UWB Localization Modeling for Electronic Gaming

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Abstract—**Ultra-wideband (UWB) technology is very popular in indoor localization due to its high accuracy, which can lead to enhanced user experience in indoor motion gaming. In this paper, we introduce results of empirical measurement and modeling of the statistics of localization error in a typical indoor motion gaming scenario. Both time of arrival (TOA) and received signal strength (RSS) estimations are modeled, and the multipath dispersion, human body influence and bandwidth effects are analyzed.**

Keywords—ultra wideband (UWB), indoor localization, motion gaming, body area network (BAN), time of arrival (TOA), received signal strength (RSS), obstructed line of sight (OLOS).

I. INTRODUCTION

With the exponential growth of the video gaming industry new challenges emerge. Motion gaming has become a standard feature in every gaming system. To enhance the user experience innovative localization and tracking techniques are introduced. These techniques have their trade-offs [1][2][3][4], For popular motion gaming applications such as table tennis, an accurate localization and fast motion tracking are needed. So we should find a new one that can apply into more games like tennis for two players, which need the accurate relative position as well as getting rid of the human body effect. Therefore, ultra-wideband (UWB) has been chosen.

UWB technology has been recognized as an ideal candidate for providing positioning information in indoor environments, in which the traditional services provided by e.g. the GPS are usually not available, unreliable or inaccurate. It offers a vast unlicensed frequency band, which also allows novel uncoordinated ways of access to spectrum resources. UWB is a new horizon for short distance localization within 3 meters, which is very applicable to motion gaming scenarios. By modeling a resource management problem as a game, some aspects of a real-world implementation have to be relaxed. For instance, the number of players in a game is conventionally assumed constant but in real networks it changes over time. Furthermore, the available computing power of wireless sensor nodes is limited because of energy and simple hardware constraints. Hence, games require utility functions with low complexity.

Our contribution in this paper is the introduction of channel models for statistical error of multipath and bandwidth effect that arise in line of sight (LOS) and obstructed line of sight (OLOS) system scenarios such as obstructing antenna by human hand. We define two models, the root mean square delay spread (τ_{rms}) and total power, to detect hand cover or not. The models can be applied to indoor motion gaming systems to improve its accuracy, agility and function.

This paper is organized as follows: Section II describes the application scenarios, the measurement system and the method for data collection. In section III, data analysis on the measured data and channel modeling are developed. Finally, we show our conclusions in Section IV.

II. SCENARIOS AND MEASUREMENT

Traditional table tennis is an indoor sport, and since its inception of motion gaming is mainly used in indoor environments. For this reason, table tennis is one of the games that stands to gain the most from accurate space location and fast reaction. So we choose it as a better choice for analysis and research in our scenario. To make the scenario more reasonable, we set it in a complicated indoor environment to simulate the real gaming scene.

Two possible scenarios have been introduced in our measurement. The first one is LOS condition where the receiving antenna on the motion controller has a direct line of site to the transmitter on the television. The second case is the OLOS condition where the user's hand covers or obstructs the LOS case due to the controller motion We measure the Time-of-Arrival (TOA) using UWB antenna, one is on the television display, and another is on the motion controller in the user's hand. Besides, we use a digital laser tape to measure the real distance. Then repeat the measurement 500 times to measure and calculate the error of TOA for each location. During the measurement process, we change the bandwidth from 100MHz to 2.5GHz to analyze the effect of bandwidth in localization error and the error's variance of indoor gaming localization

To measure the behavior of target node and base stations, a vector network analyzer has been employed in our measurement system. The measurements were carried out in the Atwater Kent Laboratory of Worcester Polytechnic Institute, using two UWB directional antennas which have been connected to both transmit and receive port of the network analyzer through low loss RF cables. Moreover, a power amplifier has been added at the transmitter (TX) port of network analyzer to achieve better signal to noise ratio (SNR) at the receiver (RX) side. The vary frequency of operation of the network analyzer from 3 GHz to 8GHz.We choose 9 locations for measurement that are in the area of a 1.525m *1.370m rectangular. Fig. 1 shows the measurement system and the testing points in the grid region.

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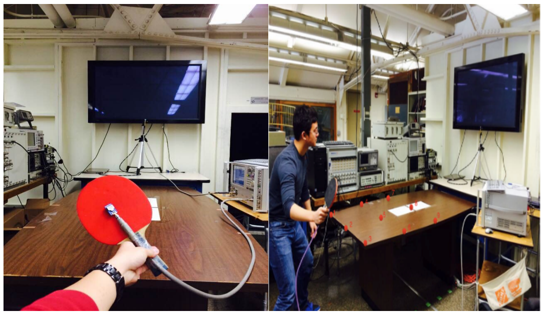


Fig. 1. (a) Measurement system (b) Test Points.

