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Received Signal Strength Estimation in Vehicle-to-Vehicle Communications Using Neural Networks

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ABSTRACT

Received signal strength (RSS) is a major performance metric in vehicular communication system design. Experimental measurements of the RSS for vehicular communications are not cost effective. Therefore, off-the-shelf ray-tracing packages are deployed to substitute the costly measurements with RSS simulations. However, the simulation process is too time-consuming if the RSS is required over a long interval of time. We propose a new RSS estimation approach using neural network (NN) to reduce the computation time. First, ray-tracing is used for simulating the RSS in some instances of time and training the NN. Then, the NN is deployed to estimate the RSS afterward. We apply the new approach to an antenna placement problem in vehicle-to-vehicle (V2V) communications. The numerical results show that RSS computation time reduces significantly by using the proposed estimation approach, and the approach is as effective as ray-tracing in the RSS simulation for the antenna placement problem in vehicular communications.

KEYWORDS

Antenna placement, neural networks, received signal strength, vehicular communications, wireless propagation.

1 INTRODUCTION

Today, increasing number of vehicles has led to a dramatic increase in traffic jam and car accident occurrences. Therefore, researches on mobile automotive communications for the purpose of safe driving have attracted much attention. Communicating traffic information between vehicles-to-vehicles (V2V) in a right time and right place plays a major role in reducing the endangerment [1]. Having traffic information and sufficient knowledge of a vehicle surrounding, a driver can react appropriately in different events, such as, over-speed, inappropriate distance, or failure to stop at red lights. Due to the mobility of vehicles, the wireless channel should be deployed for communicating the traffic information.

Wireless channel suffers from several impairments such as path-loss, multipath, and shadowing. The signal strength on the receiver is affected dramatically by these impairments both in non-line-of-sight and line-of-sight propagations. However, appropriate antenna placement on the transmitter and the receiver can reduce the channel impairments effects and improve the signal strength on the receiver antenna. Accordingly, the received signal strength (RSS) can be considered as a mean of an antenna placement appropriateness.

The RSS can be measured experimentally, but this approach is too specific, i.e., the results will depend on the specific scenario which has been considered. Generalizing the experimental results requires repeating the experiments for many different scenarios of traffic pattern and geographical area models which is not cost effective. Therefore, simulation softwares, such as, Radio-Wave Propagation Simulator (RPS), are deployed for less expensive RSS computation instead.

RSS measurement and simulation in vehicular communications have been addressed in some research works. The RSS measurement of V2V communications among parked vehicles at 900 MHz has been addressed in [2]. For an urban area, simulation and evaluation of the V2V communication channel at 5.9 GHz, has been carried out in [3]. The RSS has been measured at

3.5 GHz and 5.2 GHz, respectively, in rural area [4] and urban and highway area [5]. An error model for inter-vehicle communications in highways at 5.9 GHz frequency band has been proposed in [6]. Influence of antennas placement on the V2V communication channel is investigated in [7].

All of the aforementioned RSS measurements and simulations are valid for a set of time instances where the measurements or simulations have been carried out. In other words, the RSS values over the whole interval of time are not determined because RSS computation in all moments is very time consuming and not efficient.

To reduce the computational time of RSS simulations, we suggest estimating RSS based on some simulated values. In other words, we use a simulator once for RSS simulation in some random moments. The simulated RSS values are fed to an estimation method to estimate the RSS afterward. We deploy neural network (NN) for the estimation. The simulated RSS at the sample moments are used to train the NN. Our proposed approach is advantageous in terms of reducing the computation time because, first, the estimation is performed much faster than the simulation process with the cost of some negligible errors, second, the RSS simulation for a small number of sampling instances is required to determine the RSS over the whole interval of measuring time.

