LOCALISATION SYSTEMS AND LOS/NLOS IDENTIFICATION IN INDOOR SCENARIOS

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Chapter 1

Introduction

Currently, indoor localisation techniques have received an increasing focus due to the growing wireless mobile applications and services provided in indoor scenarios. It is possible to mention some examples of these kinds of applications and services like advertising of free parking, location based audio explanation in museums, targeted advertising to provide location based marketing, localisation in a disaster area, etc. However, indoor localization remains still challenging nowadays mainly because of the impossibility of the off-the-shelf (COTS) WiFi devices to provide a fine-grained channel information value to estimate the propagation distance between the target and Anchor Nodes (ANs). Another challenge in indoor positioning is the error induced by multipath effect, and Line of Sight (LOS)/ Non Line of Sight (NLOS) conditions. This makes even more difficult to relate the channel information with the propagation distances between the target and Anchor Nodes (AN). Actually the lack of LOS propagation is the reason for poor performance in indoor positioning[1] .

Awareness of LOS/NLOS conditions becomes an important property not only for location based applications and services in indoor environment, but also for overcoming the adverse impact of NLOS transmissions in any kind of wireless services. For example with the knowledge of LOS/NLOS the transmitter could tune the power or the data rate to achieve a more reliable communication. Another example of the use of LOS/NLOS identification is improving the accuracy in the location estimation in indoor positioning systems. Awareness of LOS/NLOS could be a crucial factor in taking most reliable information to determine the location of a device in indoor environments. In this way LOS/NLOS identification could be a pre-requisite for accurate indoor localization system.

This report outlines a summary of two approaches to determine LOS and NLOS conditions in radio-frequency transmissions. The first LOS/NLOS identification approach is based on Received Signal Strength Information (RSSI) taken from the MAC layer and processed by machine learning algorithms[2]. The second approach detailed in [1] uses the capability of the off-the-shelf WiFi devices of capturing Channel State Information (CSI) from the physical layer in the widely used Orthogonal Frequency Division Multiplexing (OFDM) systems.

The remainder of this report is organized as follows. Chapter II presents a preliminary background about positioning and LOS/NLOS identification. Chapter III introduces indoor positioning systems based on RSSI, which is the most common approach used nowadays for positioning in indoor environments. This chapter also presents a novel positioning approach based on Channel State Information (CSI) named FILA[3]. Chapter IV presents two approaches for LOS/NLOS identification. The first approach called Identification and Mitigation of Non-line-of-sight conditions Using Received Signal Strength is based on RSSI [2]. The second approach is based on CSI and it is named PhaseU [1]. Chapter V concludes this report.

Chapter 2

Preliminary background

Some preliminary knowledge about PHY and MAC layer of the IEEE 802.11n standard are relevant in this work.

2.1 IEEE 802.11n standard

IEEE 802.11n is a further development of IEEE 802.11-2007 standard including many enhancements that improve wireless LAN reliability and throughput. This amendment aims to improve the physical layer rate transmission defining High Throughput (HT) options. MAC layer transmissions achieve 100 Mbps as maximum data rate transmission. Despite the aforementioned improvements, IEEE 802.11n maintains compatibility with IEEE WLAN legacy solutions defined in standards 802.11a/b/g. IEEE 802.11n improves the physical transfer rate to 600Mbps by incorporating a new modulation scheme.

2.2 Orthogonal Frequency Division Multiplexing (OFDM)

OFDM is a digital multi-carrier modulation method for wideband wireless communication. OFDM is widely used in IEEE 802.11 a/g/n [3]. Some of the main characteristics of OFDM are:

1. Parallel transmission of orthogonal frequencies with distribution of bits over different channels.
2. Distance of middle frequencies are orthogonal to each other.

2.3 Physical layer in IEEE 802.11n

Advanced signal processing and modulation techniques have been adopted in physical layer to take advantage of the ability to receive and/or transmit simultaneously through multiple antennas in MIMO techniques. In OFDM systems, data are modulated over multiple subcarriers in different frequencies and transmitted simultaneously. The physical layer presents a value to estimate the channel status in each subcarrier. This value is named Channel State Information (CSI).

