

Identification and Modeling of Radio Wave Propagation Channel in Industrial Environments

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ABSTRACT: Wireless technology in industrial environments is considered due to potential for saving in cable cost, high flexibility in factories, tracing the products and increasing optimization of process. Optimized use of wireless technology advantages is not possible without exact recognition of channel. Thus, this paper presents an exact model to describe ultra wide band channels (UWB) based on channel impulse response based on Saleh-Valenzuela industrial environments by a new cluster identification algorithm. In the model, multi-path interference, fading and frequency and time dispersion effects were considered to increase accuracy and practicality of model. Two different approaches are considered for validation of proposed algorithm. In the first approach, propagation channel IEEE802.15.4a is simulated in Matlab environment and is identified by relevant algorithm. In the second approach, by real data of measure impulse response of channel, algorithm efficiency is evaluated. Both mentioned approaches showed strong performance of proposed algorithm in estimation and identification of channel in industrial environment.

KEYWORDS: Channel impulse responses, Clustering channel impulse responses, Ultra wide band wireless technology, Saleh-Valenzuela model

I. INTRODUCTION

In the past decades, based on successful use of wireless technologies in administrative and domestic environments, wireless communication has received much attention in industrial environments. In 2008, investment Development Company in the report stated that demand for production of wireless products for control, supervision and industrial applications observed 19% growth for the next five years [1]. The great advantages of wireless communication compared to wire communication in industrial environments was the main factor of demand growth in this field. The low cost of installation and setup of wireless can be a good advantage to absorb users. In wireless communication, installation, maintenance of numerous cables is reduced. Industrial environments are harsh and elimination of cables leads to high flexibility to make changes in factory [2-4]. Despite many advantages in wireless communication, lack of a good model for wireless propagation in domestic environments, this technology is not developed. Performance limitations of each wireless system are determination by the relevant environment. Thus, we need a propagation model with great features of relevant environment.

In the past 20 years, only a few researchers presented the results of their measurement as statistical models to propagate wireless waves in domestic industrial environments. In Reference [5-9], Rappaport, and C. McGillem published some papers explaining the details of wireless propagation in industrial environments. In these papers, UHF measurement results (1300 MHz) of 5 factories from India are collected including narrow band and wideband. The measurements are

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performed by a signal generator and digital oscilloscope in UHF frequencies of about 1300 MHz. The measured data are used for extraction of various narrow channels and power delay features to determine multi-path channel parameters. Finally, four measurement types of ultra wide band (UWB) channels were reported. In Reference [10, 11], the first indoor industrial measurements of UWB was published based on 10 measurement sites in a small landfill hall in Sweden. A statistical model based on measurement of industrial UWB channel is presented in Reference [12]. The author believes that due to the limitation of set of data, the model is not a general one. In Reference [13], the development of a Locally Coherent Ultra-Wideband for industrial environments. In Reference [14], the measurement results are presented in a laboratory as a small model of an industrial environment and path deviation and time dispersion parameters are computed. The initial results of above researches are used to model IEEE 802.15.4a channel. Indeed, the limited measurements mean that the results are preliminary and it is difficult to achieve an independent for location general result.

The tendency for Multipath Components (MPC) in impulse response with ultra wide band to form cluster was reported 20 years ago [15]. By increase of bandwidth, measurement of channel frequency response, time separation power of channel impulse response are increased. For ultra wide bands, using multi-path components for time classification is observed with exponential decay feature.

In Reference [16], a clustering algorithm is proposed for measured channel impulse response. The authors believe that this algorithm is unsuccessful in detection of the clusters interfering (as occurred in dense environments). Recently in Reference [17, 18], improved methods are proposed regarding local maximum search and clusters delay. The selected cluster is not the best fit for measurement data.

Various researches have been conducted to model the channel of ultra wide band systems. Most of the studies are based on path loss model and time discrete multi-path impulse response model. In UWB channel propagation, frequency dependence is a barrier to use similar models of narrow band channels. The models in which frequency effect is ignored, cannot be used in wide band systems. The best and complete model as defined based on time discrete multi-path impulse response is SV model. This model showed that multi-path components entered as in cluster, these clusters were composed of some rays. This model was accepted by IEEE802.15.4a committee as a standard to describe ultra wide band systems [19-21].

SV is a model to describe channel and it requires four parameters of $\lambda, \Lambda, \gamma, \Gamma$. These values are reported based on the comparison with the measured data under different conditions as residential room, administrative room, outdoor, etc. standardization and with Tables. To work with the model, we should refer to these Tables. Dependence on these Tables can be problematic. For example, putting an object as metal sheet on a corner as its dimensions are considerable compared to the dimensions of room and can reduce the accuracy of parameters of Table or using a model for industrial places as measurement is done for it and this makes the weakness of model as specific [22, 24].

