Detection of the LOS/NLOS state change based on the CIR features

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***Abstract*—As one of the most promising indoor localization technologies, ultra-wide band (UWB) system attracts lots of attentions due to its high accuracy, low complexity and low-power consumption. However, as one of the most important factors to guarantee accurate position estimation, accurate non-line-of-sight (NLOS) detection remains as a very challenging problem. During the experiments, if the mobile station (MS) move from line-of-sight (LOS) state to NLOS state or from NLOS state to LOS state, dramatic change of the features extracted from channel impulse response (CIR) can be observed. However, if the MS stays in the same state, no big changes can be observed. Based on these observation, four approaches (moving average based-, slope based-, wavelet based-, and time series analysis based approach) are proposed to identify the CIR state change (LOS to LOS, LOS to NLOS, NLOS to NLOS and NLOS to LOS). If the initial state is known, the current state can be determined with the accurate state change identification.**

***Index Terms*—UWB, NLOS, LOS, CIR, CIR state change detection**

I. Introduction

Since most of the human activities take place in buildings, indoor localization attracts lots of attentions. As one of the most accurate systems, UWB indoor position estimation can be realized based on time of arrival (TOA), time difference of arrival (TDOA), angle of arrival (AOA), received signal strength information (RSSI) or their combinations [1], [2], [3]. Due to the fine time resolution of the UWB signals, the time based TOA and TDOA offer better accuracy compared to AOA and RSSI.

A LOS path is a straight line signal propagation path, which connects the MS and base station (BS), without any obstruction. If the direct signal propagation path is obstructed, the signal reaches the receivers with time delay through the direct path or by reflected, diffracted or scattered paths, which is defined as NLOS. Under NLOS condition, a non-negligible positive bias will be added to the UWB measurements, which lead to inaccurate position estimation.

Lots of approaches have been proposed for NLOS detection. An overview of these approaches can be found e.g. in [4]. Among all these methods, the channel statistics based approach is one of the most effective method for NLOS identification [5], [6]. The main drawbacks of the current channel statistics based approaches are: firstly, huge amount of training data are needed for accurate NLOS detection. Secondly, the training model cannot be universal used in different indoor environments. Once the indoor environment changes, new training dataset need to be collect to insure accurate identification. Another method for NLOS detection is to combine UWB with an inertial measurement unit (IMU). In [7], [8], the accurate UWB measurements are selected with the help of the IMU measurements based on the Triangle Inequality Theorem. However, for these two papers, how to determine the optimal threshold for accurate measurements selection is a very challenging issue.

In this paper, the NLOS detection is realized based on the detection of the LOS/NLOS state change. Based on our observation, the CIR features during the state change from LOS to NLOS or NLOS to LOS have significant different characters compared to LOS to LOS or NLOS to NLOS state. Four different approaches are proposed for the identification of the state change: moving average (MA) based-, slope based-, wavelet based-, and time series analysis based approach. The main advantage of these proposals is that these methods can be universal used in different environments with the same UWB components. Furthermore, compared to the current channel statistics method, less data need to be collected during the training phase. The rest paper is organized as following: section II introduces the experimental hardware setup, the CIR, the extracted features from them and the technical background. Four proposed approaches and the training detection results with one of the feature are explained in section III. Furthermore, the advantages and disadvantages of each proposed approach are described. The feature, which contains the optimized parameters, with the best detection accuracy for every approach is show in this section. In section IV, the best three state change detection methods are selected and compared with the testing data, followed by the conclusions in section V.

II. Technical Background Statement

Every UWB measurement is obtained based on the corresponding CIR. If the received CIR is under NLOS condition, the corresponding measurement is not accurate. Thus the selection of the accurate measurement is the same as the selection of the CIR under LOS. The CIR(t) is the sum of

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all received pulses and can be described by the following equation:

$$c(t) = \sum_{k=1}^{K} a_k \delta(t - \tau_k) \tag{1}$$

Where K is the total number of the multipath components, a_k and τ_k represent the amplitude and time delay of the k^{th} arrived path. τ_1 is the arrival time of the first arrived path and $\tau_{strongest}$ is the arrival time of the strongest path.