2.3.1 Channel State Information CSI

Channel State Information is a value that represents the state of the channel in terms of phase and amplitude for each subcarrier in frequency domain. Unlike to RSS, which only has one value per packet, CSI defines multiple fine-grained values from the physical layer (one per subcarrier) to estimate the state of the channel. CSI mathematically can be represented in each subcarrier as:

$$H(f_k) = |H(f_k)|e^{j\angle H(f_k)} \tag{2.1}$$

$H(f_k)$ represents the CSI value at the subcarrier level with frequency f_k. $|H(f_k)|$ denotes the amplitude and $\angle H(f_k)$ the phase in this subcarrier. CSI describes how a signal propagates between the transmitter and the receiver device in both amplitude and phase. CSI also reveals the combined effect of scattering, fading and power decay with distance over the received signal [3] .

2.4 MAC layer in IEEE 802.11n

More efficient use of the available bandwidth is implemented in the MAC layer. Two improvements in the MAC layer are Block Acknowledgement and Frame Aggregation. Frame Aggregation can aggregate different upper layer payloads to one MAC layer payload and reduces the MAC layer overhead. Block Acknowledgement is used to confirm the reception of multiple unicast frames, which can further reduce the MAC layer overhead.

2.4.1 Received Signal Strength RSS

RSS is a measurement of the power present in a received radio signal. Because of multipath effect, RSS is the average of the signal power received through different paths at specific location.

Chapter 3

Indoor Positioning Systems

Indoor position systems have acquired special attention due to the growing number of location-based applications and services. Although Global Positioning System (GPS) works with high accuracy in outdoor scenarios, it is well known that GPS is not suitable for indoor scenarios due to the disability of GPS signal, to penetrate in-building materials [3]. Therefore, the attention is mainly focused on WiFi-based localization systems due to its open access and low cost properties.

3.1 Indoor Positioning Systems by RSSI

Many work to deal with the problem of localization have been done until now. The most common approaches are based on RSSI, which can be adopted to compute the distance between a sender and a receiver device. Power level decreases when the distance increases according to propagation loss model [3]. Indoor fingerprinting positioning systems typically are based on RSSI [4]. This kind of systems typically have two main phases: Off-line/training phase and on-line phase. In offline phase, values of RSSI are collected from distinct known locations. These locations and their RSSI values constitute the Reference Points (RP). RPs are used to determine the position for an unknown location taken in the online phase of the system. In online positioning phase, RSSI value is collected from an unknown location, which is named the Test Point (TP). Through some algorithms and based on RPs obtained in the training phase, the location for the TP is derived. Positioning phase could use the k-nearest neighbour algorithm to select the k-nearest RPs based on Euclidean distance. Furthermore, localisation algorithms use either probabilistic or deterministic methods to perform positioning [4].

Authors of [3] pointed out that a simple relationship between received signal power and the distance between the transmitter and receiver cannot be established in indoor environments. They claim that the use of RSSI in indoor positioning systems is not suitable because of two principal aspects: First, RSSI is not an fine-grained value. Therefore, it is difficult to attain accurate values from RSSI. Second, RSSI is easily affected by multipath effects. This effect is even more severe in indoor environments due to the presence of different kinds of in-buildings materials. Because of RSSI value is easily affected by the multipath effect, some approaches based on more stable values have been proposed. One of these approaches are indoor positioning systems based on CSI.

3.2 Indoor Positioning Systems by CSI (FILA)

In OFDM systems, Channel State Information is a value that estimates the channel at subcarrier level. CSI contains information about the transmission channel by subcarrier per each transmitted packet. Therefore, it is possible to obtain multiple CSI measurements at one time in contrast to RSSI. FILA [3] uses the fine-grained information attached from CSI in OFDM at subcarrier level to propose a novel localisation system for indoor environments. The main contribution in FILA is the use of the PHY layer information (CSI) to improve indoor localisation performance. Results of FILA demonstrate that this approach overcomes traditional RSSI-based methods. Evaluations of FILA were implemented in commercial 802.11 wireless cards, specifically Intel 5300 wireless card. CSI data information is gathered through an open CSI tool program by installing a modified driver for this wireless card. After collect CSI from 30 subcarriers, FILA approach consists of three steps:

1. CSI Processing: The objective of this step is to reduce the error introduced by multipath fading and shadowing. Success results in positioning estimation depend on the effective reduction of outliers and noise from CSI. In order to reduce the estimation error, FILA proposes a multipath mitigation mechanism to distinguish LOS signals in time domain. CSI represents the channel response in the frequency domain. By applying IFFT it is possible to obtain the channel response in time domain. FILA filters out the CIR whose power are smaller than 50% of the LOS connection. After that CSI in frequency domain is reobtained through applying FFT. In FILA the effective CSI is obtained also exploiting frequency diversity to compensate the small-scale fading effect. Effective CSI is calculated as follow:

$$CSI_{eff} = \frac{1}{K}\sum_{k=1}^{K}\frac{f_k}{f_0}|A_k|, k\epsilon(-15, 15), \tag{3.1}$$

   f_0 is the central frequency, f_k is the frequency of the subcarrier k, and $|A_k|$ is the amplitude in that subcarrier.

