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LOS/NLOS Identification Based on Stable Distribution Feature Extraction and SVM Classifier for UWB On-Body Communications

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Abstract

This paper presents a technique for identifying between both Line-Of-Sight (LOS) and Non-Line-Of-Sight (NLOS) propagation schemes for UWB on-body context. In the last few years, a great attention has been paid to wireless communications for body area networks especially since the IEEE 802.15.6 standard has been released. We focus at first to extract only the pertinent information using Stable Distribution compared with statistical techniques, and secondly to classify it using Support Vector Machine (SVM) with as main goal to identify between the two LOS and NLOS phenomena. We propose a technique to make the classification easy between LOS and NLOS contexts for UWB on-body communications. Our approach gives a good recognition rate of 87.5%, better than other methods in the same context.

Keywords: *Ultra-wideband (UWB); Line-of-sight (LOS); Non-line-of-sight (NLOS); Stable distribution; Support Vector Machine (SVM); On-body communications.*

1. Introduction

Body Area Networks (BANs) have received a considerable attention in the last few years. With IEEE 802.15.6 standard, BANs use ultra-wideband (UWB) in several domain like telemedicine, medical applications and communications for on-body situations. The UWB technology is adapted to indoor localization thanks to a fine delay resolution and obstacle-penetration capabilities.

Thus, UWB represents hopeful technology for localization applications in harsh environments and critical applications [1,8,13,15] in many domains including medical or military [2,3,4], notably for wireless personal area networks (WPANs) and especially for modern telemedicine systems using the IEEE 802.15.6 standard. BANs have a great potential for UWB medicine systems and channel models have been standardized. In this context, this work will only consider CM3 and CM4 (CM: Channel Model) for LOS/NLOS body surface to body surface UWB, and for LOS/NLOS body surface to external UWB respectively [18]. The UWB systems consist to transmit a very short pulse of few nanoseconds over either a large frequency bandwidth from 500 MHz to several GHz, or a relative bandwidth larger than 20% of central frequency, according to the specification of the Federal Communication Commission (FCC). A lot of challenges remain before implementation of UWB can be deployed on a large scale. These include signal acquisition, multi-user interferences, multipath and NLOS propagations [1,2,13,14]. The latter case is especially critical for most location-based applications because the NLOS propagation introduces positive bias in the estimation of distance, which can seriously affect the performance of localization. There are several techniques to deal with ranging bias in NLOS phenomena, which we classify as identification techniques. More details about NLOS identification techniques can be found in [1,2,8,15]. In [1] the

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non-parametric method is tested to distinguish between the LOS and NLOS conditions especially for localization using LS-SVM (Least Square Support Vector Machine). The authors evaluate two conditions with two scenarios, parametric and non-parametric, and obtain a classification rate of 84% for the first scenario and 91% for the second using LS-SVM. In [2], with the same aim to localization, an identification and mitigation technique is used with the same situations as in [1], giving only 60% of identification with an accuracy of less than 1 meter.

In this paper, we propose a technique of identification and demonstrate the need for LOS and NLOS identification for several domains like mitigation and localization for on-body communications. Our approach is based on stable distribution using SVM technique [5]. These techniques will be detailed in the section 3. The objectives are to obtain a better identification with a good mitigation or localization. The measurements used were collected from a measurement campaign performed by Body-centric Wireless Sensor Lab (Body WiSeR) [9,17] with low loss coaxial cables to measure the transmission response [3]. The rest of this paper is organized as follows. The proposed methods are presented in the section 2. The section 3 is devoted to global discussion and results, before the conclusion.

2. Experimental data

With the aim to study the characteristics of UWB, we worked with the data collected by the Antenna & Electromagnetics Group (Body WiSeR). All the parameters for the measurement are presented in Table 1.
All the measurements were collected in a room that is 3m high and which geometry is described in Fig. 1. More informations can be found in [9,17].