III. Data Analysis and Channel Modeling

A. Distance Error in Measurement

In indoor localization, the localization accuracy suffers from several errors generated by scenario and measurement. Let ϵ represent the total error between the real distance d_r obtained from digital laser measurement, and estimated distance d_e obtained is from $d_e = c\tau_e$, where c is the speed of light and τ_e is the time-of-arrival measured by network analyzer. The total error ϵ is affected by measurement error ϵ_m, multipath effect error ϵ_e and shadow fading error ϵ_s. ϵ_m can be neglected by adding a mounted measurement in free space for every scenario and bandwidth. The result d_0 only includes the measurement error, which means $\epsilon_m = d_0 - d_r$. Therefore, ϵ can be written as

$$\epsilon = |d_0 - d_r + \epsilon_e + \epsilon_s| \tag{1}$$

In our scenario, we do static data collection at different positions with different bandwidths, and we get the distance error information is following Gaussian distribution. For this distribution, we will analysis the mean and variance of distance error and try to find out the modeling to define the relationship among mean, variance, multipath, bandwidth and hand cover.

B. Channel Modeling on Effect of Multipath

In indoor environment, the alteration of surroundings has big effect on transmitting path, and multipath situation will lead to change of distance error and accuracy. In our scenario, each test point has different multipath situation due to the variety of distance to RX. Therefore, the distance is the main parameter of the change of multipath effect. Since we do measurement statically in each point, we can see the mean of error introduced by different position is little from Fig.2.

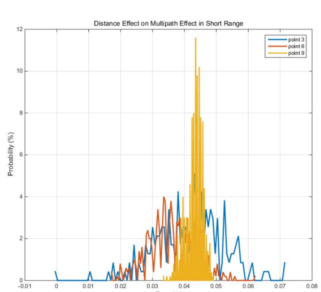


Fig. 2. Error in different position

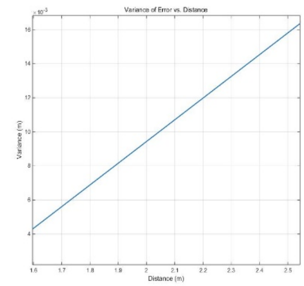


Fig. 3. Multipath effect on variance.

Fig.2 shows us the fact that means of error in different position changes slightly, however, variance changes a lot. Therefore, the multipath effect is mainly concentrating on the variance of error.

Fig.3 shows the multipath effect on variance in our indoor short-range localization. The relation can be expressed as

$$\sigma_d^2 = 0.01275d - 0.01607 \tag{2}$$

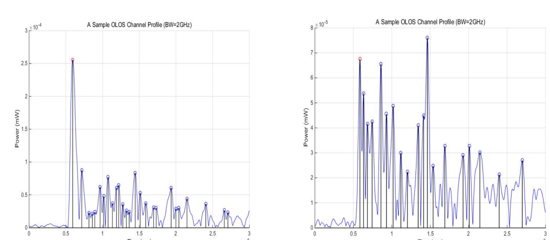
Where σ_d^2 is the variance of distribution function of distance error distribution, and d is the distance from TX to RX. From this function we can find that the multipath effect in indoor short distance UWB localization is relatively small.

C. Channel Modeling on Effect of Human Body

In motion gaming like table tennis, human body always plays an important role in localization error [5]. It contributes to multipath and OLOS by hand covering on the controller's antenna. Fig. 4 shows the measurement channel profile for a 2GHz bandwidth at 5.5GHz operating frequency. From Fig.4 We can see that when we use antenna signal to localize user movement, the effect of hand is obvious and significant.

There are mainly two parameters to measure the change of multipath, RSS and TOA. In RSS, we use total power of the peaks to detect the hand cover. Total power is the sum of power of peaks over given threshold. The value of total power shows the signal strength received by receiver. By analyzing the total power, we can determine the power boundary of LOS and OLOS by hand cover.

Fig.5 shows the waves form of twos scenarios, LOS and OLOS, and we can see that the total power of OLOS is dramatically smaller than LOS condition.



(a) LOS (b) OLOS

Fig. 4. Measurement of channel profile in 2 GHz

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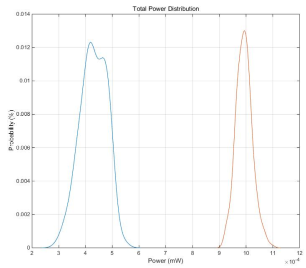

Fig. 5. Hand cover effect of total power received.

From the measurement data, we find out that there is a statistical mean of power drop from LOS to OLOS by hand cover. The relation can be expressed as

$$m_{power}(LOS) = m_{power}(OLOS) + P_{gap} \tag{3}$$

Where $m_{power}(LOS)$ is the mean of total power of LOS, $m_{power}(OLOS)$ is the mean of total power of OLOS, and P_{gap} is the power gap from LOS to OLOS. $P_{gap} \in (6\text{mW}, 12\text{mW})$.