2. Calibration Phase: The goal of this step is to derive the relation receiver-transmitter based on CSI. The proposed model to related the effective CSI (CSI_{eff}) with distance is as follow:

$$d = \frac{1}{4\pi}\left[\left(\frac{c}{f_0 \times |CSI_{eff}|}\right)^2 \times \sigma\right]^{\frac{1}{n}}, \tag{3.2}$$

c is the wave velocity, σ is the environment factor, and n is the path loss fading exponent. Both path loss fading exponent n and σ depend on the environment. Both environment factor n and σ must be calibrated for each AP. In this case FILA implements a training supervised algorithm to do so.

3. Localisation: The objective of this step is by applying trilateration method estimate the position of the target object. Based on distances between the target object and anchor nodes (AN), the position of the target object is determined by applying a simple trilateration algorithm. Distance between anchor nodes and target object is easily obtained by using the effective CSI values with a suitable propagation model and the coordinates of each AN. The Linear Least Squeare (LLS) method is applied to establish the coordinates of the target object as the center of the reference range intersection.

The accuracy of FILA is determined by comparing with the corresponding RSSI-based approach. Authors claim that FILA outperforms the corresponding RSSI-based approach by around three times.

Chapter 4

LOS/NLOS Identification

The attenuation because of NLOS propagation is responsible for a poor communication quality . It is responsible also of the violation of the theoretical signal propagation model. The primary source of errors in indoor localisation systems is multipath propagation caused by multiple reflections that overlap with the direct LOS subcarrier at the receiver side[3]. Accuracy of indoor localisation systems is decreased due to multi-path effects mainly in NLOS transmissions. The arriving signals in the receiver side is composed of reflected signals [2], and therefore, introduction of LOS/NLOS identification techniques become into important factor to improve the accuracy of indoor localisation systems. It has been demonstrated that the lack of LOS propagation is the major cause of poor wireless experience. Lack of LOS propagation leads to high packet losses and low data rates transmissions. Normally, NLOS propagation reduces the stability of received signal strengths (RSS)[1]

4.1 LOS/NLOS Identification by RSSI

This subsection summarizes the technique named Identification and Mitigation of Non-line-of-sight conditions Using Received Signal Strength[2]. The approach explores features from RSS to build an effective technique in NLOS/LOS discrimination.
The NLOS identification technique in [2] is based on RSS measurements in WiFi networks. This approach uses a specific machine learning algorithm (Support Vector Machine). Based on beforehand taken measurements the method tries to characterize the transmissions on distinct conditions to establish the difference between LOS and NLOS.

4.1.1 NLOS Feature Extraction

The aim of this task is to extract typical features from collected RSS samples. Proposed features include the mean, the standard deviation, Kurtosis, the Rician K factor and x^2 goodness of fit test parameters. Hypothesis testing of this approach is defined as follows:

$$\begin{aligned} H_1 &: \alpha \leq \alpha_t, LOS conditions \\ H_1 &: \alpha > \alpha_t, NLOS conditions. \end{aligned}$$

Hypothesis is tested by both mentioned machine learning approaches. The features used to build the model are: Mean (μ), standard deviation (σ), Kurtosis factor (κ),Skewness (ς), Rician K factor, Goodness of fit parameter (X^2). Mean μ and the standard deviation σ alone are not enough to distinguish NLOS conditions. However, combined with others features these values can help to identify NLOS conditions. Kurtosis (κ) factor is a measure of the peakedness of the probability distribution[2]. RSS measurements tend to follow a Rayleigh distribution in NLOS [2]. Skewness (ς) measures the asymmetry of the probability distribution. LOS measurements should be more symmetrical than NLOS samples [2]. The Rician K factor is defined as the ratio between the power in the direct path and the power in other scattered paths. In NLOS, Rician K factor is expected to be zero. The (X^2) Goodness of fit parameter shows the distance between the RSS measurement and the underlying distribution. The problem with using this variable is that its value depends on the number of samples.