Table 1: Parameters of Body WiSeR database

Parameters	Values
Frequency range	3-10 GHz
Frequency sampling	4,37 MHz
Maximum time delay	228.8 ns
Maximum observable distance	68.6 m
Frequency span	7 GHz
Maximum temporal resolution	0.14 ns
Maximum spatial resolution	43mm
Time bin size	0.14 ns
Transmit power	0 dBm
IF bandwidth	3 KHz / 101 dBm

3. Proposed approach

In this section, we present our method to identify between the classes and specially to distinguish between the LOS and NLOS phenomena for UWB on-body communications. We begin by testing the statistical method and we describe our choice of a method based on stable distribution for feature extraction and SVM for identification. In the remainder of this paper, we focus on techniques that identify the effects of LOS and NLOS phenomena. This identification helps in many domains like localization and mitigation, but the aim of this approach is to obtain a good rate of signal recognition with a better identification. In [1,2,8], NLOS has been used for identification, localization and mitigation, with the same objectives in all these works: to find a method that facilitates the task for a good identification. In the literature, the NLOS conditions are presented by a signal more attenuated and that has smaller energy and amplitude; in LOS conditions, the signal is strong and presents high energy and amplitude. Generally, for the on-body communications the information is presented by physiological signals, and the rate of such signals is much lower compared with other applications of UWB [1,2]. Fig. 2 shows an obvious difference between LOS and NLOS situations. Therefore, it is necessary to choose a good method for extraction and classification.

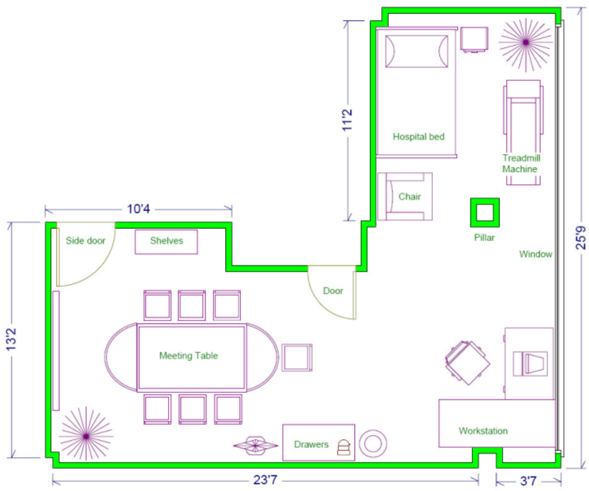


Figure 1: Dimensions and geometry of the Body Centric Wireless Sensor Lab where the indoor radio propagation measurements are performed. The sensor lab height is 3 m

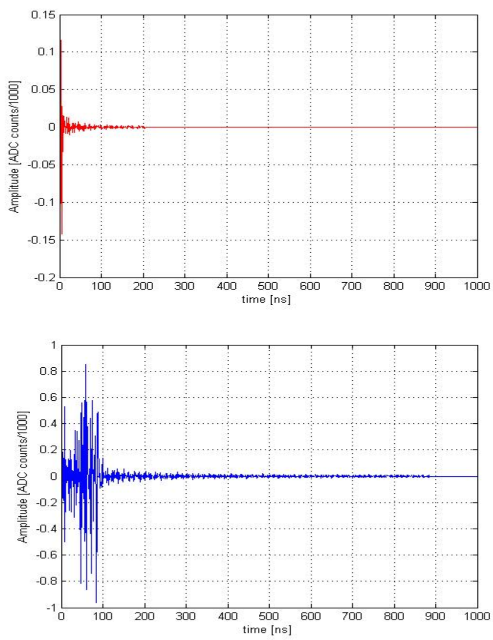


Figure 2: Difference between LOS and NLOS for on-body communications

The proposed methods rely on two main phases: learning phase and testing phase.

In the first phase, the raw data are used to extract reliable features based on stable distribution, which is then used to learn models in on-line situation. These features are then used to find SVM classifier corresponding to different conditions of the component. The method is based on a non-destructive control: the acquired signals are processed to extract features in the form of stable distribution coefficients (μ, c, α and β) used to find the SVM classifier for on-body communications.

In the second phase we proceed to the identification based on the test parameters presented by an off-line phase as shown in Fig. 3. For the feature extraction we calculate six statistical parameters from the time domain data presented in § 3.1, to first prove the choice of our method, and secondly to test the results with our approach using SVM classifier as shown below in Fig. 3. These feature parameters are kurtosis, entropy estimation, mean and variance. In this work, we divide the on-body data into LOS and NLOS matrices. For better training and testing of on-body communications we have only selected six features. The selected features are kurtosis, mean, entropy estimation, RMS, energy and variance, because they give the best separation between the classes. We then compare the results with the four parameters obtained from stable distribution.

