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Fast Fading Influence on the Deep Learning-Based LOS and NLOS Identification in Wireless Body Area Networks

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Abstract

In the article, the fast fading influence on the proposed DL (Deep Learning) approach for LOS (Line-of-Sight) and NLOS (Non-Line-of-Sight) conditions identification in Wireless Body Area Networks is investigated. The research was conducted on the basis of the *off-body* communication measurements using the developed mobile measurement stand, in an indoor environment for both static and dynamic scenarios. The measurements involved five different people with diverse body parameters. The proposed DL approach allows identifying the LOS and NLOS conditions with efficiency over 99% for selected scenarios, which include the fast fading component.

1 Introduction

The development of an electronic devices and their computational power growth has undoubtedly contributed to the evolution of AI (Artificial Intelligence) and ML (Machine Learning), including DL (Deep Learning) aspects. The possibility of patterns self-recognition, solving non-linear problems or dataset prediction made DL methods great opportunities for development not only the computer science, robotics or multimedia issues, but also modern radiocommunication networks.

There are many potential applications of DL methods both in the design of modern fifth generation (5G) radio networks as well as in the improving performance of existing systems. The emergence of the IoT (Internet of Things) concept, in which very important element is the localization of people and objects in different propagation environments, determines current trends in scientific research focused on communication e.g. between cars (V2X), industrial machines (M2X) or people and fixed infrastructure.

A very dynamic development of the UWB (Ultra Wideband) radiolocalization systems, used mainly in indoor environment, has also resulted in an increased research interest e.g. in WBANs (Wireless Body Area Networks), in which the influence of the human body on the radio link cannot be omitted. It is known that variable propagation conditions affect the accuracy of localization in the RTLS (Real Time Locating Systems) [1]. The identification of direct visibility conditions LOS (Line-of-Sight) or lack of them, i.e. NLOS (Non-Line-of-Sight), is an important element of localization systems, which allow increasing the accuracy of localization services in case of obstacles occurring between network nodes, e.g. through the systematic error of radio distance measurements compensation. In WBANs, the occurrence of the NLOS conditions is usually identified with the human body shadowing the direct visibility between the wearable node and the external node located outside of the human body, which corresponds to the *off-body* communication.

In the recent state of the art, many methods have been proposed, which in real time can detect variable propagation conditions based on the received signal strength or the radio CIR (Channel Impulse Response) analysis, e.g. threshold methods, threshold methods with additional filtration or solutions based on ML [2-6].

The goal of the conducted research is to extend the results and proposed DL approach described by the authors in [7], by analyzing the influence of the fast fading component on the classification efficiency. The possible application of the developed DL method in real-time systems requires performing research and analysis, among others, in terms of the selecting learning datasets methods and the classification dependencies that can occur in the different environments for various human movement scenarios. Thus, the measurement campaign includes the static and dynamic scenarios, and their influence and mutual dependency on the obtained LOS and NLOS conditions identification efficiency is analyzed.

2 Proposed Deep Learning Approach

An extensive, more detailed description of the proposed DL approach, the manner of its development and performance analysis is described by the authors in [7]. In this section, only general information about the proposed approach are given.

Developed DFNN (Deep Feedforward Neural Network) allows achieving high efficiency of LOS and NLOS conditions identification in UWB WBANs for *off-body* communication based on the analysis of two CIR parameters, i.e. Total Power (TP) and First Path Power (FPP). Taken approach, where not whole CIR response is analyzed, thus e.g. no convolutional layers are needed due to the limited input parameters, can be successfully used in real-time systems, even on devices with low

computational capabilities with the remaining high classification efficiency.

Provided research has shown that the optimal (considering the computational effort and classification efficiency results) DFNN architecture includes two hidden layers, each consisting of 50 nodes and sigmoidal function as a non-linear activation function should be used. Due to the usage of the LogSoftmax function in the output layer, the learning process was determined and controlled by the NLLL (Negative Log Likelihood Loss) function [8]. Based on its result, the ADAM (Adaptive Moment Estimation) algorithm was used for the DFNN architecture optimization process [9].