4.1.2 Machine Learning Approaches

The Support Vector Machine (SVM) algorithm is chosen as supervised machine algorithm method. This classifier can be used also as a regressor to estimate dependent variables. The SVM approach is also suitable for potential use in mobile devices because of the high level of quality in generalization and the easy training process.

Different indoor environments must be considered in the training phase of the classifier algorithm. Accuracy of NLOS/LOS identification techniques can be affected easily by external interferences included people walking around and other signals. Despite people cannot block the LOS signal, people can alter the received WiFi signal, which leads to the variation of the measurement distribution. Interference produced by walking people was considered by taking two categories of samples in [2]. The first category was taken during nights and weekends without people around. The second group was collected during office hours with many people walking around the corridors and offices. To identify NLOS conditions the classifier is feed with a set of features (discussed in previous sub section) as input. Output results will be the corresponding classification of the set of features. This approach has an overall misclassification rate of 0.0909 using the best feature set (σ, κ_r, x^2). The average distance estimation error is of 2.84m [2].

4.2 LOS/NLOS Identification by CSI

Awareness of LOS and NLOS conditions constitute an important key to deal with the adverse impact of NLOS propagation over wireless services and applications. For example having NLOS/LOS awareness different model parameters in transmissions could be applied to maintain high quality services.
PhaseU[1] attempts to build a scheme for LOS/NLOS identification in both static and mobile scenarios with commercial WiFi devices. PhaseU explores features of CSI on commodity off-the-shelf (COTS) WiFi devices.
Phase information after an appropriate sanitization and integration process is an excellent indi-

cator to determine different behaviour between LOS and NLOS signal propagation[1]. Specifically, PhaseU proposes that phase difference, over two antennas behave differently in LOS and NLOS conditions[1]. However, the raw phase information obtained with the CSI tool provided by the modified driver of the wireless card is not directly usable due to the great level of randomness that these measurements involve. The main insights and contributions of PhaseU are:

1. PhaseU is the first work which uses PHY layer information of WiFi to establish LOS and NLOS identification in multipath dense indoor scenarios.

2. PhaseU applies phase difference over antennas as a new feature to distinguish LOS and NLOS propagation signal.

3. PhaseU is implemented on commodity WiFi devices. Experiments in different indoors scenarios show that both mobile and static operation LOS and NLOS detection rate achieves around 95 and 80 percent respectively.

4.2.1 Exploring Phase Features

NLOS paths typically involve more reflections than LOS transmissions. This leads to the fact that the spatial randomness of LOS and NLOS differs. Randomness behaviour typically is manifested in amplitudes and phases of the signal. Not only NLOS conditions determine the randomness in received amplitudes but propagation distance and other factors like obstacle blockage are responsible for attenuation of signal amplitudes. However, phase shifts change periodically over propagation distances making the phase a robust feature in contrast to amplitude signals. It is impossible to obtain true phases from commodity wireless devices, and therefore PhaseU recommends to perform a linear transformation on raw phases to eliminate the timing offset π_1 and the unknown phase offset π_2 at the receiver side. For LOS/NLOS identification PhaseU employs variance of the calibrated phase as feature.

4.2.2 Measurement of Phase Variances

A dataset was built by collecting 200 groups of measurements over different LOS and NLOS conditions. Unfortunately, variance of the calibrated phase is not enough to perform an effective discrimination over LOS and NLOS conditions but it is possible to note that the phase variance in NLOS tends to be larger than LOS. Despite no clear gap can be found but this characteristic leads to explore more conspicuous phase difference in space and frequency diversity.

