An Enhanced Neural Network Algorithm using Wi-Fi Fingerprinting

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ABSTRACT *- Pervasive positioning provides uninterrupted positional information in both indoor and outdoor locations for a wide spectrum of location based service (LBS) applications. With the rapid enlargement of the low-cost and high speed data communication, Wi-Fi networks in many metropolitan cities, strength of signals broadcasted from the Wi-Fi access points (APs) namely received signal strength (RSS) have been smartly adopted for indoor positioning. In this paper, a Wi-Fi positioning algorithm based on neural network modeling of Wi-Fi signal patterns is planned. This algorithm is based on the associationamong the initial parameter setting for neural network training and output of the mean square error to obtain better exhibiting of the nonlinear highly complex Wi-Fi signal power propagation surface. The test results show that this neural network based data processing algorithm can suggestively improve the neural network training surface to achieve the maximum possible exactness of the Wi-Fi fingerprinting positioning method.*

Keywords: *indoor positioning; neural network; Wi-Fi fingerprinting.*

I. INTRODUCTION

Universal positioning technologies include but are not limited to Global Satellite Navigation Systems (GNSS) such as the American Global Positioning System (GPS), cellular and Wi-Fi networks, Radio Frequency Identification (RFID), Ultra-wide Band (UWB), ZigBee, and their integrations. Amongst these placing technologies, Wi-Fi networks with the IEEE 802.11 license free communication standard have been rapidly established in many metropolitan cities, e.g., in Australia, Hong Kong SAR of China, and Taiwan.

The essential function of Wi-Fi networks is to provide a low-cost and operative platform for multimedia communications. In accumulation, the propagation of Wi-Fi signals, if properly modeled, can deliver real-time positional material of mobile devices in both indoor and outdoor situations. Dissimilar Wi-Fi positioning approaches include Cell-Identification (Cell-ID), trilateration and fingerprinting. Completedescription of these methods can be founded.Cell-Identification is the humblest method for signal strength based positioning systems such as cellular mobile network and Wi-Fi positioning. Though, only very crude positioning results container be obtained.

At an indefinite mobile device's position where signal strengths from m numbers of nearby contact points (Aps) can be detected, the AP's position with the strongest detected RSS would be used to approximate the position of the mobile device. For example, if RSS2 from AP2 is the strongest among RSSi from APi, for $i = 1, 2, \ldots, m$, then (X2, Y2) will be used to approximate the mobile device's situation. With this approach, the accurateness would be contingent on the effective signal propagation distance, as well as density and distribution of the APs installed. This approach was additional improved by the weighted centroid localization (WCL). For the trilateration approach, the mobile device's situation, generally in two dimensions, is strongminded using a set of unrushed distances from the nearby known APs. Least squares explanation is normally applied when more than two reserves are observed.

It should be noted that the terrestrial land measuring techniques adopt restrained distance as raw observations, while for the Wi-Fi based techniques, the raw data are RSSs, therefore a RSS-to-distance alteration method is to be applied, and the known APs' positions will be preserved as control points. The general RSS-to-distance translation approach is by curve fitting with for example, parabolic or logarithmic regression, constructed on free space propagation model. By further seeing the complex real site circumstances such as path loss of signal due to reduction, reflection and refraction, as well as the geometrical effects on length resection, dissimilar RSS-to-distance conversion algorithms such as the Gaussian process regression and the arithmetical path loss parameter valuation were proposed.

Concerning the fingerprinting approach that is more suitable for indoor surroundings, it has the advantage that the APs coordinates are not required in the position fortitude process. Though, it requires preliminary efforts of database development. The database, also called radio map Figure 1, comprises a collection of calibration points at dissimilar locations in the area where Wi-Fi placing is to be performed. The database expansion process is normally carried out if there are no important factors that would seriously affect the RSS patterns due to for example, rearrangement of large objects and removal or addition of fixed structures in the Wi-Fi positioning area.

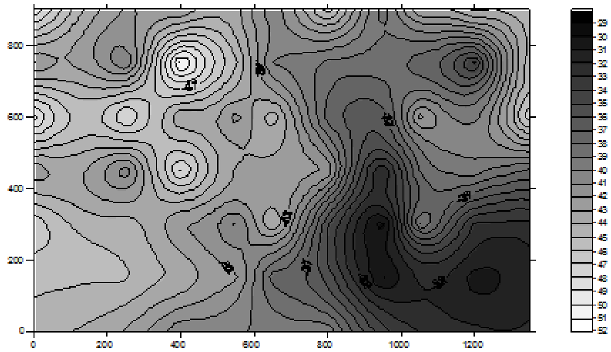

Fig 1.An example of radio map generated from a Wi-Fi signal strength database

In real-time positioning, the RSSs composed at an unknown position are associated with radio map's pattern. The pattern evaluation algorithms can be frequentlyconfidential into deterministic and numerical approaches which include point matching, area established probability and Bayesian network. Current research outputs on the statistical methods include but not limited to, for example, the Expectation–Maximization (EM) algorithm, Reporting Area Estimates, and floor fortitude algorithms for Wi-Fi positioning in multi-story buildings proposed.