Thus, to eliminate the above problem, to describe UWB channel impulse response consistent with SV model in new environments, a cluster identification algorithm as compatible, rapid and scientific compared to current commercial methods is used. Also, compared to the previous works, the proposed method has the following advantages:

- Implementation of MPC search algorithm in this approach reduces small scale fading that is inherent in channel measurement.
- This algorithm reduces the number of searching of clusters considerably and algorithm is much flexible.
- The iterative nature of the algorithm and the manner in which the cluster selection rules are layered makes it possible to be used as independent tool for analysts.
- Mostly, format of parameters of model is described as IEEE802.15.4a and can be used directly in simulations.

The study is organized as followings:

Second section is regarding a description for UWB channel impulse response in new environments by a cluster identification algorithm by computer for measured channel impulse response based on SV model.

Third section deals with a logical propagation model in which multi-path interferences, fading and frequency and time dispersion. This model is implemented and evaluated. By real measured data of channel impulse response, the proposed algorithm is validated.

Finally, fourth section is about conclusion and brief results of study.

II. ALGORITHM OF UWB CHANNEL IDENTIFICATION IN INDUSTRIAL ENVIRONMENTS

Channel is called the propagation environment in which signal passes from transmitter to receiver. The highly exactly the environment, the better the design of communication systems and the better the performance. UWB propagation environment systems are industrial environment and sending signal in this channel achieves receiver from various paths like other wireless channels and multi-path phenomenon is created. If a single pulse enters the channel with feeding, a train of pulses exits and each one has multi-path component as shown in Figure 1. Thus, signals reach receiver with different ranges, phases and delays.

Thus, SV model shows that multi-path components enter in clusters and are used to model UWB channel [25]. The arrival of these components is defined by statistical models namely Poisson. The time interval between the arrival time of multi-path components is described based on exponential statistical distribution. The channel in this model is described with four parameters of cluster decay (Γ), ray decay factor (γ), cluster arrival rate (Λ) and ray arrival rate (λ).

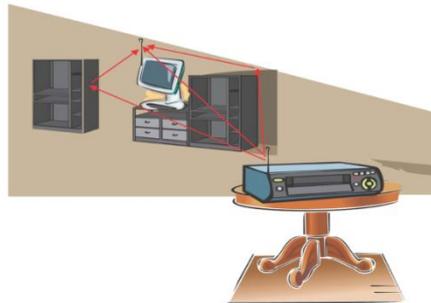


Figure 1- A simple model of UWB channel multi-path

Ray arrival rate is indeed the arrival rate of paths inside each cluster. Cluster arrival rate is smaller than ray arrival rate. The arrival of ray of each cluster is described based on Poisson. A curve of UWB channel is shown in Figure 2. Channel impulse response is written as follows:

$$h(t) = X \sum_{l=0}^L \sum_{k=0}^K \alpha_{k,l} \delta(t - T_l - \tau_{k,l}) \tag{1}$$

Where, $\alpha_{k,l}$ is multi-path gain of kth ray of lth cluster. T_l is the arrival of the first path of lth cluster. L is total number of clusters in CIR and K_l is total number of MPCs in lth cluster. $\tau_{k,l}$ is arrival delay of kth path within lth cluster. X indicates shadowing effect.

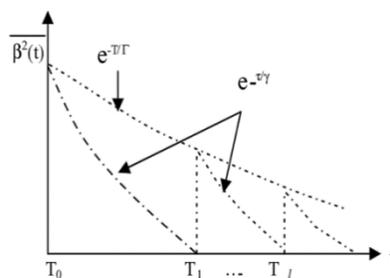


Figure 2- S-V chart [25]

The first step for channel analysis is the evaluation of propagation loss. Path loss for channel model is as narrow path loss model. Path loss is used for statistical analysis of logarithmic distance and it is given by?

$$PL_{dB}(d) = PL_0 + 10n \log_{10} \left(\frac{d}{d_0} \right) + 20 \log f + X_{\sigma} \tag{2}$$

Where, PL_0 is the average path loss in reference distance and d distance between receiver and transmitter, n is path loss component of topology, f is frequency, X_σ is a random variable for shadow modeling (big scale fading). Random variable of shadow is considered as Gaussian distribution with zero mean and standard deviation σ . Also, d_0 is favorite distance as one meter.

for UWB communication, frequency dependence of path loss is shown in Equation (3). In this equation, it is assumed that these two are independent and as the product of separate terms:

$$PL_{dB}(d, f) = PL_{dB}(d) + PL_{dB}(f) \quad (3)$$

According to [26], frequency dependence of path loss for systems with wide band is expressed by simple power law as Equation (4):

$$PL(f) \propto f^{-2K} \quad (4)$$

Where, K is uniform descending slope as frequency response of channel.

Small-scale fading describes amplitude of a signal as changing with relatively small scales in spatial situation. To model small-scale fading in industrial environments, Nakagami distribution is used for high flexibility. Nakagami distribution is shown in Equation (5):

$$f_x(x) = \frac{2}{\Gamma(m)} \left(\frac{m}{\Omega}\right)^m x^{2m-1} \exp\left(-\frac{m}{\Omega} x^2\right) \quad (5)$$

Where, $m \geq 0.5$ is Nakagami factor, $\Gamma(m)$ Gamma function and Ω is the mean squared value of amplitude (distribution parameter).