3 Measurement scenarios

Most of the currently designed WBANs find their application in environments with a harsh radio wave propagation, where the multipath phenomenon is strongly emphasized. It has a large impact on the efficiency of methods for determining the direct visibility conditions between nodes and the CIR interpretation. It is known [2, 10, 11] that the nature of the radio channel changes is different for static and dynamic scenarios in WBANs and the presence of the fast fading component, related to the human movement, significantly affects the radio channel characteristics as a function of the time.

Due to the previously mentioned issues, it was decided to perform static (S1) and dynamic (S2) measurement scenarios for *off-body* communication in a typical indoor environment and determine the impact of the fast fading on the learning effectiveness of the proposed DL method. Measurements scenarios were conducted in the hall and corridor of the Faculty of Electronics, Telecommunications and Informatics at the Gdansk University of Technology, respectively. It should be noted, that presented measurement scenarios were very similar to the previous ones described in [7], however, they were extended by the static scenarios.

All scenarios were carried out by attaching the stationary reference node (RN) to a tripod at a 1.2 m height, and the mobile node (MN) on the torso (TO) or at the waist (WS) of a moving person. The nodes consisted of the DecaWave DWM1000 radio module, operating at 6489 MHz with a 499.2 MHz bandwidth, where the bitrate was 6.8 Mbps. The selected device is compliant with the IEEE 802.15.4-2011 standard [12]. A detailed description of the developed mobile measurement stand can be found in [2, 11].

The measurements were carried out by three women (W1, W2, W3) and two men (M1, M2) with different body parameters. Each person participated in the selected measurement scenarios to be able to check the effectiveness of the proposed DL method in different conditions, i.e. women in the hall, while men in corridor environment. In addition, only men (M1, M2) were participated in the static scenario, while for dynamic case all people were involved. In the Table 1 selected parameters of people participating in the measurements, Body Mass Indexes (BMIs), heights h_{MM} of wearable device montage placements and realized measurements scenarios, are presented [7].

Table 1. Selected parameters of people participating in the measurements [7].

	Height (m)	**Weight (kg)**	**BMI**	**MN**	h_{MM} **(m)**	**SCN**
W1	1.75	56	18.3	WS	1.10	S2
W2	1.68	56	19.8	WS	1.10	S2
W3	1.76	74	23.9	WS	1.10	S2
M1	1.72	60	20.3	TO	1.35	S1, S2
M2	1.75	93	30.4	TO	1.35	S1, S2
W – Woman, M – Man; BMI – Body Mass Index; WS – Waist; TO – Torso; MN – Montage; SCN – Scenario;						

In static scenario person equipped with mobile node was standing in eight selected places (every 1 m) at distances from 1 m to 8 m from RN, facing toward it in LOS case and in opposite direction in NLOS. In dynamic scenarios person was walking toward RN for LOS and walking away for NLOS conditions. Therefore, the NLOS conditions were caused only by the human body shadowing. Each person performed 20 gaits and selected parameters of the CIR, i.e. TP and FPP, were estimated with a 25 measurements per second.

4 Analysis of the obtained results

During the measurements, about 50,000 pairs of the CIR parameters were obtained for all measurement scenarios (about 40,000 for dynamic scenarios and about 10,000 for static ones). The two analyzed, TP and FPP, parameters create a two-dimensional space where each measurement scenario is expressed by a selected set of points

$$\boldsymbol{p}_i(TP_i, FPP_i), i = 0, 1, \dots N-1 \quad (1)$$

where N is the number of points in considered scenario. In the first place, the scattering of these points was checked for grouped sets of values, i.e. for LOS, NLOS conditions and S1, S2 measurement scenarios. This scattering was calculated by determining the Euclidean metric $d_E(\mathbf{p}, \overline{\mathbf{p}})$ [dB] between the gravity center $\overline{\mathbf{p}}$ of the rectangle described on a given set of points $\mathbf{p}=\{\boldsymbol{p}_0, \boldsymbol{p}_1, \dots, \boldsymbol{p}_{N-1}\}$.

