Classification of LOS/NLOS Mobile Radio Channels

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1 Introduction

A key distintive of the mobile radio channel is the presence or absence of a line of sight (LOS) path between transmitter and receiver. The wireless channel can be modeled as a multipath environment with copies of the transmitted signal arriving at the receiver due to reflections, diffraction, and scattering from surrounding objects. If the multipath is dominated by a strong LOS path, the channel is considered LOS. Performance is generally degraded if the LOS path is blocked or significantly attenuated resulting in a non-line of sight (NLOS) channel. The goal of this work is to construct an efficient, reliable classifier for distinguishing between the LOS and NLOS channels.

Knowledge of the state of the channel can be used in several applications [1]. Radios are used for position location and range estimation. Time-of-arrival (TOA) and received signal strength (RSS) are correlated with the distance between the radios and used in this application. In a LOS channel, an accurate estimate of the distance between radios can be obtained. Techniques have also been developed to improve the distance estimates in a NLOS channel. An accurate classification of the channel is needed for correct estimation of the range. Another application for LOS/NLOS classification is cognitive radios. With knowledge of the LOS/NLOS state of the channel, the radios can be optimized for the channel in order to acheive the best possible performance.

1.1 Project Aims

The four specific aims this project seeks to accomplish are as follows:

1. **Classify a wireless channel as LOS or NLOS using pattern recognition:** Given two radios in which one/both of the radios is/are mobile, it is desirable to know the state of the channel in real time. The variation over time in the received signal strength (RSS) of narrowband signals will be used to differentiate LOS and NLOS channels.

2. **Identify defining features for extraction:** Theoretical models of LOS and NLOS mobile channels will be used to indentify key differences in the RSS variation.

3. **Compare the effectiveness and complexity of two algorithms:** Compare two supervised learning algorithms based on the neural network architecture.

4. **Evaluate the classifier's performance:** Understand how the number of RSS samples, the sampling frequency, and the mobility of the radios affects performance.

2 Background

Most research in LOS/NLOS channel state classification has focused on UWB measurements. In this work, narrowband measurements which lack time-domain resolution will be used for classification. This section describes previous work then develops the theoretical model of the mobile channel and discusses the differences between the LOS and NLOS channel.

2.1 Previous Work

Much work has been done to identify the NLOS channel using ultra-wideband (UWB) channel measurements. In [2] a method for NLOS indentification based on ultra-wideband channel measurements and hypothesis testing is developed. [3] present binary hypothesis testing and a neural network architecture using wideband measurements. UWB and wideband measurements have finer time resolution and are able to detect individual multipath components. The previously mentioned work makes use of the root mean square (RMS) delay spread as a primary feature for NLOS identification. In regards to narrowband signals, a NLOS identification method based on range estimates from narrowband signals was developed in [4].

2.2 Theoretical Channel Model

A simple representation of a multipath channel is shown in Figure 1. In the figure, multipath is shown due to reflections. In addition to reflections, diffraction and scattering produce multipath components. A group of rays arriving with similar direction and time delay are called a cluster. It is not uncommon that paths such as those shown in Figure 1 will arrive as a cluster [5]. Figure 2 shows two plots of the channel impulse response (CIR) due to multipath. The general form of the channel impulse response (with the exception of noise) is

$$h(t) = \sum_{k=0}^{K(t)-1} \alpha_k(t) e^{j\theta_k(t)} \delta(t - \tau_k(t)) e^{j\mu_k t}. \tag{1}$$

where $K(t)$ is the number of multipath components and $\alpha_k(t)$, $\theta_k(t)$ $\tau_k(t)$, and μ_k are the magnitude, phase offset, time delay, and Doppler frequency shift, respectively, of the k^{th}

