RF ENVIRONMENT BEHAVIOR MODELING BASED ON 3-D RAY-TRACING AND NEURAL NETWORKS TO MITIGATE MULTIPATH IN INDOOR POSITION ESTIMATION

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ABSTRACT

This paper proposes a robust methodology for radio frequency (RF) environment modeling and channel profile estimation by associating three dimensional ray-tracing and neural networks (NN) techniques. A complete solution has been developed based on this model with the aim of improving the performance of position estimation in environments with strong multipath behavior such as indoor and disaster scenes. The effectiveness of the proposed solution has been successfully validated through practical test scenario characterized with high multipath. Measurement results demonstrated that the accuracy of position estimation has been improved by 44%.

1. INTRODUCTION

The existing emergency networks require highly accurate position estimation of the rescuers to properly coordinate the rescue operations. Such environments are characterized with strong multipath behavior where the multipath components can be more prominent than the direct path signal compromising the accuracy of the estimated position in disaster scenes. Since the multipath phenomena dominates most of the environment characteristics in such scenario, an radio frequency (RF) model is proposed to characterize the behavior of the channel using a combination of three dimensional ray-tracing (3-D RT) and neural networks (NN) techniques. This model is used to estimate the error due to multipath problem and to improve the performance of the position estimation.

In order to achieve the channel modeling task, empirical and deterministic methods can be used. The empirical techniques offer low computational cost, but also low accuracy; whereas, deterministic techniques, which are based on the calculation of electromagnetic field, offer high accuracy at the expense of very high computational complexity. Ray-tracing (RT) techniques are deterministic methods that provide high accuracy without excessive computational cost. 3-D RT algorithm is able to provide a very accurate multipath profile characterization of the channel for several points of the scenario, but for large scenarios with intensive ray launching and high resolution grid, the computational and storage burden could be excessive. In these cases, we propose NN to characterize the multipath of the channel for any point of the scenario using the channel profile provided by 3-D RT algorithm. It is shown in this work that NN was able to 1) predict the delay between the direct path and the most powerful multipath component for all possible positions in reasonable terms; and, 2) improve the location estimation accuracy by using the information on the delay profile of the multipath.

The rest of the paper is organized as follows. In section 2, we present the proposed methodology for RF environmental modeling and explain how it can be used to improve the location estimation. Section 3 describes the hardware implementation and experimental results. The conclusions are presented in Section 4.

2. PROPOSED METODOLOGY FOR HIGH ACCURACY POSITION ESTIMATION

In a disaster scene, it is vital to accurately estimate the position of each emergency team involved in rescue operations. The disaster scene can exhibit strong multipath behavior which causes erroneous position estimation. In this section, we will explain how to overcome this problem. At first, several position estimation techniques will be compared. After selecting the appropriate technique for our application, channel modeling with 3-D RT and NNs will be described. This model is used to mitigate multipath and improve location estimation.

2.1. Selection of position estimation

When the rescue teams are in indoor environments, it is not possible to use the common geo-location methods such as global positioning system (GPS). There are several methods described in the literature that can be used to achieve the goal of locating rescuers in a disaster scenario [1]-[6]. The most prominent methods are relative signal strength (RSS), time of arrival (TOA) and time difference of arrival (TDOA). The salient features of each methodology are briefly summarized in Table 1.

In the proposed solution, we have used TDOA, as it does not require synchronization between the transmitters and the receivers. However, TDOA needs synchronization between transmitters which is more feasible from a practical point of view as compared to synchronization between transmitters and unknown receiver as required by TOA.

Table 1: Location Estimation methods

Location Estimation		
Relative Signal Strength	**Time of Arrival**	**Time Difference of Arrival**
• Distance is calculated based on relative signal strength of each antenna to estimate the distance between the emitter and the receiver	• Position is calculated based on time of arrival between emitter and receiver	• Distance is calculated based on time difference of arrival between several transmitters to one receiver
• Does not require synchronization between emitter and receiver	• Requires synchronization between emitter and receiver	• Does not require synchronization between emitter and receiver
• Highly prone to environment effects	• Requires fewer base stations compared to TDoA	• Requires synchronization between emitters

2.2. 3-D Ray Tracing and Neural Networks Channel Model

The proposed channel modeling is based on a combination of 3-D RT and NNs that provide a very accurate full multipath profile characterization of the channel for any point in the scenario, estimating the error due to Multipath in TDOA location estimation.

2.2.1. Ray-Launching and Tracing

As it is illustrated in Figure 1, ray-launching techniques [7] [8] are based on identifying a single point on the wave front of the radiated wave with a ray that propagates along the space following a combination of optic and electromagnetic theories.