In the Figure 1 the obtained empirical CDF (Cumulative Distribution Function) Euclidean metrics of UWB CIR parameters for static S1 and dynamic S2 scenarios are presented. Due to the fact that only men performed both measurement scenarios, only their results were straightly compared.

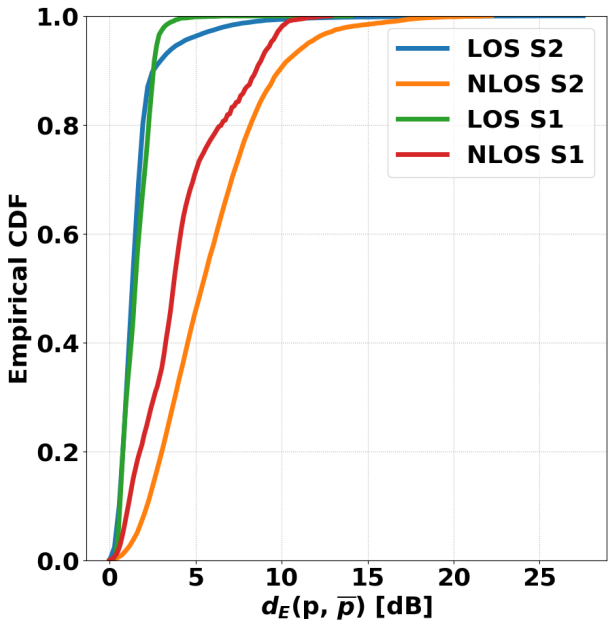

Figure 1. Empirical CDF of UWB CIR parameters in relation to set points mean values for S1 and S2 scenarios.

As expected, the analysis of the obtained results clearly shows a greater scatter of the received FPP and TP in NLOS conditions comparing to the LOS conditions, as well as for the dynamic scenarios relative to the static scenarios in NLOS conditions. Regardless of the analyzed scenario, in LOS conditions similar CDF results were obtained, however, the impact of human movement on the obtained CIR parameters values is visible. For 95% of the obtained results, the $d_E(\mathbf{p},\overline{\mathbf{p}})$ metric does not exceed 2.8 dB for static S1 scenario and 4.1 dB for the dynamic S2 scenario. The average values of TP and FPP parameters were -80.5 dBm and -83.4 dBm for the S1 scenario and -80.2 dBm and -83.4 dBm for the S2 scenario, respectively.

In the case of the NLOS conditions, a significant impact of both fast fading component caused by human motion and the body shadowing direct component by the human body is visible. For 95% of the obtained results the $d_E(\mathbf{p},\overline{\mathbf{p}})$ metric does not exceed 9.4 dB for the S1 scenario and 11.6 dB for the S2 scenario. The mean values of TP and FPP parameters were significantly lower in comparison to LOS conditions and were -86.3 dBm and -102.4 dBm respectively for the S1 scenario and -90.3 dBm and -103.3 dBm for the S2 scenario.

Comparing the standard deviations of the obtained $d_E(\mathbf{p},\overline{\mathbf{p}})$ metrics, it can be noticed that they are smaller for static scenarios – 0.8 dB for LOS and 2.6 dB for NLOS conditions – relative to the corresponding values for dynamic scenarios, i.e. 1.6 dB for LOS conditions and 3.2 dB for NLOS conditions.

