the Personal Digital Assistant (PDA). The modified program connects through Bluetooth



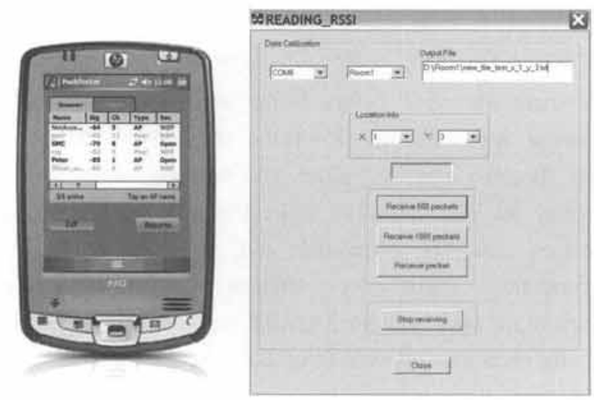

(Figure 5) Description of implementing data collection, PDA collects the RF signals from the APs, measure the RSS, then send it through Bluetooth to the Base station (labtop) where the training and inferring are both performed

protocol to a laptop, which plays the role of the base station, getting the RSS data of all APs in the range and sends the data to the laptop. It can update the RSS status at a rate defined by users, or after every $\Delta t$, which can be changed as an option of the program interface on the PDA by users.

The work of collecting data are carried out on the flight for both training and tracking stages. A program runs at the base laptop at the same time which collects the data, writes it to a file indicated by typing for the purposes of both training and inferring using Matlab software. In practice, only training phase needs to be run at the based, then the training knowledge is put into the mobile device where the inferring phase is performed so that the data load sent to the base can be reduced. However, in the scope of research, we have let the base do both training and inferring phase because it is more convenient to debug and handle.

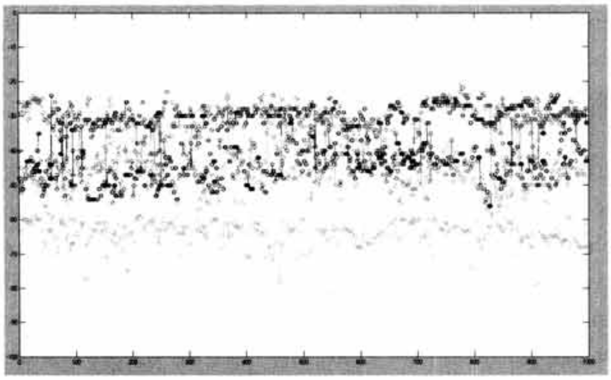
(Figure 6) illustrates the framework of the data collecting while (Figure 7) shows the interface of the programs we write for data collecting. Note that the signal strength values are measured in dB.

The collected data always needs the preprocess of noise filtering where the outliers (values that are too high or too small that do not make sense) and the ripple noise




(Figure 6) Interfaces of the programs for collecting data

are partly eliminated. (Figure 7) is the result of collecting data for training phase, 5 strongest readings from APs are plotted in different colors. 1200 samples in 4 minutes while the PDA is kept still. The fluctuation is significant even when the mobile device is not moved or not rotated, the RSS values change even tens of times. Noise filtering is carried out by eliminating the outliers with the width of 1.5-deviation (that means if any value causing the distance to the mean is bigger than 1.5 times of the deviation will be discarded), and then by using a simple low FIR filter.



(Figure 7) High noise input RSS readings of 5 strongest (nearest) APs, each RSS value from an AP is displayed in one color at a reference points. Note that the unit of measurement is in [dBm] and the values vary in high ranges