Each ray propagates in the space as a single optic ray, with its associated electric field provided by:

$$E_i^{\perp} = \sqrt{\frac{P_{rad} D_t(\theta_t, \phi_t)\eta}{2\pi}} \frac{e^{-j\gamma r}}{r} x_t^{\perp} L^{\perp} \quad (1)$$

$$E_i^{\parallel} = \sqrt{\frac{P_{rad} D_t(\theta_t, \phi_t)\eta}{2\pi}} \frac{e^{-j\gamma r}}{r} X_t^{\parallel} L^{\parallel} \quad (2)$$

where $D_t(\theta_t, \phi_t)$ is the directivity of the transmitter antenna in the direction of the outgoing ray, P_{rad} is the radiated power, η is the impedance of the propagation medium, r is the distance from the transmitter antenna, and γ is the complex propagation constant in the material given by:

$$\gamma = \alpha + j\beta = j\omega\sqrt{\mu\varepsilon(1 - j\tan\delta_e)} \quad (3)$$

When this ray finds an object in its path, two new rays are created: a reflected ray and a transmitted ray. According to optical theory these new angles can be calculated by Snell's law.

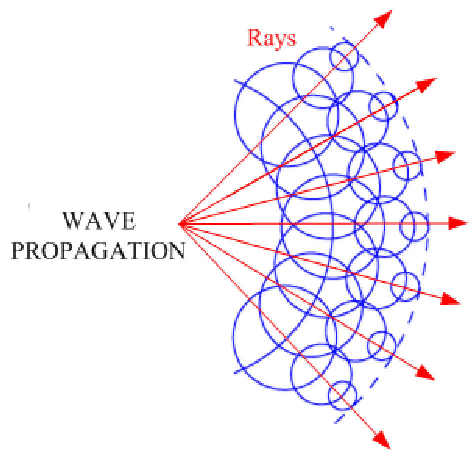

Figure 1: Wave front propagation with rays associated with single wave front points.

Figure 2 shows the scenario which is actually a part of the third floor of the University of Calgary information and communication technologies (ICT) building. There are many big objects such as walls and furniture that are responsible for strong multipath scenario based on their electromagnetic properties such as permittivity, permeability, and shape of the object. Based on the interaction of these objects with electromagnetic rays, there are several ways to improve the accuracy of the ray-launching predictions. A better environment characterization with more realistic 3-D object shapes and a more precise characterization of the electromagnetic properties of these objects will improve the accuracy of the ray-launching predictions without an increment of the computational and memory burden. Moreover, it is also possible to improve the accuracy by launching more rays, or, increasing the resolution of the grid at the expense of more computational complexity and memory requirements.

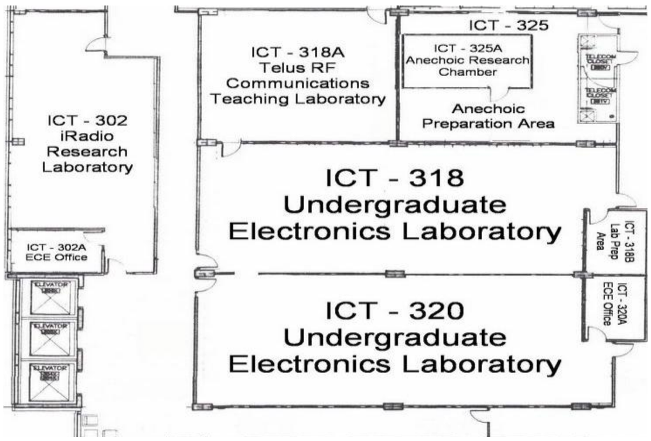

Figure 2: Map of the modeled scenario.

2.2.2. Neural Networks

The 3D ray launching technique relies on modeling the scene under consideration and launching rays in every direction to model the RF environment. Therefore, the increase in the number of rays causes an increase in the computational burden. Moreover, even with denser ray launch (rays transmitted in every direction) it is not possible to capture the profiles at every point in space. Considering these aspects, we need a device to store and to predict positions in the space that are not provided by the 3D ray-tracing method. We propose neural networks as the most suitable candidate for this pattern recognition problem [9]-[11]. We have selected the feed forward NN for pattern recognition as shown in Figure 3, for its lower complexity and better accuracy compared with other NNs, such as Elman, Hopfield, recurrent and radial basis function NNs. All the NN structures are developed and compared in MATLAB 2008, using advanced NN functional settings. The NN has two hidden layers and one linear output layer. The first hidden layer has 4 neurons with a 'logsig' activation function given by $f = 1/(1-e^{-x})$ while the second hidden layer has 17 neurons with a 'tansig' activation function given by $f = (e^{x} - e^{-x})/(e^{x} + e^{-x})$.