1. Leveraging Space Diversity. The idea is to exploit the key feature in IEEE 802.11n/ac MIMO to increase the variance difference in NLOS and LOS by considering variance of phase difference over a pair of antennas. The measured phase difference between two antennas is defined as follows:

$$\triangle\hat{\phi_i} = \triangle\phi_i - 2\pi\frac{k_i}{N}\triangle\delta + \triangle\beta, \tag{4.1}$$

$\triangle\phi = \phi_{i,1} - \phi_{i,2}$ is the difference of the true phase, $\triangle\delta = \delta_1 - \delta_2$ is the difference of timing offset and $\triangle\beta = \beta_1 - \beta_2$ is the constant phase difference which is unknown. The phase difference caused by different timing offsets is close to zero and therefore it is negligible in $\triangle\hat{\phi}_i$. It is possible to obtain the same $\triangle\beta$ at different time by shifting the phase difference to be zero mean[1]. For scattering scenarios and antenna sizes larger than half WiFi wavelength, received signals at different antennas should be independent. Then an important inference can be done, the variances of phase difference of two antennas is the sum of individual variance on each antenna [1].

$$\sigma^2_{\triangle\hat{\phi}_i} = \sigma^2_{\phi_{i,1}} + \sigma^2_{\phi_{i,2}} \tag{4.2}$$

Authors of PhaseU argue that to identify LOS and NLOS conditions, variance of phase difference over two antennas is a suitable feature on commodity WiFi devices.

2. Enhancement via Frequency Diversity. The idea is to incorporate spectral signatures to strengthen the feature used to identify LOS and NLOS signal propagation. Frequency diversity is exploited by the fact that signals have diverse fading behaviour with different frequencies and signals attenuate differently across the frequency band when penetrating blockages. However, weak LOS and NLOS signals induce a large variance whereas strong NLOS and LOS signals induce small variances.
   PhaseU proposes to build a frequency-selected feature based on variance of phase difference as metric to distinguish NLOS and LOS signal propagation, this metric is called p-factor.

$$\rho = \frac{\sum_{i=1}^{n} \sigma^2_{\triangle\hat{\phi}_i} |H(f_i)|}{\sum_{j=1}^{n} |H(f_j)|}, \tag{4.3}$$

   $|H(f_i)|$ is the mean amplitude of a pair of antennas at the subcarrier i, p-factor incorporates frequency and space diversity. CSI information collected from commodity devices can contain outlier values, and therefore a filter is adopted to eliminate these values. PhaseU uses Hampel filter for this task.

4.2.3 Identification

By calculating the variance of phase difference of a set of samples, a binary hypothesis test can be established to test LOS and NLOS conditions.

$$\begin{aligned} p < &: p_{th}, LOS conditions \\ p > &: p_{th}, NLOS conditions \end{aligned}$$

p_{th} is a pre-defined threshold. In addition the use of more than two antennas can yield to improve the accuracy by extending the hypothesis test using the median of p-factors on different antenna pair combination.

$$\begin{aligned} med(p_{i,j}) \leq &: p_{th}, i \neq j, LOSconditions \\ med(p_{i,j}) > &: p_{th}, i \neq jNLOSconditions, \end{aligned}$$

where $p_{i,j}$ denotes p-factor in any pair of antennas i, j.
PhaseU is extended to mobile scenarios by introducing inertial sensors to determine moveless moments to take samples and perform this LOS/NLOS method identification.

4.2.4 Performance

PhaseU experiments show that the method attains a LOS rate of 94.35% with false alarm of 5.91% using 500 packets. Detection rates of 91.61% and 89.978% are achieved even using 10 packets. Time required to process PhaseU is highly influenced by the number of packets. Authors claim that PhaseU can perform accurate LOS identification in 1 second when 10 packets are used.

Chapter 5

Conclusions

There are many wireless applications and services that can take advantage from line of sight (LOS) and non-line of sight (NLOS) detection. Indoor positioning systems are an special area of this kind of applications. Because of Global Positioning System is not suitable in indoor environments, several works have been done based on WiFi technologies about localisation for indoor scenarios. Major of these researches are based on computing the position based on Received Signal Strength Information (RSSI). However, this approach tends to have some estimation errors because RSSI is greatly varied by multipath effect. However RSSI is still the most advanced technique used nowadays.

Channel State Information (CSI) is a fine-grained feature of the PHY layer, which explores the frequency diversity in OFDM systems. This information has demonstrated to be more stable than RSSI.

Awareness of LOS and NLOS propagation is a key to deal with the NLOS effect and, it could also be used as pivotal primitive to improve the accuracy of indoor localisation systems. PhaseU is an approach that exploits CSI on commercial WiFi devices. Specifically PhaseU is focused on phase information which after calibration could be used for LOS identification. PhaseU is a good starting point in the use of CSI taking advantage of growing use of MIMO technology in commodity WiFi devices.

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