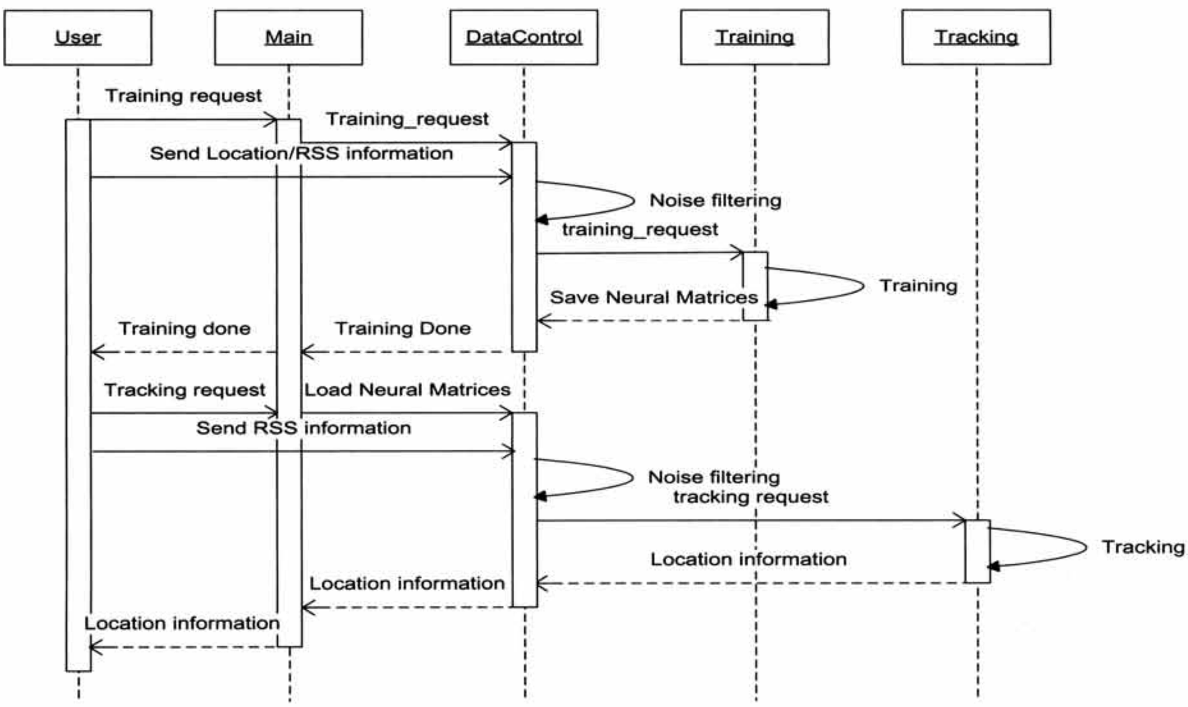
4.2 Experiment results

Using the data collecting methodology described in Section 4-1, we collect the data on the flight and write to a file whose content can be seen in (Figure 10). For training phase, each file is the result of the measured RSS of RF signal collected in 4 minutes with 1200 samples for one reference points. For inferring phase, the new file is used on the flight (nearly real-time) by the inferring Matlab program. The program actually does not only read the data from the file, but also updates or renewed the file when it is too long.

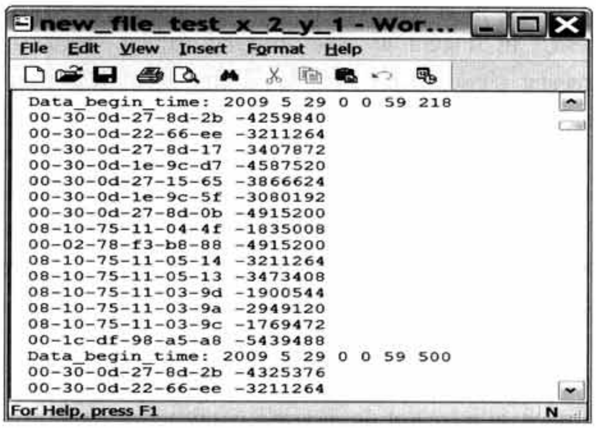
(Figure 8) is the work flow that is consistent with the design in (Figure 4). The "training request" triggers a training phase which uses the filtered input RSS vector and the prior knowledge of the device position at reference points to train the Neural Network. The learnt knowledge is store under the form of Neural Matrices. The estimating phase is triggered by a "tracking request" and the Neural Matrices are loaded for ready. The input data RSS is also noise filtered, then the knowledge presented by Neural Matrices translates the input RSS into distance vector. Distance vector is used by the PPE's first phase to reveal the device's position.

The number 'neuron' in the hidden layers is 20 and the chosen transfer function is Logsig as in equation. For the purpose of increase accuracy, we deploy 5 APs in the settings where the area for testing is 84 m2. This is just because we can utilize the frame work of our previous MMLP method [25] to break down the big region into smaller ones. What we are aiming at here is to improve the accuracy of a small scale of the previous problem. The monitoring area is plotted in (Figure 10), where the resolution for the learning phase is 1m x 1m.

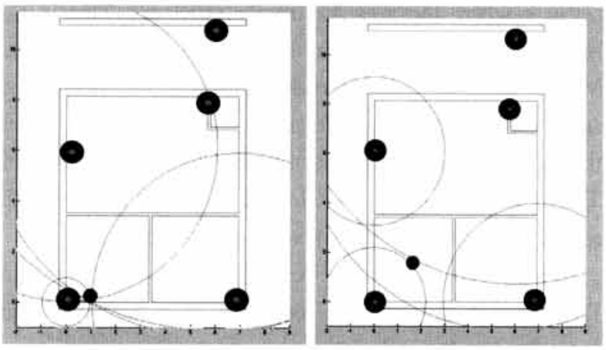
The result of the online testing can be seen in <Table 1> in which the time of testing is 5 minutes for each run, the location calculation is perform on the flight at




(Figure 8) Details of the work flow for the system where Training and Estimation stages are design to work separately (that means the training is not on the flight at the same time with the Estimation phase), depending on the request of users




(Figure 9) Collected data is written into a file, at each time step there are many APs' readings and only strong signal ones are kept due to their significance



(Figure 10) Ideal estimated position and the real estimated position. 5 nearest APs are plotted in the monitoring area

the base (Laptop). Movement speed of the person carrying the mobile PDA is slow, through a given path with given stop positions. At each step on the path, the person stands still for 20 seconds. The results in Table 1 are the average values in 20 times runs of recording and estimating.