To evaluate the performance of the proposed RSS estimation method, we apply it to the antenna placement problem in V2V communications, where the RSS is used as a decision metric for locating the transmitter and receiver antennas. We compare the effectiveness of the estimated RSS (achieved by our proposed method) with the simulated RSS (achieved by a ray-tracing simulator) in solving an antenna placement problem. Using RPS simulator, we simulate the RSS for different cases where one of the transmitter/receiver antennas is fixed on a vehicle, and the other is located in different places on another vehicle. Then, for the same cases, we use the proposed estimation method for the RSS computation. Comparing the RSS values computed by the two methods, we show that, while the estimation method is faster than the RPS simulation, the latter is as effective as the former in solving the antenna placement problem.

The rest of the paper is structured as follows. In Section 2, the system model including the transmitter and receiver antennas, traffic characteristics, and wireless channel, as well as the urban models are presented. Section 3 explains the ray tracing approach for RSS measurements using RPS simulator. In Section 4, our proposed NN and its parameters are presented. Section 5 demonstrates the numerical results of RSS simulation using our proposed approach for an antenna placement problem. Finally, Section 6 concludes the paper and explains our further research.

2 SYSTEM MODEL

The characteristics of wireless channel, urban area and traffic distribution, as well as the antenna models are explained in this section.

The wireless channel impairments, such as, multipath propagation, path-loss, shadowing, and Doppler effects are vital processes which should be taken into account in the RSS measurements. The multipath propagation causes the transmitted signal to arrive at the receiver, not only from a direct propagation path, but also from multiple existing paths between the transmitter and the receiver. Due to the different power loss over distances and shadows, the received signal is a combination of all scattered, reflected, and diffracted electromagnetic waves from other objects in the transmission media. The received waves have different attenuations, time delays, phase shifts, arrival angles, and polarization, which cause the frequency-selectivity, direction-selectivity, and time-variant behaviour of the wireless radio channel.

An urban area containing moving vehicles, buildings, and trees is considered.

Three types of vehicles are used: vans, buses, and small vehicles. Antennas can be located on every vehicle or other objects, but we have placed them only on small vehicles in this work. A transmitter antenna is located on the roof of a vehicle, and a receiver antenna is located at different places of another vehicle in each instance of our simulation. The vehicles have different speeds with respect to

each other. The vehicles are perfect electrical conductors with cubic shapes and different sizes.
Rectangular boxes model the buildings located at 0.1m from the road side. The permittivity, εr, of the buildings and the trees equals 2.25-j0.05 and 2.25-j0.035, respectively.
The dimensions of the objects compared to the wavelength should be small enough (approximately, 10 time smaller). So, the frequency is set to 1.8 GHz. The antennas are isotropic. Therefore, the RSS is independent of the angle of arrival in the receiver.

3 RPS IMPLEMENTATION

The system model parameters are set and the urban area is implemented in RPS simulator in this section.
RPS has the geographical map generating facilities. The map generator locates the environment objects on the map and assigns the electrical parameters, such as, permittivity, εr, permeability, μr, and the standard deviation of the surface roughness, σ, to the objects. The objects material parameters are set based on the chosen frequency band. These parameters affect reflections, diffractions, and transmissions of rays. Figure 1 shows the traffic distribution and the urban area implemented in RPS. The transmitter speed, the receiver speed, and the distance between them are important parameters in the RSS simulation. The transmitter and the receiver speeds are 80 Km/h and 55 Km/h, respectively. The initial distance between the transmitter and the receiver is 80 m. The simulation is run until the distance reaches 120 m.

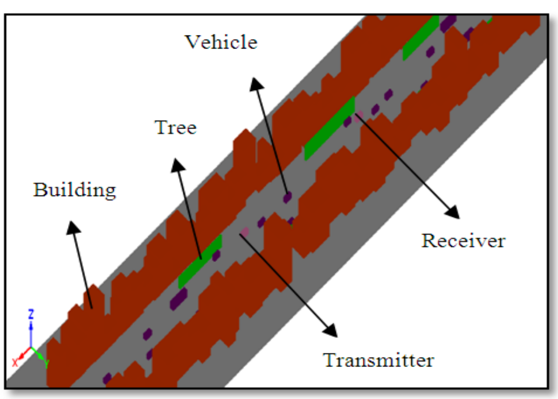

Figure 1. Implemented V2V communication scenario in RPS.