One mobile station (MS) and one base station (BS) are used in the experiments. The chip used for the UWB system is the Decawave DW1000. The BS and different blockages (such as human, water, thin metal etc.) are fixed at the predefined positions. The distance between them changes from 0.5, 1, 2, 3 to 10 m. The MS was hold by the human. The distance between the BS and MS is always larger than the distance between the BS and the blockages. The human walked back and forward so that the signal propagation between the MS and the BS changed from LOS to NLOS and back to LOS again. It is found during the experiments that despite of the change of the distance or environments, the CIR feature state change can always be observed. Thus, if the initial LOS/NLOS state is given, based on the state change, the NLOS can be detected.

The received CIR are discrete points, which can be seen as a vector. Different characteristics can be observed for CIRs under LOS and NLOS, as shown in Fig. 1. In this paper, ten features are extracted from CIR, including mean excess delay, root-mean-square (RMS) delay spread, standard deviation, maximal amplitude, rise time to the maximal amplitude, received signal energy, kurtosis, skewness, form factor and crest factor. The calculation of these features can be found in [9]. These features can be used for NLOS classification based on machine learning. However, these features extracted from CIR are different in different environments. Thus, in order to insure the identification accuracy, new training dataset need to be collected if the environment changes. However, regardless of the environments, significant difference can be observed between the unchanged state (LOS to LOS, NLOS to NLOS) and the changed state (LOS to NLOS, NLOS to LOS) of the feature. Assuming a MS is in clear LOS to BS and then move to NLOS state. After stay under NLOS for certain time, it move out and is in clear LOS again. The values of kurtosis during the whole process is presented in Fig. 2. Clear NLOS/LOS change can be observed.

If the state change can be detected, the NLOS detection can be realized after the initialization. In the MA and wavelet based approach, the threshold for state change, the optimal length of the MA window and the proper reference value need to be determined. The predictive model need to be trained in the time series analysis based approach. Similar as MA approach, the threshold for state change and the optimal window length are essential for detection. Thus, in order to determine these parameter, the data are divide into two groups: in the first group, the initial state is LOS, the threshold is used to determine if the state change to NLOS or remain as LOS. In

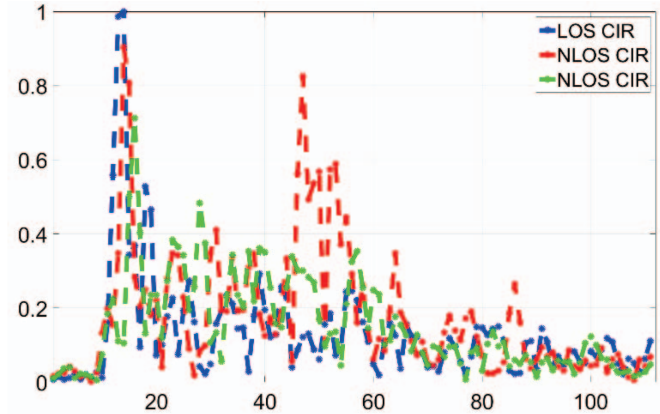

Fig. 1. CIRs under LOS and NLOS

the second group, the initial state is NLOS, again a threshold need to be decided to detect the state change.

III. State Change Detection Algorithms Description

Four different methods are used for state change detection: MA based-, slope based-, wavelet based-, and time series analysis based approach. In this section, all the methods will be descripted. During the training phase, the feature after optimization of the best threshold, window length, wavelet level or prediction step with best detection accuracy for each approach is determined.