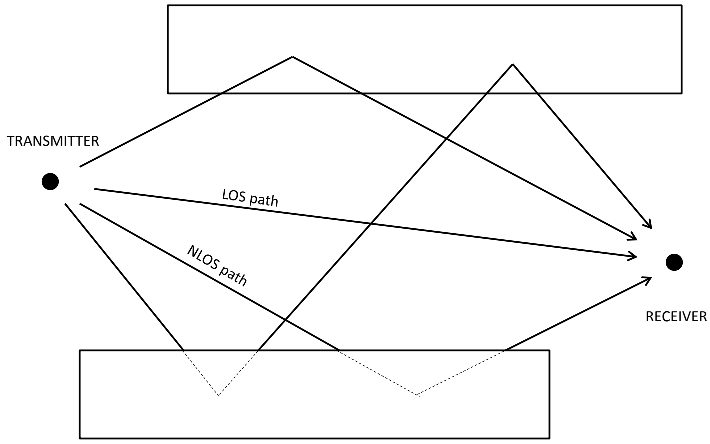

Figure 1: Representation of a multipath environment

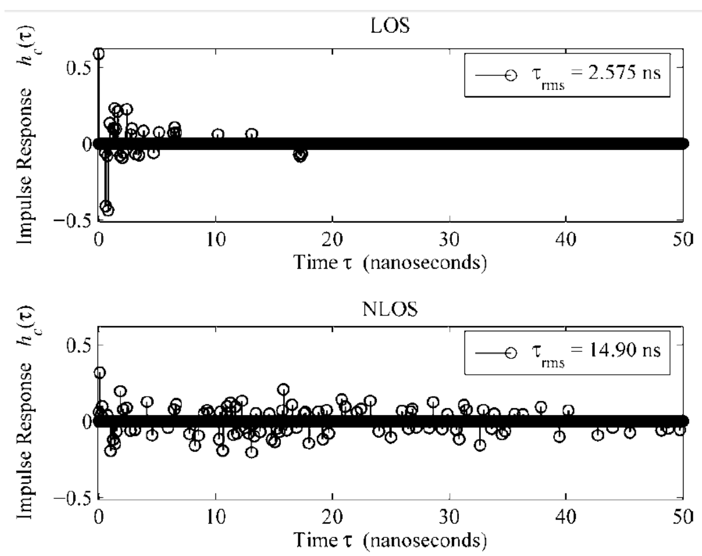

Figure 2: Channel impulse response (CIR) based on ultra-wideband measurements of the indoor channel. The CIR of a LOS channel is shown in the upper plot and in the lower plot is the CIR of a NLOS channel. The plot is taken from [2] with original measurements conducted as a part of [6].

multipath component. Dependence on time is given in each parameter because the channel changes with time in a mobile environment. The general form of the transmitted signal is

$$s(t) = \Re\left\{p(t)e^{j\omega_c t}\right\}. \tag{2}$$

where $p(t)$ is the baseband pulse shape and ω_c is the carrier frequency. The received signal, $r(t)$, (once again without noise) is

$$r(t) = s(t) * h(t) = \Re\left\{\sum_{k=0}^{K(t)-1} \alpha_k(t)e^{j(\omega_c(t-\tau_k(t))+\theta_k(t))}p(t-\tau_k(t))e^{j\mu_k t}\right\}. \tag{3}$$

When the transmitted signal is narrowband, the simplification $p(t) \approx p(t-\tau_k(t))$ can be made. This is called the *narrowband assumption* and is valid for signals with inverse bandwidth (B^{-1}) greater than the RMS delay spread (σ_τ) of the channel [7]: $\sigma_\tau << B^{-1}$. Looking back at Figure 2, the physical interpretation of this concept is that the rate of change of the signal envelope (baseband pulse) is very slow relative to the multipath delays. This simplification can not be made in for the carrier, $e^{j\omega_c(t-\tau_k(t))}$. Thus, the following representation for the receive signal is derived:

$$r(t) = \Re\left\{p(t)e^{j\omega_c t}\sum_{k=0}^{K(t)-1} \alpha_k(t)e^{j(-\omega_c\tau_k(t)+\theta_k(t))}e^{j\mu_k t}\right\}. \tag{4}$$