II. NEURAL NETWORK MODELING

From the above introduction of the fingerprinting locating approach, it is probable to consider the co-ordinates ((x,y) in 2-dimensional case) of a point as a function of the signal strengths from several access points,

{si}, i = 1, 2, …, m, where, $x = f(s1, s2, \ldots, sm)$ and $y = g(s1, s2, \ldots, sm)$.

If a sample of uniform or random dissemination of points with known positions and the signal strengths from those access points can be restrained accurately, the minimum norm as shown in Equation or some well-known statistical methods can occasionally give a fairly good estimate of the position of any other points in this region based on the restrained signal strengths at this position.

As illuminated in the previous section, the customary statistical methods based on some smoothing calculation may fail to capture the widely fluctuating characteristics of these wave patterns produced by those access points. This clarifies the high errors in Wi-Fi positioning inside certain buildings.

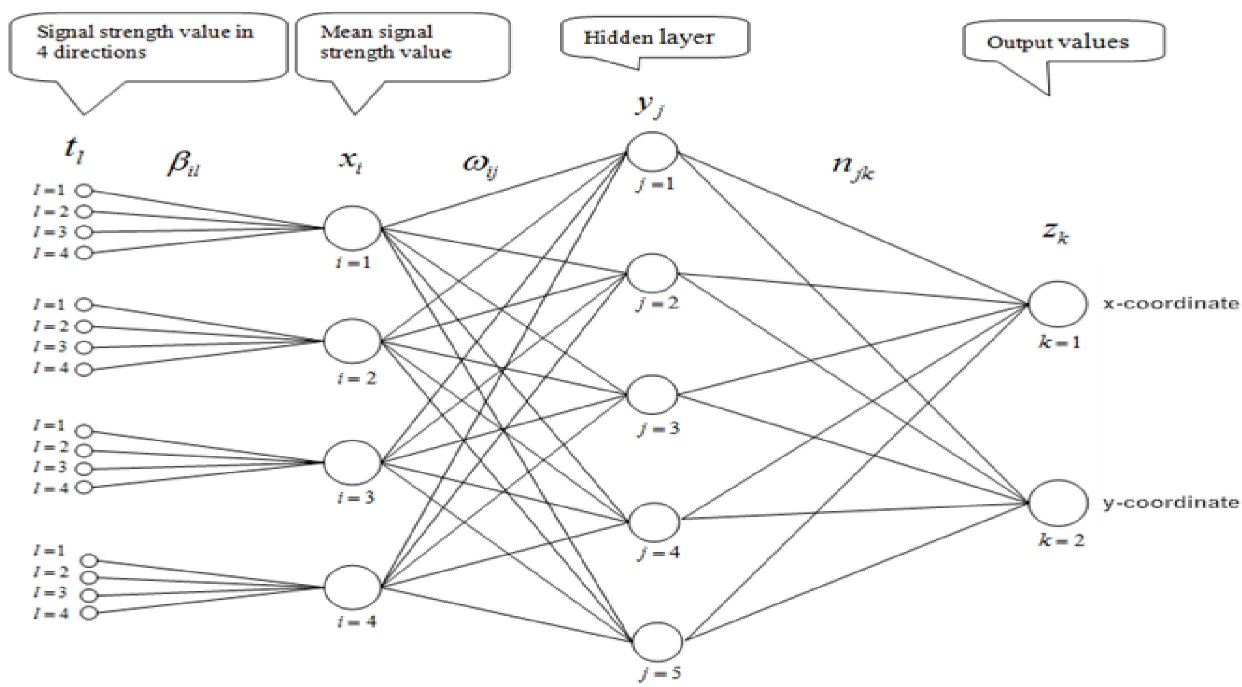

Fig 2. A three-layer feed-forward Neural Network for Wi-Fi positioning

Here the summary is taken over the entire training set. We shall see that the success of our culture process be contingent on whether we can get the smallest possible value for the above sum of squares of their alteration or, in other words, the best learning surface that defines the actual RSS pattern produced by all the access points covering the whole region.