Training data is collected in all 'morning', 'afternoon' and 'night'. However, for tracking, the result at night

<Table 1> Root mean square error (RMSE) (meters) for different times of the day, 20 runs average for each value

| Time for testing | Position in | RMS Error |
|---|---|---|
| Morning | Hallway | 2.14 (m) |
| | Big-room | 2.22 (m) |
| | Small-rooms | 2.42 (m) |
| Afternoon | Hallway | 2.31 (m) |
| | Big-room | 2.44 (m) |
| | Small-rooms | 2.41 (m) |
| Night | Hallway | 2.09 (m) |
| | Big-room | 2.23 (m) |
| | Small-rooms | 2.34 (m) |

gives the lowest error of estimation. It can be seen that the hallway give highest. The average RMSE for the system is therefore 2.31m.

It can be seen that the position in the Big-room is estimated with least error. It is because this room is covered in the good ranges of 5 APs. Meanwhile, the Small-rooms give second least error and the Hallway give the worst estimation. However, the estimated position is adjust to "reasonable position", or in other words, there is no probability for the device to be anywhere beyond the Hallway ($y$ > 11.5m). The estimation is forced to a more reasonable position ($y_{max}$ = 11.5m) if this situation occurs, and therefore, the accuracy is improved.

Note that previous MMLP method decides if the device is at a reference point. Therefore the decision making for a point is actually an area around that point to compare with a random path in any point. The area around each point is approximately [5m x 5m].

<Table 2> Comparison between MMLP and our proposed method in terms of accuracy

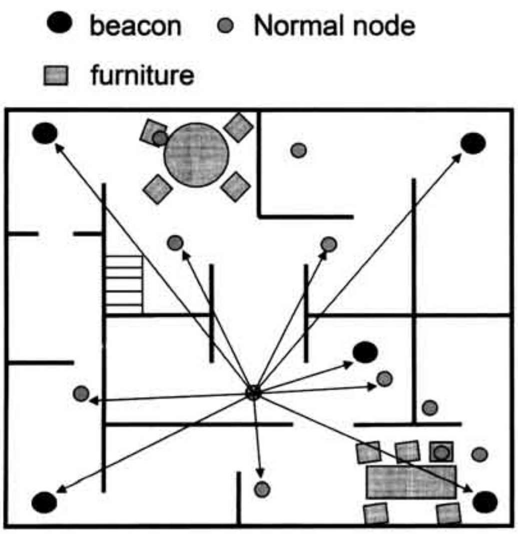
| Time for testing | MMLP | ANN and PPE |
|---|---|---|
| Hallway | 0.316 | 0.271 |
| Big-room | 0.325 | 0.281 |
| Small-rooms | 0.342 | 0.288 |

The tracking phase decides what room is the mobile device is in when the device is at the center of the room. Obviously, the accuracy is improved with the proposed method. It can be actually regarded that the proposed method can perform the semi-tracking task to the mobile device in the monitoring area. By "semi-tracking", we imply that the complete cycle of positioning and predicting is not considered or the information of past estimations are not used for future prediction to reduce the error. However, when the device is in the monitoring area, the estimated coordinates can be any position instead of at grid points that other methods usually gives. In other words, the method avoid discrete results of 'yes/no in cell" method in learning classification method. This can increase accuracy because of the average mechanism of continuous results. As we mention before, the relation between RSS readings and the distance is study therefore the distance vector can be considered to be unbiased without much calibration. The Neural Network engine actually does the calibration.

Moreover, it is remarked that the combination of ANN and PPE reveals some advantages over other learning methods like standard ANN, MMLP, SVM, etc., if the readings of some APs are absent in the tracking stage while the training stage records them and uses them for learning. Then the classification suffers bad from the absent dimension in the input vector. Meanwhile, by interpreting the knowledge of the AP readings into distance, this absence can be tolerated because the output distance vector can be obtained (with absent dimension, of course) and PPE can be applied after that normally.

## 5. Conclusions and future work

This paper proposes a method for indoor localization based on the RSS value of RF signals collected from AP readings. The Fingerprinting technique based on machine learning is the main focus of this paper. Although there are drawbacks for the Fingerprinting methods, Machine learning-based Fingerprinting Localization are currently the best choice to get a high enough accuracy for indoor localization. The key contribution of "Neural Network and PPE's first phase based Localization" is trying to position the actual continuous coordinates of the mobile device instead of several target/reference points or several cells in the monitoring area. In the other word, we present the necessity of utilizing collaborative methods to improve the accuracy of position estimation when the mobile device is close to a group of other mobiles by estimating the distances to the neighbors and then applying PPE's phase 2. Although the necessity and the efficiency of collaborative methods are fully discussed, particularly the PPE's phase 2, the work has not been done with hardware in reality experiments. The raw estimations will be carried out with the measurements from normal nodes (mobile devices) to APs and to neighbor devices as the input data for PPE's phase 2 as in (Figure 11). This should be our next future work in which the accuracy can be improved (see analysis in [23]).




(Figure 11) Applying PPE's phase 2 for indoor localization.References

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