Based on the analysis under the research presented by the authors in [7], it indicates that the selection of a dataset with a smaller dispersion of the CIR parameters as a learning dataset may cause a decrease in the efficiency of identifying LOS and NLOS conditions in WBANs using the proposed DL method. Thus, it was decided to conduct research of the efficiency η of LOS and NLOS conditions identification of the proposed DFNN network for learning datasets containing both dynamic and static scenarios. Due to the fact that only men performed both measurement scenarios, only their results were analyzed as the learning datasets. It is worth noting that the learning datasets were fully disjoint, i.e. the test datasets were the data results for other measurement scenarios than the learning datasets, e.g. the learning dataset was the results for the M2 person for the S2 scenario, while the test dataset were the results for the M1, M2 for the S1 scenario. Obtained data for women W1, W2, W3 always appeared in the test datasets and as previously mentioned they were conducted in different indoor environment (hall) than for men (corridor). During the learning process 64 element batches were used, and the results presented in this article were obtained after 100 full iterations of the learning dataset. In the Table 2 the obtained effectiveness results of the proposed DL method for one-person and two-person learning datasets were presented.

Table 2. The effectiveness η results of the proposed DL method.

Scenario for learning dataset	Learning dataset	Effectiveness η [%]
S1	M1	92.2
	M2	89.5
	M1, M2	90.1
S2	M1	99.6
	M2	92.7
	M1, M2	99.3

The presented results clearly show that better classification efficiency results were obtained if the learning datasets contained data from dynamic scenarios, which include the fast fading component influencing the CIR, thus are more scattered. Regardless of the learning dataset, data from static scenarios did not allow obtaining an efficiency classification of LOS and NLOS conditions above 93%. This is due to the different nature of the changes, including smaller scattering of CIR parameters relative to the dynamic scenarios, which (in addition to the path loss mean value changes and the occurrence of slow fading) also contain the fast fading component [2, 10]. In this case, DFNN is not able to recognize changing patterns appearing during human movement and misclassification problem occurs.

In the cases where the learning data were a single-person dataset for M1, a two-person M1, M2 and dynamic S2 scenarios, the classification efficiency was over 99%, which is higher result than previously presented in the literature [4]. Obtained results clearly proves the usefulness of the proposed DL approach even if validating datasets included measurements for various people in different indoor environment (hall). The relatively low

results for the M2 person are associated with his higher BMI (that comes from higher fat and muscle tissues) relative to the other people participating in the measurement campaign. This means that during DL hyperparameters estimation the learning data should be based on the measurements for a person with the lowest BMI possible, so that the network would be sensitive to changes in conditions of the human body's shadowing the direct visibility of WBAN nodes.

Undoubtedly, in a real-time radiolocalization systems, both static and dynamic scenarios, where people move in the area covered by the localization services, should be taken into account. Based on the obtained results, it can be concluded that fast fading phenomenon that affects the estimated UWB CIR have a significant impact on the effectiveness of the proposed DL method. In the case when learning datasets consist of the data for static scenarios only, the obtained efficiency of identifying LOS and NLOS conditions may be even 10% lower than for datasets with fast fading component included.

5 Conclusions

In the article the impact of the fast fading component on the DL efficiency used to identify LOS or NLOS conditions in UWB WBANs is presented. The research was carried out on the basis of measurements using the developed mobile measurement stand, in a real indoor environment, i.e. hall and corridor, for five people with different body parameters, both for static and dynamic scenarios. The DFNN architecture enabling high efficiency of the LOS and NLOS classification conditions to other methods described in the current state of the art was presented. The influence of the fast fading occurrence, associated with the multipath propagation phenomenon, on the effectiveness of direct visibility conditions detection between WBAN nodes was also analyzed.

The results of the performed analysis indicated that dynamic scenarios – due to the presence of an additional fast fading component – are characterized by a greater values dispersion relative to static scenarios, which have significant impact on the method of selecting learning data for the developed DNN. If the reference datasets include the data influenced by the fast fading phenomenon, it is possible to obtain an identification results up to 99.6%, if learning datasets are derived from people with a relatively low BMI (i.e. low fat and muscle tissues), regardless of the operation scenario.

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