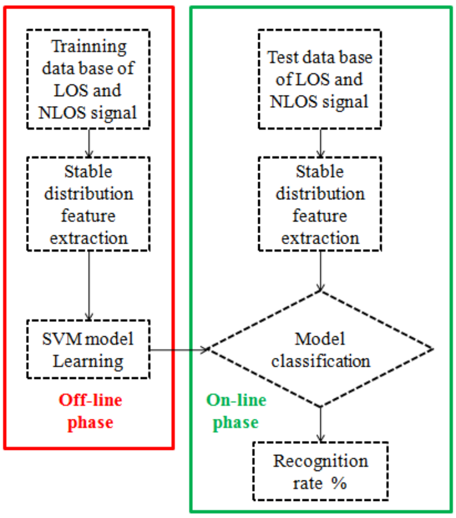


Figure 3: Proposed approach

3.1. Statistical feature selection

In this part, we describe the statistical features used in literature and that are needed to distinguish between the different classes, and in this work between the two LOS and NLOS phenomena. In [1,2,16], basic statistical methods are used for feature extraction to prove others methods. With the same idea and for the feature extraction, we are using some statistical methods compared with our own but for medical applications. The features we will consider are as follows:

1) *Energy of the received signal:*

$$f(x) = \int_{-\infty}^{+\infty} |\mathrm{r(t)}|^2 \mathrm{dt} \qquad (1)$$

2) *Mean excess delay:*

$$\tau_{MED} = \int_{-\infty}^{+\infty} t\varphi(t)dt \qquad (2)$$

where $\varphi(t) = |r(t)|^2/\varepsilon_r$

3) *RMS delay spread:*

$$\tau_{RMS} = \int_{-\infty}^{+\infty} (t - \tau_{MED})^2 \varphi(t)dt \qquad (3)$$

4) *Kurtosis:*

$$k = \frac{1}{\sigma_{|r|}T}\int_T r(t) - \mu_{|r|}|]\,dt \qquad (4)$$

where $\mu_{|r|} = \frac{1}{T}\int_T |r(t)|dt$ and $\sigma^2{}_{|r|} = \frac{1}{T}\int_T [|r(t) - \mu_{|r|}|]^2 dt$

5) *Entropy:*

$$H(X) = E[I(X)] = E[-ln(P(X))] \qquad (5)$$

Where E is the expected value operator, and *I* is the information content of *X*.

6) *Variance:*

$$Var\,(x) = \int x^2 f(x)dx - \mu \qquad (6)$$

where μ is the expected value.

3.2. Stable distribution

Although the probability density function for a general stable distribution cannot be written analytically, the general characteristic function for any probability distribution is determined by its φ(t) by:

$$F(x) = \frac{1}{2\pi}\int_{-\infty}^{\infty} \varphi(t)e^{-ixt}\,dt \qquad (7)$$

A random variable X is called stable if its characteristic function can be written as:

$$\varphi(t;\mu,c,\alpha,\beta) = exp\,[it\mu - |ct|^{\alpha}(1 - i\beta sgn(t)\Phi)]$$

Where *sgn(t)* is the sign of *t* and Φ is given by $\Phi = tan(\pi C\alpha/2)$ for all α except α=1 in which case: $\Phi = -2/\pi\ log(t)$. Such distributions form a four-parameter family of continuous probability distributions parameterized by location and scale (μ and c), two shape parameters (α and β), β roughly corresponding to the measures of asymmetry and concentration. The Alpha-Stable are rich classes of probability distributions that include the Gaussian (α=2), Cauchy (α=1) and Lévy (α=5) classes; all have the above property: it follows that they are special cases of stable distributions (Fig. 4).

In our approach, we are fitting the data with stable distribution based on McCulloch method [12]. With this method we obtained four consistent estimators in terms of five sample quantiles, and tabulated the values of the four estimators.