When we detect a power mean gap between the range of P_{gap}, then we can detect a LOS and OLOS switch by hand cover in the scenario. Total power is very easy to collect, and when the indoor scenario is not complicated, it will perform well. But there are numbers of factors will change it, like power absorption of tables, walls and roof, this means that accuracy of total power detection is related lower in crowed environment. However, the problem will be solved if we introduce TOA in to consideration.

Since UWB system sends and receives pulses in communication, the time-of-arrival is very accurate in UWB indoor localization. We use τ_{rms} (the root mean square delay spread) to as TOA detection of hand gesture change. τ_{rms} is a value generated from multipath environment [6], which can be express as

$$\tau_{rms} = \sqrt{\overline{\tau^2} - (\overline{\tau})^2} \tag{4}$$

$$\overline{\tau^n} = \frac{\sum_{i=1}^{L} \tau_i{}^n |\beta_i|^2}{\sum_{i=1}^{L} |\beta_i|^2} \qquad n=1,2 \tag{5}$$

In these functions, τ is the time delay in different transmitting paths, and $|\beta_i|^2$ is the corresponding peak power of each τ, L is the number of all paths in the measurement environment.

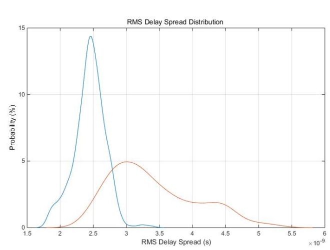

Fig. 6. Hand cover effect of τ_{rms}.

From Fig.6, we can find the mean of τ_{rms} separated in two clusters of LOS and OLOS. Thus the TOA method of detection solves the problem of RSS detection. The expression of TOA method can be expressed as

$$\tau_{rms}(LOS) = \tau_{rms}(OLOS) + \tau_{gap} \tag{6}$$

Where $\tau_{rms}(LOS)$ is the root mean square of delay spread of LOS, $\tau_{rms}(OLOS)$ is the root mean square of delay spread of OLOS, and τ_{gap} is the time gap from LOS to OLOS. $\tau_{gap} \in (0.5\text{ns}, 1\text{ns})$.

By determining the mean gap P_{gap}, τ_{gap} of RSS and TOA, we can detect hand gesture movement. Identifying little movement like hand turnover and switching from one hand to two hands, which is very common in sport games, will improve the motion gaming.

D. Channel Modeling on Effect of Bandwidth

After study on multipath and hand cover effect of error, we are going to continue our research on bandwidth effect of distance error. We apply transmitting signal with bandwidth from 100MHz to 2.5GHz to unfold the secret within bandwidth effect of short-range indoor localization [7].

We choose three typical points to do the study on bandwidth. And for these three points, Table I shows the effect of different bandwidth on different location and different hand cover conditions.

Fig.7 and Fig.8 are the comparisons of mean and variance of error in LOS and OLOS conditions from 100MHz to 2.5GHz bandwidth. We can see hand cover generate large errors in mean and variance. What's more, with increase of bandwidth, the accuracy and stability improve a lot. After curve fitting, we generate the function of m_B and σ_B^2 as

$$m_B = \begin{cases} \alpha_L e^{\gamma_L B} + \beta_L e^{\lambda_L B}, LOS \\ \alpha_O e^{\gamma_O B} + \beta_O e^{\lambda_O B}, OLOS \end{cases} \tag{7}$$

$$\sigma_B^2 = \begin{cases} \varphi_L B^{\psi_L} + C_L, LOS \\ \varphi_O B^{\psi_O} + C_O, OLOS \end{cases} \tag{8}$$

Where B is the system-operating bandwidth. The values of parameter α_L, $\beta_L, \gamma_L, \lambda_L, \alpha_O, \beta_O, \gamma_O, \lambda_O, \varphi_L, \psi_L, C_L, \varphi_o, \psi_o, C_o$ are got from curve fitting. And the big amount of measurement samples give the idea that for most of the data, we always have $\alpha_O > \alpha_L$, $\varphi_o \gg \varphi_L$ and $\psi_o \approx \psi_L$.