The transmitted signal is separated from the channel terms in (4). The channel is now a multiplicative term which will be defined as $\gamma(t)$. The carrier time delay and phase shift will be combined to create one term: $\phi_k(t) = \omega_c\tau_k(t) - \theta_k(t)$. Finally, the characteristics of the channel change slowly with respect to the time period of interest. However, the channel will undergo rapid changes in fading due to constructive and deconstructive addition of the multipath components. Thus, for the observation interval the parameters can be considered time-invariant. After these simplifications, the multiplicative channel is

$$\gamma(t) = \sum_{k=0}^{K-1} \alpha_k e^{-j\phi_k}e^{j\mu_k t} \tag{5}$$

2.3 NLOS Channel Model

This model was used by Jakes [8] for the NLOS channel. He further assumes that the multipath magnitudes are all roughly equal and introduces a scaling factor to normalize the average channel gain (path loss is considered separately). The NLOS channel is defined to be

$$\gamma_{NLOS}(t) = \sqrt{\frac{1}{K}}\sum_{k=0}^{K-1} e^{j(\mu_k t-\phi_k)} \tag{6}$$

where the phases ϕ_k are uniformly distributed over $[0, 2\pi)$. The Doppler frequency is defined as $\mu_k = \omega_c \frac{v}{c} \cos\left(\frac{2\pi}{K}k\right)$ where v is the velocity and c is the speed of light. This model allows us to create a time varying model of the mobile wireless channel for use in classification. The distribution of the channel magnitude, $|\gamma(t)|$, is a Rayleigh random variable [7].

2.4 LOS Channel Model

In addition to a strong LOS multipath component, the LOS channel experiences the same multipath properties as the NLOS channel. The channel magnitude for LOS channels are known to have a Ricean distribution [7]. The power of the LOS component is given with respect to the power of the NLOS components. The letter K is generaly used for this ratio. However, due to the use of K for the number of multipath components, we will use K_R to indicate the ratio. K_R is defined as

$$K_R = \frac{\alpha_0^2}{\sum_{k=1}^{K-1} \alpha_k^2} = \alpha_0^2. \tag{7}$$

where the scaling factor has been changed to $\sqrt{1/(K-1)}$ to match the number of NLOS paths. The magnitude of the LOS component is

$$\alpha_0 = \sqrt{K_R}. \tag{8}$$

The LOS channel model is

$$\gamma_{LOS}(t) = \sqrt{K_R} e^{j(\mu_0 t - \phi_0)} + \sqrt{\frac{1}{K-1}} \sum_{k=1}^{K-1} e^{j(\mu_k t - \phi_k)} \tag{9}$$

2.5 Background Summary

In this section, channel models were developed for LOS and NLOS channels. The magnitude of the channel will be used to simulate the RSS measurements at the receiver. In addition to the multipath, zero-mean Gaussian noise will be added to the received signal.

3 Research Design and Method

The raw data available for use in classification of the channel state is a set of RSS measurements over time. From the discussion of the theoretical model for LOS and NLOS channels in the Background section, two approaches to classifcation emerge. The first approach follows the traditional structure of pattern classification. In the first classification approach, which will be called CA1, features are identified and extracted from the RSS measurements. The mean signal strength, variance, maximum deviation from the mean, and slope are all potential features to explore in CA1.

The second approach, CA2, uses the raw data (RSS measurements) as the classifier input. As discussed in the Background section, each channel state has a different probability distribution for the RSS measurements. Thus, in CA2 the classification task is one of identifying the underlying distribution from a set of samples.

The Neural Network architecture is chosen for this classification problem. A multilayer perceptron (MLP) classifier will be implemented with backpropagation of training error for weight modification. The neural network structure including the number of layers and the number of perceptrons in each layer will be determined after further study of the neural network.