3.3. Support Vector Machine

The support vector machine (SVM) is based on a simple idea that originated in statistical learning theory by Vapnik [5]. This simplicity comes from the fact that this technique uses a simple linear method, but applied in high-dimensional feature space non-linearly related to the input space. It represents one of the most broadly used classification techniques because of its robustness, its performance and its rigorous underpinning compared to other techniques like neural networks[6].

For the identification, support vector machines separate the different classes of data by a hyper plane[7]

$$(w,\varphi(x)) + b = 0 \qquad (8)$$

corresponding to the function

$$F(x) = sign\,((w,\varphi(x)) + b) = 0 \qquad (9)$$

where F(x) is a predetermined function, and w and b are unknown parameters of the classifier.

These parameters are determined based on the training set $\{X_k l_k\}_{k=1}^{N}$, where $X_k \in R^n$ and $l_k \in \{-1,+1\}$ are the inputs and labels, respectively. In some cases, the two classes can be separated and the SVM determines the separating hyper plane that maximizes the margin between the two classes. Generally, most practical problems involve classes that are not separable. In this case, the SVM is obtained by solving the following optimization problem:

$$argmin_{w,b,\varepsilon} \frac{1}{2} ||w||^2 + \gamma \sum_{k=1}^{N} \varepsilon_k \; with \; l_{ky} (X_k) \geq 1-\varepsilon_k, \forall k \quad (10)$$

where ε_k are slack variables that allow the SVM to tolerate misclassifications and γ controls the trade-off between minimizing training errors and complexity [2].

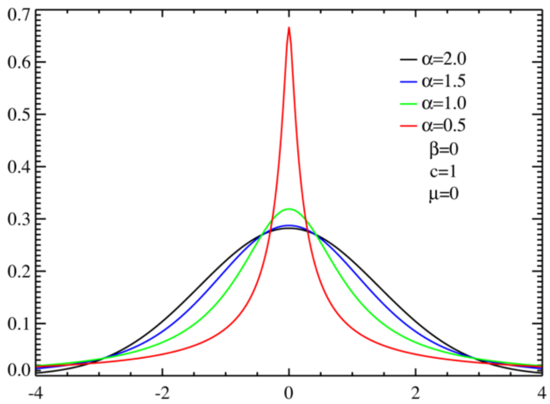


Figure 4: Stable distribution

4. Simulations and results

All identification methods have been tested with the data obtained from Body WiSeR laboratory measurements as described in [9,17]. The measurements are based on the scenarios for in-body and on-body communications. In this work, we are only interested in on-body communications. For on-body communications, especially for this database, the LOS scenarios are presented in 1 to 56 sensors and the NLOS are presented in 57 to 110 sensors (see Fig. 5). We have constructed a matrix for the LOS case and another one for the NLOS. We start our approach by studying the impact of LOS and NLOS in different situations. First, we proceed in the study of the impulse response as shown in Fig. 6: the impulse response remains constant in the LOS case but falls for the NLOS case. Secondly, we study the power delay profile in the two conditions; the results are presented in Fig. 7: the difference between LOS and NLOS case **is** due to the difference of multipath arrival **times**. We can see a huge difference between the two phenomena in **both** situations.

Next, we proceed with three scenarios. In the first scenario we begin to classify the raw data LOS and NLOS using SVM method. In this case, the recognition rate between LOS and NLOS is 50%. In the second scenario, we extract only some information from data using statistical methods described in section 3. We use kurtosis, mean, entropy, RMS, energy and variance to extract only the pertinent information and we use the SVM classifier. In this case, we still get the same recognition rate of 50%. In the third scenario, we extract the pertinent informations from data using stable distribution. Information about α, β, γ, c is described in Table 2. After having reduced the size, we proceed to the identification using SVM. The results of the comparisons between this work and those presented in [1,2,16] are shown in Table 3.

Finally, we have proceeded to fit the data in different situations using normal, logistic, t Location-scale, generalized extreme value methods, as well as our own. In all fitting scenarios for the two LOS and NLOS situations, we found that only the stable distribution permits to cover all data: results are shown in Fig. 8 and Fig. 9.

Compared to other techniques, Table 3 shows that our approach gives a recognition rate for BAN communications very close to those obtained in [1] and [2] for PANs. Our approach has been validated for PANs in [16], and this work demonstrates that it also gives good results for on-body communications compared with statistical methods of extraction.