A. MA based Approach

Assuming the length of the window in moving average is n, the average value after discarding the biggest and smallest value in the window is calculated. During the initialization, the state of the first window is given (assuming in LOS state), the average value of the first window is used as reference. Two thresholds need to be decided. The first one is used as compared value for LOS state change detection, the second one for NLOS state change detection. If the difference between the average value of the second window and the first window is great than the first threshold, then the CIR state change from

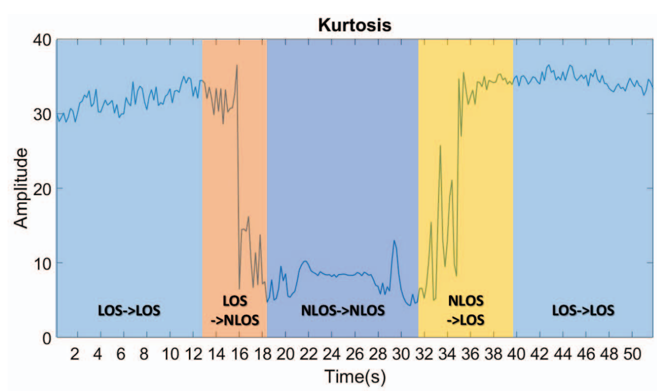

Fig. 2. Kurtosis NLOS/LOS state change

LOS to NLOS, otherwise, it is still in the LOS state. If the state changed, the reference value is the average value of the second window. If the state remain unchanged, the reference value keeps the same. If the measured range is 30 cm larger than the real range, this measurement is considered as inaccuracy. Most of the time, in our experiments, the detected changed range point might not be exactly the real NLOS start/end range point, as seen in Fig. 3. The distance between the real and measured NLOS start/end point is also a very import factor to determine the accuracy.

As mentioned, two different groups are used to find the optimal threshold and window length. In the first group, the initial state of the data is LOS. After remaining LOS state for a certain time, the state of the data change to NLOS. The data is divided into two parts. The first part is LOS to LOS and the second part is LOS to NLOS. The detection is only considered as accurate, if no state change is detected in the first part and if the state change is detected in the second part. In the second group, the initial state of the data is NLOS. The definition of accurate detection is the same as in the first group. The distance between the real and measured NLOS start/end point need to be considered as well.

Fig. 4 shows the detection accuracy and average distance error based on the feature RMS delay spread with different thresholds and window lengths. If the accuracy is equal to 1, no misdetection occur and all state changes are detected. Which means, only the corresponding thresholds and window length of the red blanks can be used. It can be seen in the table, for LOS initial state, while the threshold equals to 7.67 and window length is 5, the detection is accurate and the minimal distance between the real and measured NLOS start occurs. Overall, the detection accuracy is good and the average distance error is over 2 points.

B. Wavelet based Approach

Wavelet based approach is very similar to MA based approach. The only difference is instead of determining the window length, the wavelet level need to be decided. After the calculation of the approximation coefficients (as show in Fig. 5), the first value coefficient is set as reference. Again, two thresholds need to be determined. The rest process is the same as MA based approach. The structure flowchart of these two approaches can be found in Fig. 6. Fig. 7 show the detection results based on the approximation coefficients of RMS delay with different levels and thresholds. The detection accuracy becomes much worse after wavelet level 4. For NLOS initial state, the most accurate results happens while the threshold equal to -10.33 and the wavelet level is 2.

C. Slope based Approach

Different as the MA and wavelet based approach, no reference value is needed for the slope based approach. The