The aforementioned wireless channel impairments, explained in Section 2, are considered in the ray tracing simulators.
After implementing the system model, the RSS is simulated at different moments. We need a number of random inputs to train the NN. We use a series of simulated RSS at random moments for this purpose. Based on the numerical results of the implemented scenario (see Section 4), if the number of samples is less than 115, the NN is not trained appropriately. With respect to the relative speed of the transmitter and the receiver, samples should be taken every 0.05 on average to achieve 115 samples.
Figure 2 demonstrates dominant multipath components of running the simulator once. The transmitter antenna is on the front bumper of a vehicle and the receiver antenna is on the roof of another vehicle.

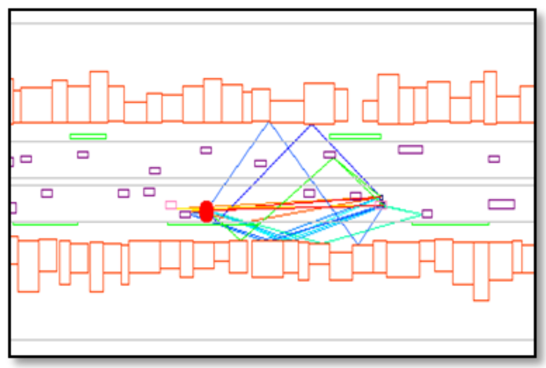

Figure 2. Multipath demonstration using RPS.

4 NEURAL NETWORK DESIGN

Designing an NN includes the selection of its architecture, model, learning algorithm, and activation functions of neurons according to the requirements of a problem. We design an NN for estimating the RSS at the receiver antenna of a moving vehicle for the V2V communication scenario described in Section 2 and 3.

4.1 NN model

Model selection for the NN is a function approximation problem. Due to the high efficiency, a Back-Propagation NN, with one (or more) sigmoid-type hidden layer(s) and a linear output layer can approximate any arbitrary (linear or nonlinear) function [8]. A perceptron network with one output layer is selected for this work. Figure 3 shows the architecture of a generic perceptron network. The network consists of three layers: an input layer, a hidden layer (with a sigmoid activation function), and an output layer (with a linear activation function).

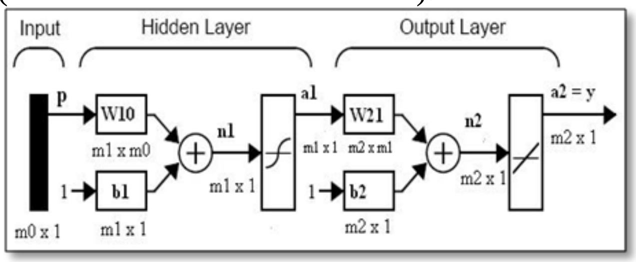

Figure 3. Architecture of a generic NN.

4.2 Input layer

The input layer is determined from the features of the inputs. Here, the input layer consists of 115 samples of time obtained from the implemented scenario with RPS.

4.3 Input layer

Hidden layer extracts the characteristics of the input pattern. In this work, to determine the number of neurons in the single hidden layer, we use a hit-and-trial method. It was found that with only 8 hidden neurons a small training error is achieved. Sigmoid activation function of hidden layers is expressed as [9]:

$$a_{i1} = \frac{1}{1+e^{-jn_{i1}}} \qquad (1)$$

where j, is the symbol of complex number, a_{i1}, containing the outputs from the hidden neurons, is the i^{th} element of a1 vector, and ni1, containing the inputs fed to the hidden neurons, is the i^{th} element of n1 vector which is calculated from:

$$n_1=W_{10}P+b_1 \qquad (2)$$

where P is the input pattern, b1 is the vector of bias weights of the hidden neurons, and W10 is the weight matrix between the input layer and the hidden layer. Rows of W_{10} are the weights of the hidden neuron.