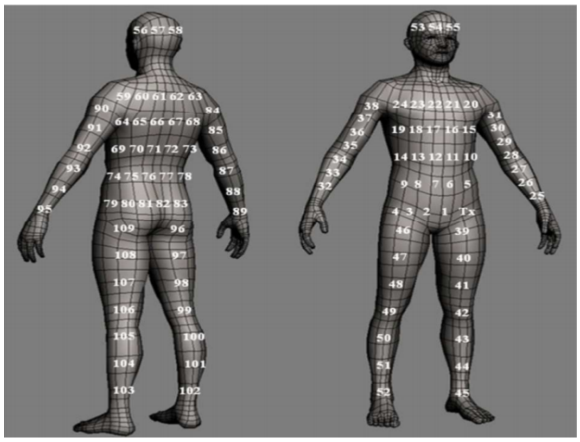


Figure 5: On-body index locations for NLOS and LOS

Table 2: The values of stable distribution parameters

Data	*α*	*β*	*γ*	*c*
LOS	0.654	-0.0087	2.41e-005	4.42e-007
NLOS	0.538	-0.0256	3.62e-0.005	8.21e-007

5. Conclusion

In this paper we described the need for LOS and NLOS paths identification for on-body communications and an approach to make this identification easier using the stable distribution for the features' extraction and support vector machine classifier for the identification. This approach gives good results with 87.5% of recognition rate compared to other statistical methods: Kurtosis, Mean, energy, RMS, entropy and variance. By using both the stable distribution and the SVM classifier we developed a technique that is capable of distinguishing two critical LOS and NLOS phenomena for on-body communications.

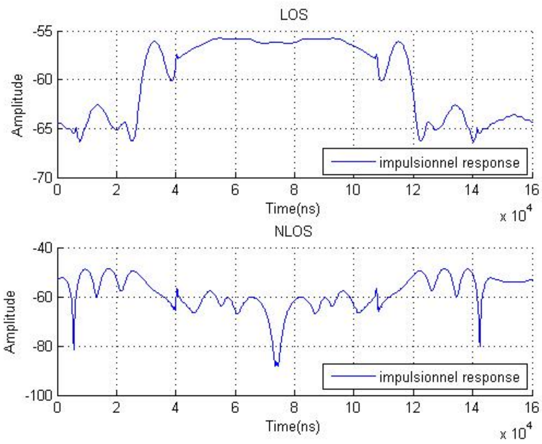


Figure 6: Impulse response for LOS and NLOS phenomena

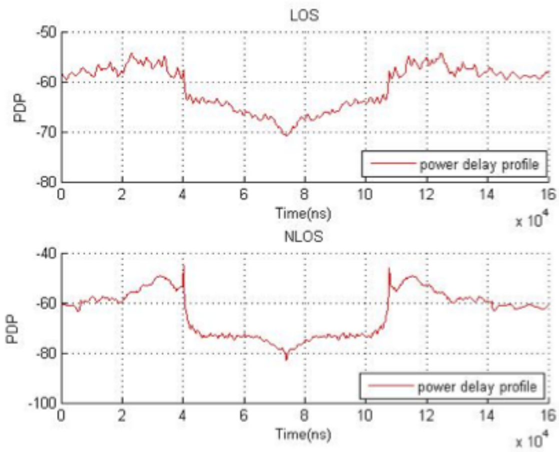


Figure 7: Power delay profile for LOS and NLOS phenomena

References

[1] Stefano Marano, Wesley M. Gifford, Henk Wymeersch, Moe Z. Win, "Nonparametric Obstruction Detection for UWB Localization", Global Telecommunications Conference, GLOBECOM 2009, IEEE, 2009, 1-6.

[2] Stefano Marano, Wesley M. Gifford, Henk Wymeersch, Moe Z. Win, "NLOS Identification and Mitigation for Localization Based on UWB Experimental Data", IEEE Journal on Selected Areas in Communications, vol. 28, Issue 7, September 2010.

[3] Z. Mohammadi, R. Saadane, D. Aboutajdine, "Ultra Wide-Band Channel Characterization Using Generalized Gamma Distributions", Image and Signal Processing, vol.7340, pp.175-182, Springer 2012.