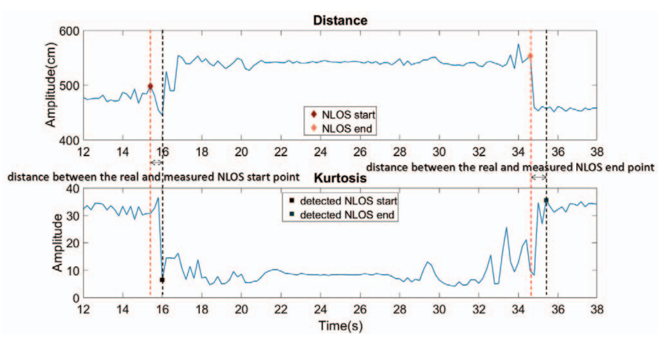

Fig. 3. Detected and real NLOS start/end range point

RMS delay, MA: Start with LOS state - Accuracy / Error

Threshold	5	6	7	8	9	10	11
3.67	0.90 / 1.55	0.95 / 1.70	0.95 / 1.75	0.95 / 1.70	0.95 / 1.80	0.95 / 1.80	1.00 / 2.35
5.00	0.95 / 1.50	0.95 / 1.60	0.95 / 1.90	0.95 / 2.05	1.00 / 2.15	1.00 / 2.65	1.00 / 3.00
6.33	0.95 / 1.50	1.00 / 1.85	1.00 / 2.00	1.00 / 2.40	1.00 / 2.85	1.00 / 3.25	1.00 / 4.00
7.67	1.00 / 1.85	1.00 / 2.10	1.00 / 2.45	1.00 / 2.85	1.00 / 3.35	1.00 / 4.00	1.00 / 4.80
9.00	1.00 / 2.20	1.00 / 2.65	1.00 / 2.95	1.00 / 3.45	1.00 / 4.05	1.00 / 4.80	1.00 / 5.45
10.33	1.00 / 3.50	1.00 / 3.45	1.00 / 3.90	1.00 / 4.60	1.00 / 5.25	1.00 / 5.95	1.00 / 6.70

RMS delay, MA: Start with NLOS state - Accuracy / Error

Threshold	5	6	7	8	9	10	11
-3.67	0.90 / 9.15	0.95 / 8.50	0.95 / 8.10	0.95 / 3.70	0.95 / 3.20	0.95 / 3.20	1.00 / 3.10
-5.00	0.95 / 5.00	0.95 / 4.55	0.95 / 3.40	0.95 / 3.15	1.00 / 2.95	1.00 / 3.00	1.00 / 2.90
-6.33	0.95 / 4.45	0.95 / 2.95	0.95 / 2.90	1.00 / 2.75	1.00 / 2.60	1.00 / 2.85	1.00 / 3.00
-7.67	0.95 / 2.75	1.00 / 2.35	1.00 / 2.40	1.00 / 2.70	1.00 / 2.85	1.00 / 3.30	1.00 / 3.65
-9.00	1.00 / 2.30	1.00 / 2.50	1.00 / 2.65	1.00 / 3.05	1.00 / 3.40	1.00 / 4.05	1.00 / 4.60
-10.33	1.00 / 2.35	1.00 / 2.70	1.00 / 3.05	1.00 / 3.60	1.00 / 4.05	1.00 / 4.65	1.00 / 5.25

Window length

Fig. 4. Detection accuracy and average distance error based on RMS delay spread with different thresholds and window lengths

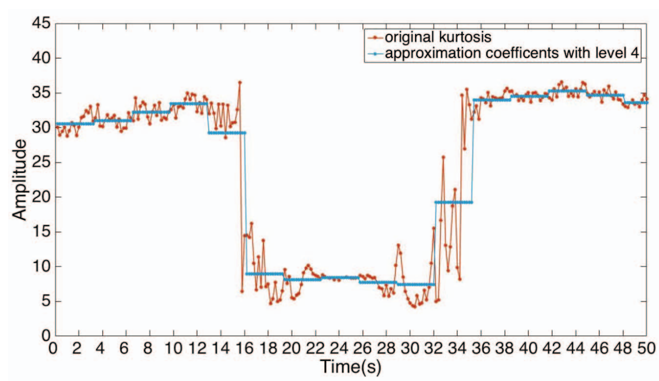

Fig. 5. Original kurtosis and approximation coefficients of the kurtosis with level 4