The learning procedure is accomplished according to back propagation [11] based on the Levenberg Marquardt trust region [12] search method to minimize the mean squared error for the training data. The working of a feed forward NN can be found in detail in [10-13]. The NN is trained with the inputs as x, y and z coordinates of the position in the space and output as delay between the direct ray and the most prominent multipath ray that is responsible for the error in the time difference of arrival.

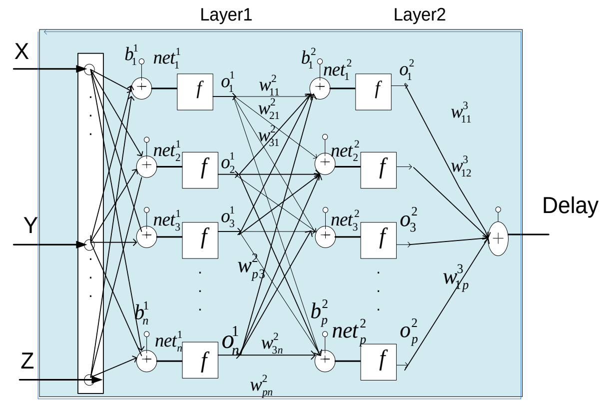

Figure 3: Feedforward neural network for pattern recognition and prediction for delay error.

First of all the whole scene was divided in coarse grid and ray-tracing has been completed as discussed in previous section. This data is used to train the neural network. Once NN is trained; it becomes a black box containing information of delay due to multipath at various points of the scene. In this simplistic form it encodes the essential information (error in delay estimation) due to RF environment. This NN now can interpolate for the points which have not been considered for the original ray-tracing, hence working as storage device for infinite data points in space. Normalized mean square error (NMSE) of 0.018nS is achieved while trained network is used with another set of data from the same scenario, where maximum error is of 0.02nS.This prediction has been able to significantly reduce the error in position estimation as discussed in section 3.1.

2.3. Integration of the position estimation solution for error minimization in TDoA

To minimize the error in location estimation due to the strong multipath we propose the following algorithm for the rescuer node (RN) and central node (CN):

1. The RN calculates its location with the TDOA method and sends its estimated location to the CN.
2. The BS estimates the error due to multipath for that location and sent back this estimated error to the rescue team.
3. The RN re-calculates its position estimation considering the error in TDOA.

This error is evaluated for the points in the range given by the initial TDOA estimation and synthesized in the orthogonal frequency division multiplexing based waveform to be sent to any rescuer. Figure 4 shows the original TDOA calculation achieved by cross-correlation of the waveforms. The actual TDOA is predicted by error estimation using aforementioned 3-D RT and NN for the rescuer's position. The rescuer can use this information to remove errors from

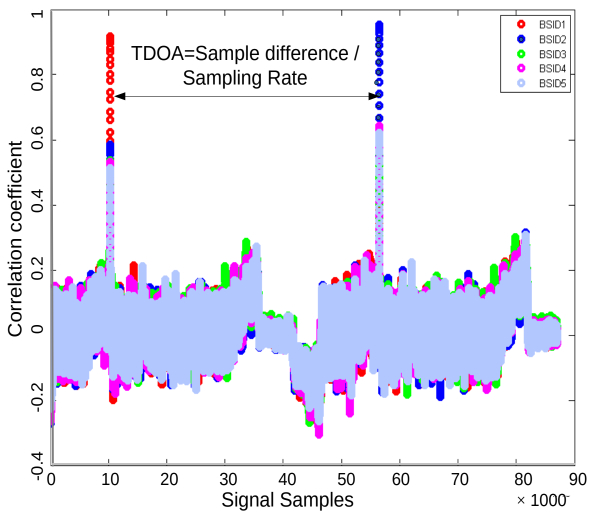

Figure 4: Estimation of delay error for synchronized transmitters.

the TDOA parameters achieved from each base station and to calculate its actual position using the TDOA method. In this way, the wireless position estimation can be done in three simple steps.

The advantage of the proposed solution is that it doesn't need a hardware upgrade in the network or in the rescue team device. It only needs a software upgrade of the device.

In the case of a mobile phone, the algorithm can be directly applied where base stations are continuously emitting synchronized signal. As these signals are captured with mobile phone, first location estimation is achieved with the calculated TDOA parameters. This initial position is not rigorously accurate due to multipath; therefore mobile station sends the located position to the base station. The base station estimates the error due to multipath and sends back the estimated error due to multipath to the mobile phone. Using this information, the mobile phone user refines the estimation of its location. With every such iteration, position estimation keeps on converging towards the true value.

3. IMPLENTATION AND EXPERIMENTAL RESULTS

To validate the proposed solution, we have implemented the full system to perform the measurements and simulations in the third floor of the ICT building at University of Calgary.