[4] J. Zhang, Z. Sahinoglu, P. Kinney, "UWB Systems for Wireless Sensor Networks", Proceedings of the IEEE "Invited Paper", vol. 97, no.2, Feb. 2009.

[5] C. Cortes, V. Vapnik, "Support Vector Networks", Machine Learning vol. 20, no.3, pp.273-297, 1995. http://dx.doi.org/10.1007/BF00994018

[6] Ming-Chang Lee, Chang To, "Comparison of Support Vector Machine and Back Propagation Neural Network in Evaluating the Enterprise Financial Distress", International Journal of Artificial Intelligence & Applications (IJAIA), vol.1, no.3, July 2010.

[7] A. Karatzoglou, D. Meyer and K. Hornik "Support Vector Machine in R", Journal of Statistical Software, vol.15, no.9, Apr. 2006.

[8] S. Venkatesh, R. M. Buehrer, "Non-Line-of-Sight Identification in Ultra-Wideband Systems Based on Received Signal Statistics", Antennas Propag., vol.1, no.6, pp.1120-1130, 2007. http://dx.doi.org/10.1049/iet-map:20060273

[9] Raffaele Di Bari, Qammer H. Abbasi, Akram Alomainyans, Yang Hao, "An Advanced UWB Channel Model for Body-Centric Wireless Networks", Progress in Electromagnetics Research, vol.136, pp.79-99, 2013. http://dx.doi.org/10.2528/PIER12082919

[10] H. El Ghannudi, L. Clavier, N. Azzaoui, F. Septier, P-A. Rolland, "Alpha-stable Interference Modeling and Cauchy Receiver for an IR-UWB ad hoc Network", IEEE Transactions on Communications, vol.58, issue 6, June 2010.

[11] Z. Mohammadi, R. Saadane, D. Aboutajdine, "Improving the Estimation of the Degrees of Freedom for UWB Channel Using Wavelet-Based Denoising", European Journal of Scientific Research, vol.79, no.4, pp.577-591, 2012.

[12] J. H. McCulloch, "Simple Consistent Estimators of Stable Distribution Parameters", Communications in Statistics - Simulation and Computation, vol.15, issue 4, pp.1109-1136, 1986. http://dx.doi.org/10.1080/03610918608812563

[13] W. Suwansantisuk, M. Z. Win, "Multipath Aided Rapid Acquisition: Optimal Search Strategies," IEEE Transactions on Information Theory, vol.53, no.1, pp.174-193, Jan. 2007. http://dx.doi.org/10.1109/TIT.2006.887509

[14] M. Z. Win, G. Chrisikos, A. F. Molisch, "Wideband Diversity in Multipath Channels with Nonuniform Power Dispersion Profiles", IEEE Transactions on Wireless Communications, vol.5, no.5, pp.1014-1022, May 2006. http://dx.doi.org/10.1109/TWC.2006.1633354

[15] J. Khodjaev, Y. Park, A. S. Malik, "Survey of NLOS Identification and Error Mitigation Problems in UWB-Based Positioning Algorithms for Dense Environments," Annals of Telecommunications, June 2010, vol.65, issue 5-6, pp.301-311, Springer 2009.

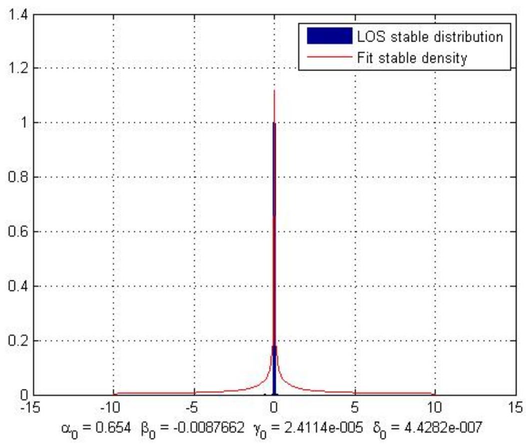
[16] M. Tabaa, C. Diou, M. El Aroussi, B. Chouri, A. Dandache, "LOS and NLOS Identification Based on UWB Stable Distribution", IEEE International Conference on Microelectronics, December 15-18, Beyrouth, Lebanon, 10.1109/ICM.2013.6734961. http://dx.doi.org/10.1109/ICM.2013.6734961

[17] Mohammad Monirujjaman Khan, Qammer H. Abbasi, Akram Alomainy, Yang Hao, "Performance of Ultra wideband Wireless Tags for On-Body Radio Channel Characterisation", International Journal of Antennas and Propagation, vol.2012, article ID 232564, 10 pages.