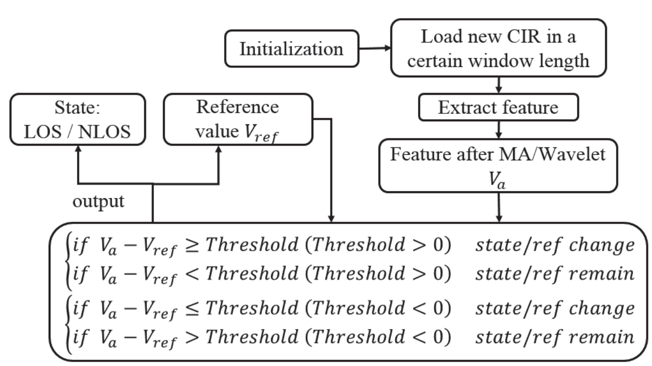

Fig. 6. Structure flowchart of MA- based and wavelet based approach

RMS delay, wavelet: Start with LOS state - Accuracy / Error

Threshold \ Wavelet level	2	3	4	5	6
3.67	0.95 / 2.55	0.95 / 3.15	1.00 / 4.75	0.75 / 8.73	0.40 / 33.75
5.00	0.95 / 2.35	1.00 / 2.25	1.00 / 3.95	0.70 / 7.93	0.35 / 32.71
6.33	0.95 / 2.25	1.00 / 2.25	1.00 / 4.15	0.65 / 7.62	0.20 / 34.25
7.67	1.00 / 2.65	1.00 / 2.55	1.00 / 4.15	0.55 / 6.73	0.15 / 32.00
9.00	1.00 / 2.65	1.00 / 2.45	1.00 / 3.85	0.50 / 9.10	0.05 / 41.00
10.33	1.00 / 3.55	1.00 / 3.95	0.95 / 5.26	0.50 / 12.30	0.00 / NaN

RMS delay, wavelet: Start with NLOS state - Accuracy / Error

Threshold \ Wavelet level	2	3	4	5	6
-3.67	0.90 / 10.85	0.95 / 6.15	1.00 / 5.05	0.80 / 9.63	0.25 / 20.40
-5.00	0.95 / 6.05	1.00 / 4.15	1.00 / 4.55	0.80 / 9.63	0.25 / 20.40
-6.33	0.95 / 3.75	1.00 / 3.55	1.00 / 4.05	0.75 / 9.80	0.25 / 20.40
-7.67	1.00 / 2.55	1.00 / 2.95	1.00 / 3.45	0.70 / 9.29	0.25 / 20.40
-9.00	1.00 / 1.95	1.00 / 2.85	1.00 / 3.45	0.60 / 10.33	0.20 / 22.50
-10.33	1.00 / 1.75	1.00 / 2.55	1.00 / 2.85	0.30 / 10.33	0.00 / NaN

Fig. 7. Detection accuracy and average distance error based on RMS delay spread with wavelet approach

gradient of a line, which has the best fit to the data in the window, is defined as a parameter, which minimizes the following equation:

$$min \sum_{k=1}^{n} (y_i - a_0 - a_1 x_i)^2 \tag{2}$$

where n is the length of the window. a_0 is a constant, y_i is the value of the feature at time i, x_i is the time and a_1 is the gradient.

Two threshold need to be selected. The state change can be detected by comparing the gradient and the threshold. Fig. 8 show the results based on the RMS delay.

D. Time Series Analysis based Approach

In this approach, two different autoregressive integrated moving average (ARIMA) models are trained: LOS to LOS model and NLOS to NLOS model. If the previous data are in LOS state, the future value can be predicted based on the previous data with the help of the LOS to LOS model. If the average difference between the predicted values and measured value is large than a predefined threshold, then the LOS is changed to NLOS state, otherwise, the state remains as LOS. The NLOS to NLOS model works in the same way. The ARIMA model is derived based on Box-Jenkin approach [10]. The detection accuracy can be found in Fig. 9.