4.4 Output layer

The output layer of the network is designed according to the requirements of the application output. Since the output of the NN is expected to produce the RSS at the receiver, the number of the output neurons is one. Thus, the pure linear activation function is selected for the output neurons and expressed as:

$$a_2=n_2 \qquad (3)$$

where a_2 shows the output layer, and n_2 is the column-vector containing the network's inputs fed to the output layer. n_2 is calculated from:

$$n_2=W_{21}a+b_2 \qquad (4)$$

where W_{21} is the weight matrix between the hidden layer and the output layer, and b_2 is the column containing the inputs of the output neurons. Each row of W_{21} matrix contains the weights for the output neuron. Simulation program has been developed to design and train the proposed NN. The program divides the training set into two parts: a) raining set (for training the network), b) testing set (for testing the performance of the network after training). The training set and the testing set were chosen to be about 3/4th and 1/4th parts of the dataset, respectively. In each of the three cases, the error corresponding to the NN has reached its lowest value. Figure 4 shows the error changes with the transmitter antenna on the front bumper of the vehicle and the receiver located on the roof.

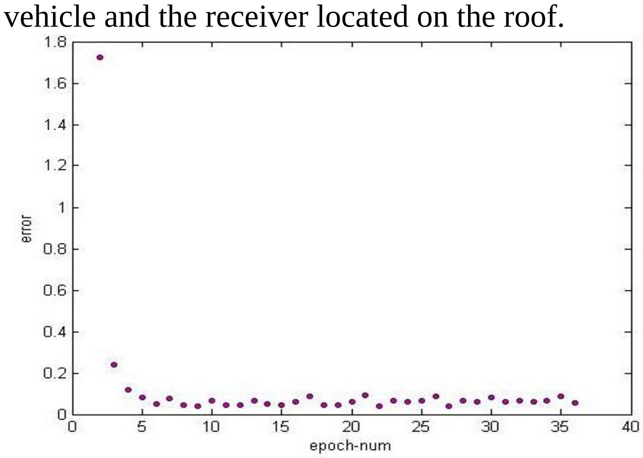

Figure 4. Trend of error change in the NN.

In the first and the second scenarios of error, decreasing trend was similar. Thus, we have avoided bringing them.

5 NUMERICAL DESIGN

The performance of the proposed RSS simulation approach is compared with the ones of RPS ray-tracing simulators in this section. The trained NN in Section 4 is used for RSS estimation in an antenna placement problem in V2V communications. A vehicle with a mounted receiver antenna on the roof is communicating with a vehicle whose transmitter antenna can be mounted on the roof, the right side, or the front bumper. The RSS is computed for the three cases, where the place of the transmitter antenna changes:

- In the first case, the transmitter is placed on the right side of the vehicle.
- In the second case, the transmitter is placed on the front bumper of the vehicle.
- In the third case, the transmitter is placed on the roof of the vehicle.

To ease the notations, the three cases are represented with “S”, “F”, and “R”, respectively.
The NN training error of “R”, “S”, and “F” cases are, respectively, 0.506%, 0.6086%, 0.5418%.
The effect of insufficient input for the NN for ”S” case is represented in Fig. 5.

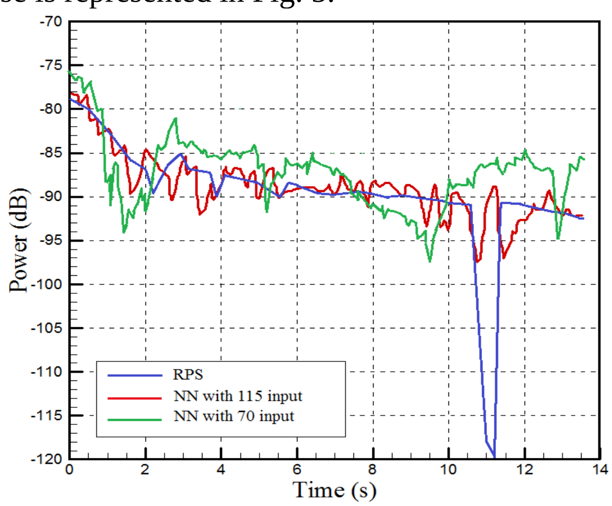

Figure 5. effect of using different number of inputs for training the NN on the RSS of “S” case.