The minimization algorithm was adapted and improved from that has been shown to be very efficient for solving a number of very problematic problems in least squares minimization. Since the impartial function is nonlinear, a simple but effective heuristic optimization method familiarized by used. It has been demonstrated to be effective in a number of complex least squares minimization problems including the training of a repeated neural network. The method contains three basic steps,

(i) Full local exploration

(ii) Partial local movement

(iii) Exploratory movements

III. ALGORITHM VALIDATION

The above algorithm was validated using data together inside a construction of the Hong Kong Polytechnic University (HKPolyU) campus, with the APs' spreading shown in Figure 3.

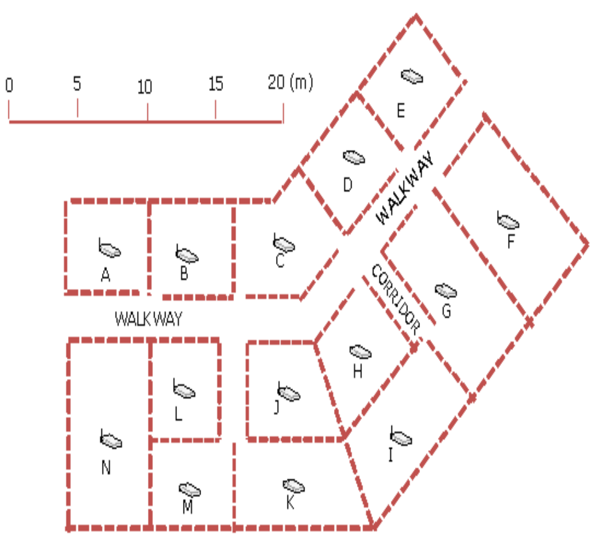

Fig3. Floor plan showing the distribution of access points in the test site.

The 14 numbers of APs were categorized according to area number from A to N separately. In our exploration, signal strength data from 3 and 4 numbers of APs were used for training by the neural network. Allwell as from other rooms within about 30 m radius. Though, in our validation process, only signals from the nearest APs were used. As the IEEE 802.11 b/g standard Wi-Fi card was used for data collection, the signals established were at the same 2.4 GHz frequency.

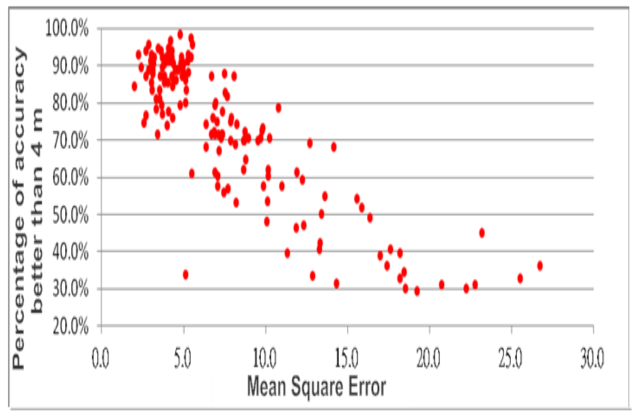

Fig 4. Relationship between mean square error and accuracy.

IV. CONCLUSIONS

From our inquiries, Wi-Fi positioning can commonly achieve 1 to 4 m of accuracy in an arbitrary Wi-Fi network area using the neural network approach. Though, the training process and parameter selection of the neural network is the key for completing the highest possible accuracy of Wi-Fi positioning results. Our untried results show that the proposed neural network advances the accuracy ofpositioning suggestively by improving the nonlinear, highly complex Wi-Fi signal propagation patterns.

To escape being trapped in a local minimum, training should be allowable to retry with dissimilar initial parameter settings and different order of AP data inputs, so that the best set of parameters (*i.e.*, the one that gives the lowest objective value) can be found. This will improve the overall accuracy. We have shown that there is a negative relationship between the mean square error value attained in our training process and the percentage of accuracy in our positioning. This means that based on the plot in Figure 6, one can repeat the training process as designated above in order to achieve the highest possible accuracy.

In our exploration, only the minimum norm point corresponding method is compared with our proposed algorithm. As spoken in the Summary section, many other operative Wi-Fi standing algorithms have been proposed lately. It would be worthwhile to further consider the strengths of each method under dissimilar geometrical, access point accessibility and distribution, and influence conditions, for emergent a reliable ubiquitous standing system with the best achievable accuracy, to also support Global Satellite Navigation Systems (GNSS) in case satellite positioning fails in highly congested outdoor environments.

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