3.1. Measurement set-up

Figure 5 depicts the experimental setup that we implemented for the position estimation validation test. This setup included nine omnidirectional antenna operating in the frequency range of of 2.4-2.5 GHz, which acted as base

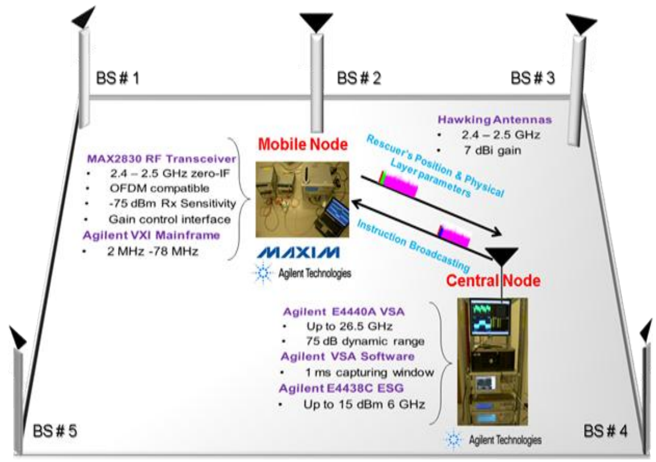

Figure 5: Hardware setup for position finding.

stations. The mobile node included the MAX2830 full Tx/Rx transceiver from Maxim along with Agilent VXI main frame with baseband ADC (Analog to Digital Convertor) modules which is used for baseband signal processing. The central node consisted of the E4440A Agilent vector spectrum analyzer (VSA) software used to capture the received TDOA signal in one fixed 1 ms window, and two synchronized E4438C vector signal generators (VSGs) from Agilent. The base stations were realized by the two VSGs.

Due to the limited number of available signal generators, we time-multiplexed the signals between two synchronized signal generators.

The TDOA signals were encoded using the downlink of the WiMax standard (signal with 5 MHz bandwidth). The first signal (reference) was transmitted through the central node and the others were transmitted through the rest of the base stations with modulation implemented in the second signal generator one by one.

At the mobile node terminal, the VSA operated in intermediate frequency (IF) trigger mode and does not require any synchronization with the transmitters. The receiver capturing window stores two consecutive frames multiplexed in time calculating the TDOA information of the base station with respect to the reference node.

To model the channel each of the antennas launched one ray each 2 degrees of θ and φ, and the grid is defined to be cubes of $\lambda/10$. After the simulation, delay error at the estimated positions of the receivers was calculated using NNs and these values were sent to the receivers.

3.2. Experimental Results

TDOA based position estimation is mostly successful when receiver is near the centre and multipath effect is minimal.

Table 2: Error in Location Estimation.

	Error before multipath correction	Error after multipath correction	Error reduction
RX1	0.8201 m	0.6017 m	26.63 %
RX2	2.6416 m	2.6063 m	1.34%
RX3	2.5846 m	1.4440 m	44.13%

Therefore, to include the worst case scenario three different positions of receivers have been observed. In the scenario of figure (2), receiver1 (Rx1) is near the geometric centre while Rx2 is the near to the periphery. Rx3 is near a joint of two walls and expected to be highly susceptible to multipath which is also confirmed with measurement results. The experiment results are shown in table 2. It can be seen that the error reduced to 0.2184 meters for receiver 1, 0.0353 meters for receiver 2, and 1.1406 meters for receiver 3. It can be noticed that Rx3 have the highest error reduction after implementing the proposed multipath corrections.

It is worth to add that for calculating delay error the difference of line of sight component and most prominent multipath component is considered here for the simplicity, although for more accuracy vector sum of all multipath components should be included. This fact and slight error in delay estimation by NN is responsible for the error after multipath correction, which can be further reduced by considering most of the multipath components. As can be seen from Table 2, after multipath correction with our simplified assumption that most prominent multipath component is mostly responsible for error in delay, the total error reduction ranges from 1.34% to 44.13% with an average error reduction of 24.03%.

4. CONCLUSION

In this paper a method to improve the accuracy and performance of a ray-tracing algorithm using feed forward neural networks has been developed. The proposed algorithm is used to improve the position estimation using TDOA. With the measurements performed in the 3rd floor of the ICT building, University of Calgary, it has been shown that with this method an error reduction up to 44.14% is achieved. With these results, we propose this method as an inexpensive solution to improve the location estimation of TDOA based algorithms for environments characterized such as emergency scenes and indoor environment. Due to the fact that the proposed method only needs a software upgrade in the device, and it is a simpler and faster approach that only requires on site beforehand measurements.

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