E. Approaches Comparison

Among these approaches, generally the slop based and the wavelet based approach have better accuracy. The advantages (+) and disadvantages (-) of each approach are explained in the following:

(a). MA filter

+: Simple and fast;

-: Reference depends on the last sequence. The proper reference is not stable and hard to decide

(b). Wavelet

+: Better accuracy

-: Reference depends on the last sequence. But compare to MA, this reference is more stable;

(c). Slope

+: Better accuracy; No reference is needed

-: High computation complexity due to line fitting process;

(d). ARIMA

+: Huge training data are needed for training the model

-: Accuracy is not good and highly depends on the trained model

As mentioned in the beginning, totally 15 features are extracted from the CIR. For each feature, all the proposed approaches are estimated.

Fig. 10/Fig. 11 shows the detection and the least average distance error based on different approaches with the corresponding feature. In Fig. 10 , the initial state is LOS, while in Fig. 11, the initial state is NLOS. As shown in these figures, if the initial state is LOS, the best solution is the slop based approach with the RMS delay. If the initial state is NLOS, the wavelet based approach contains the least average distance error. The slope based approach provide also promising results.

IV. Test Results

As shown in last section, regardless of the initial state, the slope and wavelet based approach provide good results. The disadvantage of the MA is the unstable reference value, which might lead to inaccurate detection. The best combination is the

RMS delay, slope: Start with LOS state - Accuracy / Error

Threshold \ Slope window length	8	9	10	11	12	13	14
0.83	0.85 / 1.95	0.90 / 1.90	0.90 / 1.80	1.00 / 2.00	1.00 / 2.00	1.00 / 1.90	1.00 / 2.10
0.94	0.90 / 1.90	0.90 / 1.90	1.00 / 1.95	1.00 / 2.05	1.00 / 2.00	1.00 / 2.05	1.00 / 2.45
1.06	0.90 / 1.85	1.00 / 1.80	1.00 / 2.05	1.00 / 1.90	1.00 / 2.05	1.00 / 2.30	1.00 / 2.85
1.17	0.90 / 1.90	1.00 / 1.90	1.00 / 1.95	1.00 / 1.95	1.00 / 2.05	1.00 / 2.65	1.00 / 3.20
1.28	0.95 / 1.90	1.00 / 2.10	1.00 / 2.05	1.00 / 2.25	1.00 / 2.40	1.00 / 3.20	0.95 / 3.68
1.39	1.00 / 1.95	1.00 / 2.05	1.00 / 2.10	1.00 / 2.35	1.00 / 2.80	0.90 / 3.33	0.90 / 3.94

RMS delay, slope: Start with NLOS state - Accuracy / Error

Threshold \ Slope window length	8	9	10	11	12	13	14
0.83	0.85 / 10.80	0.85 / 9.60	0.90 / 9.10	0.90 / 4.20	0.95 / 3.40	0.95 / 3.10	1.00 / 3.05
0.94	0.85 / 9.80	0.90 / 9.00	0.90 / 4.25	0.95 / 3.90	0.95 / 3.05	0.95 / 3.05	1.00 / 2.70
1.06	0.90 / 9.40	0.90 / 8.40	0.95 / 3.95	0.95 / 3.00	0.95 / 2.90	1.00 / 2.30	1.00 / 2.55
1.17	0.90 / 8.65	0.90 / 4.05	0.95 / 2.95	0.95 / 2.65	1.00 / 2.55	0.95 / 2.63	0.95 / 2.37
1.28	0.95 / 4.35	1.00 / 4.00	1.00 / 2.55	1.00 / 2.60	0.95 / 2.16	0.95 / 2.47	0.90 / 3.00
1.39	1.00 / 4.05	1.00 / 2.70	1.00 / 2.45	0.95 / 2.00	0.95 / 2.47	0.95 / 2.74	0.85 / 3.18

Fig. 8. Detection accuracy and average distance error based on RMS delay spread with slope approach