For our case, the value of measurement point 2 is

$\alpha_L = 1.277, \beta_L = 1.105\text{e} - 03,$
$\gamma_L = -2.663\text{e} - 03, \lambda_L = 9.748\text{e} - 04,$
$\alpha_O = 1.975, \beta_O = 0.3073,$
$\gamma_O = -5.103\text{e} - 03, \lambda_O = 2.253e - 05,$
$\varphi_L = 19.43, \psi_L = -2.061, C_L = 1.893e - 05,$
$\varphi_o = 1.106, \psi_o = -2.304, C_o = 5.759\text{e} - 04.$

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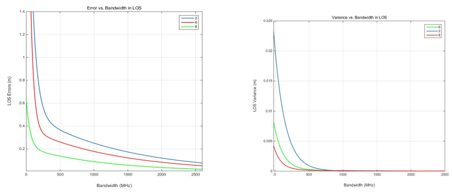

Fig. 7. Bandwidth effect on mean and variance of error in LOS.

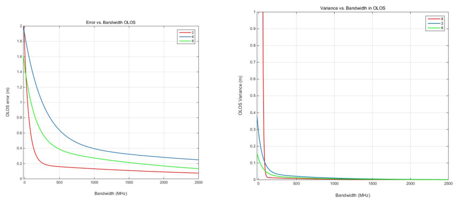

Fig. 8. Bandwidth effect on mean and variance of error in OLOS.

TABLE I. EFFECT OF BANDWIDTH IN MEAN & VARIANCE OF ERROR

Table 1

		LOS		OLOS	
		mean error (m)	variance (m)	mean error (m)	variance (m)
100M	2	1.440566237	0.010835961	1.463404187	0.08663919
	6	0.898169857	0.003383556	0.965055099	0.047934583
	8	0.266452792	0.001478321	0.520958815	0.02518481
200M	2	0.698754752	0.006248238	1.089061724	0.041910132
	6	0.391900227	0.001605646	0.692626381	0.025797019
	8	0.189659301	0.000688007	0.252306349	0.010987067
500M	2	0.388388934	3.44860E-04	0.677398825	0.020601318
	6	0.264607214	2.42012E-04	0.38297973	0.012203598
	8	1.33877E-01	1.60E-04	0.162418	0.008067763
1G	2	0.213350613	2.4175E-04	0.368055485	0.010335747
	6	0.173350613	1.59437E-04	0.282952232	7.48314E-03
	8	0.094381234	1.08326E-04	0.130925445	0.004012163
1.5G	2	0.167441797	1.1902E-04	0.324645807	0.006100814
	6	0.114238331	0.000078692	0.204431333	0.002439519
	8	0.058271	0.000048326	0.102936595	0.001015695
2G	2	0.127049728	4.90181E-05	0.292009766	0.001274593
	6	0.08898294	2.77306E-05	0.171567607	9.61108E-04
	8	0.036938211	1.40607E-05	0.095884918	7.54052E-04
2.5G	2	0.108925403	1.51904E-05	0.2459768	0.000804532
	6	0.063387735	9.76020E-06	1.34787E-01	3.09945E-04
	8	0.0203819	5.59250E-06	7.62040E-02	2.35257E-04

By the determination of mean and variance of error, the distance error ϵ now can be expressed as a function of bandwidth and existence of hand cover. The function is given as

$$\epsilon = \frac{1}{(\sigma_B+\sigma_d)\sqrt{2\pi}} e^{-\frac{(x-m_B)^2}{2(\sigma_B^2+\sigma_d^2)}} \tag{9}$$

And

$$m_B = \begin{cases} \alpha_L e^{\gamma_L B} + \beta_L e^{\lambda_L B}, LOS \\ \alpha_O e^{\gamma_O B} + \beta_O e^{\lambda_O B}, OLOS \end{cases}$$

$$\sigma_B^2 = \begin{cases} \varphi_L B^{\psi_L} + C_L, LOS \\ \varphi_O B^{\psi_O} + C_O, OLOS \end{cases}$$

$$\sigma_d^2 = 0.01275d - 0.01607$$

Where σ_B^2 and σ_d^2 are the variance based on different bandwidths and distances; m_B is the mean of error under different bandwidths.

From this function, we can determine the distance error of indoor localization on UWB when given location, system bandwidth and condition of LOS or OLOS by hand cover. This result can be extended to body area network (BAN) effect on indoor area and upgrading motion gaming system on accuracy by choosing a best-matched parameters. After what we have done right now, we are going to determine other gestures effect on indoor motion gaming localization to find out the effect of other parts of human body. When we finish this task, BAN effect on wireless motion gaming and localization will be determined for any kinds of use depending on detection of human body gestures.

IV. CONCLUTION

In this paper, we have introduced channel models for statistical behavior of localization error due to multipath, different operating bandwidths and the obstruction of motion controller antenna for indoor motion gaming. We defined two detection models by applying τ_{rms} and total power for hand cover in motion gaming. We built a database by performing 500 measurements on 9 locations using different bandwidths and body gestures.

Using empirical result of UWB channel measurements in indoor localization, we find our model closely fits the result of measurements. The models help to improve the localization accuracy, agility, broaden the field of application for typical indoor motion gaming system.

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