Six steps have been outlined for the project

1. **Develop complete theoretical model:** The theoretical model for LOS and NLOS wireless channels will be fully developed. Parameters for the channels will be obtained from publications on indoor wireless channel measurements. (See Datasets 1 & 2 below)

2. **Extract a set of defining features for use with the CA1 neural network**

3. **Develop two neural network architectures for LOS/NLOS channel state classification based on CA1 and CA2**

4. **Evaluate initial performance and modify features and neural network structure as needed** (See Experiment 1)

5. **Conduct measurements of indoor RSS with mobile radios:** This step will be completed if sufficient time and resources are available. (See Datasets 3 & 4 and Experiements 2 & 3)

6. **Evaluate final classifier performance:** Results for the neural networks developed for each approach will be compared. The affect of the number of RSS measurements on performance will be evaluated. Finally, the affects of sampling frequency and mobility will be considered as part of this stage.

3.1 Datasets

Dataset 1 & 2 Two datasets for development of the classifier will be created from the theoretical channel models. Dataset 1 will be for the LOS model and Dataset 2 for the NLOS model. Each dataset will consist of multiple subsets. The data subset will have a time series of RSS samples generated for a particular set of multipath parameters.

Dataset 3 & 4 Time permitting, RSS measurements will be taken for an indoor mobile environment. A dataset of measurements will be made for LOS channels and for NLOS channels.

3.2 Experiments

Experiment 1 In experiment 1, both classifiers (CA1 and CA2) will be tested with Datasets 1 & 2 using a K-fold cross validation. The value of K is the number of subsets in Datasets 1 & 2. One subset will be left out for the training process and then will be used for calculating the testing error. This process will be repeated for each subset. This is very similar in concept to leave one out cross-validation (LOOCV). The estimated error is the average testing error over all K subsets.

$$Err = \frac{1}{K}\sum_{i=1}^{K} Err_i \tag{10}$$

where Err_i is the testing error for the i^{th} subset which is left out during training.

Experiment 2 In experiement 2, both classifiers will be trained with all available samples in Datasets 1 & 2. Then the performance will be determined for the measurement data obtained in Datasets 3 & 4. This will give some indication of the validity of the theoretical models in training the neural networks for actual implementation.

Experiment 3 Finally, the classifiers will be trained with Datasets 3 & 4 using the same K-fold cross-validation scheme discussed previously.

References

[1] S. Yarkan and H. Arslan, "Identification of los and nlos for wireless transmission," in *Cognitive Radio Oriented Wireless Networks and Communications, 2006. 1st International Conference on*, 2006, pp. 1 –5.

[2] S. Venkatesh and R. Buehrer, "Non-line-of-sight identification in ultra-wideband systems based on received signal statistics," *Microwaves, Antennas Propagation, IET*, vol. 1, no. 6, pp. 1120 –1130, 2007.

[3] M. Heidari, N. Alsindi, and K. Pahlavan, "Udp identification and error mitigation in toa-based indoor localization systems using neural network architecture," *Wireless Communications, IEEE Transactions on*, vol. 8, no. 7, pp. 3597 –3607, 2009.

[4] M. Wylie and J. Holtzman, "The non-line of sight problem in mobile location estimation," in *Universal Personal Communications, 1996. Record., 1996 5th IEEE International Conference on*, vol. 2, Oct. 1996, pp. 827 –831 vol.2.

[5] A. Saleh and R. Valenzuela, "A statistical model for indoor multipath propagation," *Selected Areas in Communications, IEEE Journal on*, vol. 5, no. 2, pp. 128 – 137, Feb. 1987.

[6] R. Buehrer, A. Safaai-Jazi, W. Davis, and D. Sweeney, "Ultra-wideband propagation measurements and modeling final report," *DARPA NETEX program*, January 2004.

[7] A. Goldsmith, *Wireless communications.* Cambridge Univ Pr, 2005.

[8] W. Jakes *et al.*, *Microwave mobile communications.* IEEE press New Jersey, 1994, vol. 1974.