Accordingly, the use of 70 samples for training the NN is not sufficient, and the network cannot follow the inputs. However, with 115 samples (blue graph), the NN follows the inputs successfully. The rest of the results are based on training the NN with 115 samples. The output of the NN is extracted every 0.01 sec. Figures 6, 7, and 8 show the RSS for “S”, “F”, and “R” cases, respectively. In all figures, red graph shows simulated RSS by RPS, and the blue graph shows estimated RSS by the NN.
When the transmitter antenna is mounted on the roof, the RSS is smoother than the ones of “S” and “F” cases because of the increasing line-of-sight propagation components between the transmitter and the receiver antennas. Inversely, because of reducing line-of-sight components between the transmitter and the receiver in “S” case, by increasing destructive combinations of multipath components and occurring deep fading, the RSS falls down dramatically and then there exists a disruptive communication which is not acceptable.
When the transmitter antenna is mounted on the bumper, the RSS fluctuation is reduced with respect to the ones of “R” case, because in our scenario there is no shadowing vehicle between the transmitter and the receiver.

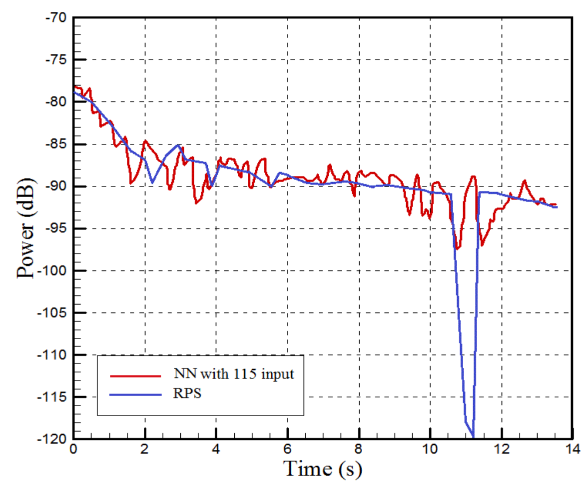

Figure 6. RSS of “S” case.

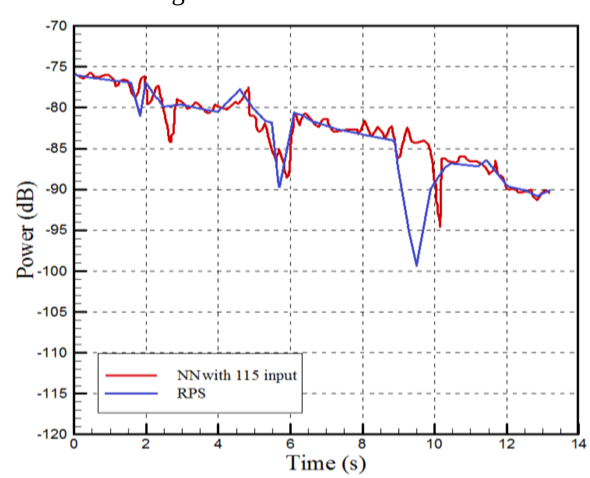

Figure 7. RSS of “F” case.