Form factor, ARIMA: Start with LOS state - Accuracy / Error

Threshold \ Prediction step	1	2	3	4	5	6	7
0.20	0.75 / 6.35	0.80 / 6.85	0.80 / 7.45	0.80 / 8.00	0.80 / 8.40	0.80 / 8.80	0.80 / 9.45
0.29	0.85 / 5.35	0.90 / 5.95	0.85 / 6.35	0.85 / 6.75	0.80 / 7.25	0.80 / 7.65	0.85 / 7.85
0.38	0.95 / 5.20	0.95 / 5.42	1.00 / 5.65	1.00 / 5.70	1.00 / 5.85	1.00 / 6.15	1.00 / 6.35
0.47	0.90 / 4.37	0.90 / 5.00	0.95 / 4.89	0.95 / 5.05	0.95 / 4.84	1.00 / 4.65	1.00 / 4.70
0.56	0.80 / 4.31	0.75 / 4.07	0.85 / 3.76	0.90 / 3.56	0.95 / 3.26	0.95 / 3.32	0.95 / 3.42
0.64	0.65 / 4.38	0.40 / 4.63	0.55 / 3.73	0.55 / 3.64	0.60 / 3.25	0.60 / 3.50	0.65 / 3.38

Form factor, ARIMA: Start with NLOS state - Accuracy / Error

Threshold \ Prediction step	1	2	3	4	5	6	7
-0.20	0.90 / 6.20	0.90 / 5.30	0.90 / 5.40	0.90 / 5.35	0.90 / 5.35	0.90 / 5.75	0.90 / 5.65
-0.29	0.90 / 4.60	1.00 / 4.90	1.00 / 4.95	0.95 / 4.90	0.95 / 5.05	0.95 / 4.90	0.95 / 4.85
-0.38	0.95 / 3.15	1.00 / 2.80	1.00 / 3.05	1.00 / 3.50	1.00 / 3.75	1.00 / 3.75	1.00 / 4.30
-0.47	0.95 / 2.32	0.95 / 2.53	0.95 / 2.47	0.90 / 2.44	0.90 / 2.44	0.90 / 2.67	0.90 / 2.78
-0.56	0.95 / 2.21	0.95 / 2.21	0.90 / 2.22	0.80 / 2.44	0.75 / 2.40	0.70 / 2.21	0.70 / 2.64
-0.64	0.90 / 1.83	0.90 / 1.94	0.65 / 1.77	0.55 / 1.82	0.45 / 2.11	0.45 / 2.11	0.45 / 2.11

Fig. 9. Detection accuracy and average distance error based on RMS delay spread with ARIMA approach

Algo/ LOS start	MA	Wavelet	ARIMA	Slope
Feature	RMS delay	RMS delay	Form factor	RMS delay
Parameters	Window length	Level	Prediction step	Fitting window
	5	3	6	9
Threshold	7.67	5	0.47	1.056
Accuracy	1	1	1	1
Boundary error	1.85	2.25	4.65	1.8

Fig. 10. Detection accuracy and the average distance error with the selected approaches and features, start with LOS

Algo/ NLOS start	MA	Wavelet	ARIMA	Slope
Feature	RMS delay	RMS delay	Form factor	Form factor
Parameters	Window length	Level	Prediction step	Fitting window
	5	2	2	10
Threshold	-9	-10.33	-0.38	0.052
Accuracy	1	1	1	1
Boundary error	2.3	1.75	2.8	1.8

Fig. 11. Detection accuracy and the average distance error with the selected approaches and features, start with NLOS

slop based approach for LOS initial state and wavelet based approach for NLOS initial state.

In the validation process, three approaches are evaluated. The first one is the slope based method. For LOS state, the RMS delay is the used feature while for NLOS state, the form factor is used. The second one the wavelet based approach. Regardless of the state, the used feature is RMS delay. The third one is the combination of slope and wavelet based approach. For LOS state, the slope based method is active. While for NLOS state, the wavelet method is used.