[18] Min Chen, Sergio Gonzalez, AthanasiosVasilakos, Huasong Cao, Victor C.M.Leung, "Body Area Networks: A survey", Journal of Special Issues on Mobility of Systems Users, Data and Computing, vol.16, no.2, 2010, ISSN 1383-469X.

Table 3: All results of extraction and classification scenarios for different identification methods compared with others results

Others	*Feature*	*Classification*	*Recognition rate*	*Network type*
S.Marano[1]	RMS, kurtosis, mean excess delay	LS-SVM	84%	PAN
S.Marano[2]	RMS, kurtosis, mean excess delay	LS-SVM	91%	PAN
M.Tabaa[16]	Kurtosis, mean, energy and entropy	SVM	86.31%	PAN
M.Tabaa[16]	Stable distribution	SVM	100%	PAN
This work	Data raw	SVM	50%	BAN
This work	RMS, mean, entropy, variance	SVM	40.38%	BAN
This work	Kurtosis, mean, entropy, variance	SVM	50%	BAN
This work	RMS, mean, entropy, Energy	SVM	50%	BAN
This work	RMS, variance, kurtosis, Energy	SVM	53.84%	BAN
This work	**Stable distribution**	**SVM**	**87.5%**	**BAN**



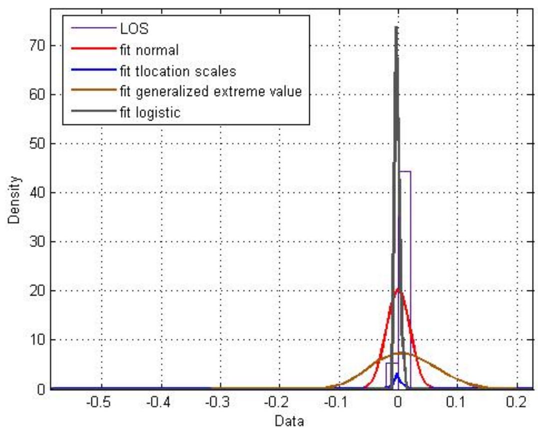
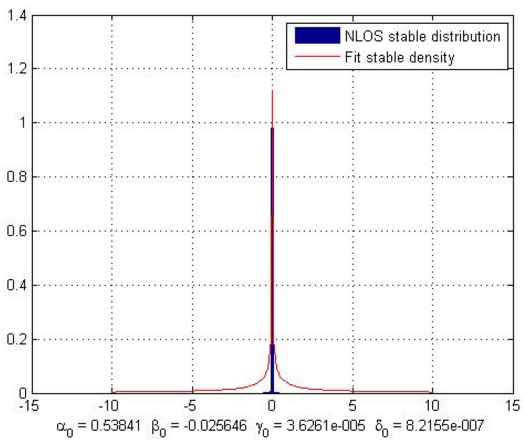


Figure 8: (a) left, LOS data and stable distribution fitting; (b) right, LOS data and other distribution fitting



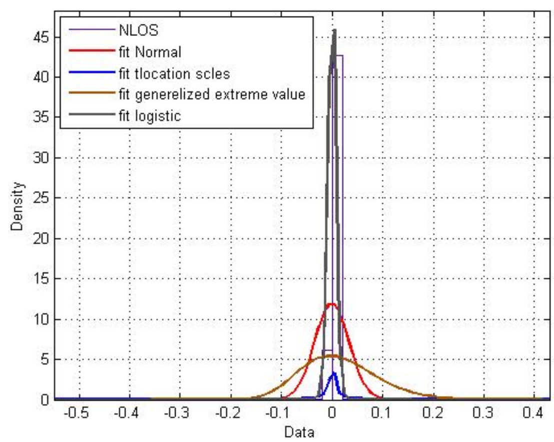


Figure 9: (a) left, NLOS data and stable distribution fitting; (b) right, NLOS data and other distribution fitting