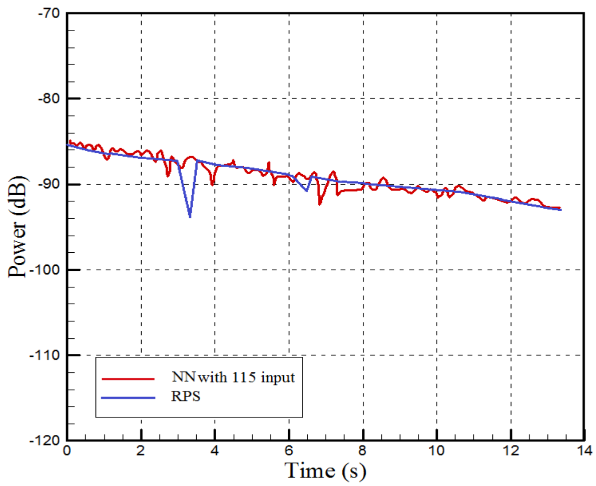

Figure 8. RSS of "R" case.

Our conducted simulation shows the RSS estimation approach is time-saving in comparison to the RSS simulation using RPS. The approximate average RPS running time, for every instance of the RSS simulation, is 8 sec. If the RSS is required every 0.01 sec, the computation time is 4608 sec when RPS is used, while the time reduces to 1720 sec using the trained NN.

6 CONCLUSION

A new RSS estimation method based on neural network has been presented for the antenna placement problem in V2V communications. Three V2V communication scenarios in an urban area where the transmit antenna is placed on the right side, the front bumper, and the roof of a vehicle and where the receiver antenna is fixed on the roof of another vehicle have been considered. The RSS values for the three scenarios have been computed using RPS ray-tracing simulator and the proposed estimation method. The numerical results demonstrate that the proposed RSS estimation method can be deployed for effectively solving the antenna placement problem. Besides, the RSS computation time of the proposed approach is much less than the ones of the RSS simulator.

7 REFERENCES

1. Car-2Car Communication Consortium website [Online]: http://www.car-2-car.org, (14.07.2012).
2. Davis, J. S., Linnartz, J. P. M. G.: Vehicle-to-Vehicle RF Propagation Measurements. In: proc. the 28th Asilomar Conference on Signals, Systems and Computers, pp. 470-474, (1994).
3. Reichardt, L., Pontes, J., Sturm, Ch., Zwick, Th.: Simulation and Evaluation of Car-to-Car communication Channels in Urban Intersection Scenarios. In: proc. the 71st IEEE Vehicular Technology Conference, pp. 1 – 5 (2010).
4. Eggers, P. C. F., Brown, T. W. C., Olesen, K., Pedersen, G. F.: Assessment of Capacity Support and Scattering in Experimental High Speed Vehicle-to-Vehicle MIMO Links. In: proc. the 65th IEEE Vehicular Technology Conference, pp. 466-470 (2007).
5. Paier, A., Karedal, J., Czink, N., Hofstetter, H., Dumard, C., Zemen, T., Tufvesson, F., Mecklenbräuker, C. F., Molisch, A. F.: First Results from Car-to-Car and Car-to-Infrastructure Radio Channel Measurements at 5.2 GHz. In: proc. the 18th IEEE International Symposium on Personal, Indoor and Mobile Radio Communications (PIMRC), pp. 1-5 (2007).
6. Zang, Y., Stibor, L., Reumerman, H. J.: An Error Model for Inter-Vehicle Communications in Highway Scenarios at 5.9GHz. In: proc. the 2nd ACM International Workshop on Performance Evaluation of Wireless Ad-hoc, Sensor, and Ubiquitous Networks (PE-WASUN '05), Montreal, Quebec, Canada, (2005).
7. Reichardt, L., Fügen, Th., Zwick, Th.: Influence of Antennas Placement on Car to Car Communications Channel. In: proc. the 3rd European Conference on Antennas and Propagation, pp. 630 – 634, (2009).
8. Demuth, H., Beale, M.: Neural Network Toolbox for Use with MATLAB: User's Guide (v. 4), The Mathworks, Inc., (2001).
9. MATLAB On-line Help Documentation.