Table. I shows the detection accuracy based on these approaches. Although the wavelet based method and the combination of wavelet and slope based approach provide less distance error. The detection accuracy is not as good as the slope based approach. The main reason is that in wavelet based approach, the reference value changes all the time. The optimal reference is very hard to be determined during the dynamic process. Thus, the slope based approach is the best option. The main disadvantage of these approaches is the detection accuracy has to be 100%. Otherwise, the rest identification results are incorrect, unless wrong detection happens again. Thus, these approaches can be used as additional information or reference and combined with other methods, such as CIR static feature detection based on machine learning. They should not be used alone for NLOS detection.

V. Conclusions

Four different approaches are proposed in this paper to identify the CIR state change. Compared to other approaches, these methods can be universally used in different environments

TABLE I
Detection Accuracy and Distance Error based on three Approaches

		LOS to NLOS	NLOS to LOS
	Accuracy	**Distance error**	**Distance error**
Slope based	100%	5.57	14.12
Wavelet based	91.84%	3.6	10.18
Combination	91.84%	3.67	6.75

with the same UWB components. The main disadvantage of these approaches is that 100% detection accuracy is required in order to guarantee accurate position estimation. However, in real case, this is very hard to achieve. Thus, these approaches are mainly combined with other NLOS detection methods and used as additional information.

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References

[1] J. Liu, H. Jing, Y. Xiang, and Z. Guan, Simulation Research of UWB location algorithm, in *2018 Chinese Control And Decision Conference (CCDC)*, Shenyang, China, 2018, pp. 4825-4830.

[2] B. Choi, K. La, and S. Lee, UWB TDOA/TOA measurement system with wireless time synchronization and simultaneous tag and anchor positioning, in *2018 IEEE International Conference on Computational Intelligence and Virtual Environments for Measurement Systems and Applications (CIVEMSA)*, Ottawa, ON, Canada, 2018, pp. 1-6.

[3] B. Jachimczyk, D. Dziak, and W. J. Kulesza, Customization of UWB 3D-RTLS Based on the New Uncertainty Model of the AoA Ranging Technique, (eng), *Sensors (Basel, Switzerland)*, vol. 17, no. 2, 2017.

[4] J. Khodjaev, Y. Park, and A. Saeed Malik, Survey of NLOS identification and error mitigation problems in UWB-based positioning algorithms for dense environments, *Ann. Telecommun.*, vol. 65, no. 5-6, pp. 301-311, 2010.

[5] K. Wen, K. Yu, and Y. Li, NLOS identification and compensation for UWB ranging based on obstruction classification, in *2017 25th European Signal Processing Conference (EUSIPCO)*, Kos, Greece, 2017, pp. 2704-2708.

[6] K. Gururaj, A. K. Rajendra, Y. Song, C. L. Law, and G. Cai, Real-time identification of NLOS range measurements for enhanced UWB localization, in *2017 International Conference on Indoor Positioning and Indoor Navigation (IPIN)*, Sapporo, 2017, pp. 1-7.

[7] Z. Zeng, S. Liu, and L. Wang, A novel NLOS mitigation approach for TDOA based on IMU measurements, in *2018 IEEE Wireless Communications and Networking Conference (WCNC)*, Barcelona, 2018, pp. 1-6.

[8] Z. Zeng, S. Liu, and L. Wang, UWB/IMU integration approach with NLOS identification and mitigation, in *2018 52nd Annual Conference on Information Sciences and Systems (CISS)*, Princeton, NJ, 2018, pp. 1-6.

[9] Z. Zeng, S. Liu and L. Wang, "UWB NLOS identification with feature combination selection based on genetic algorithm," *2019 IEEE International Conference on Consumer Electronics (ICCE)*, Las Vegas, NV, USA, 2019, pp. 1-5. doi: 10.1109/ICCE.2019.8662065

[10] G. E. P. Box, G. M. Jenkins, G. C. Reinsel, and G. M. Ljung, Time series analysis: Forecasting and control / George E.P. Box, Gwilym M. Jenkins, Gregory C. Reinsel, Greta M. Ljung. Hoboken, New Jersey: Wiley, 2016.