Squared power delay profile of impulse response of a channel is computed as Equation (6).

$$PDP(\tau) = |h(\tau)|^2 = \sum_{k=0}^{N-1} |a_k|^2 \delta(\tau - \tau_k) \quad (6)$$

III. I CLUSTER IDENTIFICATION METHOD

Our approach to cluster identification is based on identification of discontinuities in the shape of the CIR. The general form of CIR as not including MPC distortions is given by Equation (7):

$$h(t) = \sum_{l=0}^L \sum_{k=0}^{K_l} a_{k,l} \exp(j\phi_{k,l}) \delta(t - T_l - \tau_{k,l}) \quad (7)$$

Where MPCs are modeled as Dirac delta functions ($\delta(\cdot)$) and $a_{k,l}$ & $\phi_{k,l}$ are amplitude and phase of k th MPC in l th cluster [27].

If small-scale fading is avoided, PDP share is described as the product of two exponential functions.

$$E\left\{|a_{k,l}|^2\right\} \propto \exp(-T_l/\Gamma) \exp(-\tau_{k,l}/\gamma) \quad (8)$$

Where Γ and γ are cluster and intracluster decay constants as depicted in Figure 3. The arrival of clusters and MPCs follow Poisson distribution with arrival rates Λ and λ .

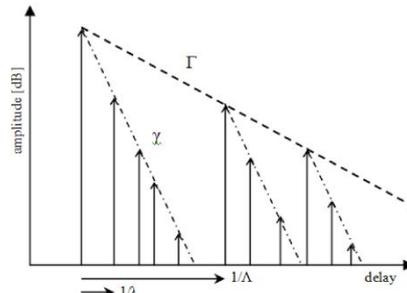


Figure 3- Model of the sparse multi-cluster channel impulse response (S-V model)

II-II DESCRIPTION OF THE CLUSTER IDENTIFICATION ALGORITHM

The goal of our cluster identification algorithm is to determine the combination of exponentially decaying clusters that fit the most significant MPCs in the power delay profile. A chart of our cluster identification algorithm is shown in Figure 4 including the three main steps as:

1) Local smoothing in time domain: The first step is to avoid small scale fading through local smoothing in the time domain. The PDF will be sampled at an interval, that is inversely proportional to the bandwidth of the measured signal. PDP smoothing is done in a two-stage process: At first to smooth rapid changes in CIR of small-scale fading, a defined averaging filter is applied as Equation 9:

$$PDP_s[m] = \frac{1}{M} \sum_{i=-\frac{N}{2}}^{\frac{N}{2}} PDP[m+i] \quad (9)$$

Where N is the user-defined smoothing interval and M is nominally equal N+1. Then mean PDP is one-tenth by k factor:

$$PDP_s[m] = PDP_s[km] \quad (10)$$

In which making time series as one-tenth reduces the chance of having remote points in analysis of linear regression. Local smoothing is a necessary step and we should consider that descending clusters are eliminated in this stage.

2) Initial search for clusters

If the interval between successive MPCs exceeds a user-defined threshold, it is a gap between distinct clusters. The number of such gaps plus 1 gives the initial number of cluster L_{init} . The user can select a good value for threshold by PDP evaluation.

3-Iterative search for clusters

The proposed cluster identification algorithm is based on expression of the MPCs on a semi-logarithmic scale so that exponential intracluster decay profiles will be displaced as straight lines with given slopes. We can use linear regression methods to determine the best fit. The search begins with the assumption that the initial number of clusters is $\hat{L} = L_{init}$ as determined by the method. The algorithm estimates goodness of fit by calculation the RMSE:

$$RMSE = \sqrt{\frac{1}{M} \sum_{m=1}^M |PDP_s[m] - g[m]|^2} \quad (11)$$

Where M is the total number of smoothed MPCs identified and $g[m]$ is the same as $g[\tau]$ sampled at intervals Nt_s . If the resulting RMSE of any cluster exceeds a specified threshold, it is assumed that an identified cluster is causing a discontinuity in PDP. In response, algorithm increments the number of clusters by one unit, tries all possible combinations of \hat{L} straight lines that one can fit to contiguous groups of MPCs to form \hat{L} clusters, then selects the combination that has the best fit, the lowest RMSE. If the best fit satisfies the error threshold criterion, the process ends and the number of clusters in the CIR is reported as \hat{L} , otherwise the number of clusters should be incremented and the process is repeated.

A comprehensive search of all possible cluster structure ensures that the best possible solution is found finally. However, the number of possible combinations increases very rapidly as the number of clusters increases and soon becomes computationally increased. During trials upon both simulated and measured CIRs, incrementing the number of clusters to represent CIR almost involve subdividing an existing cluster. IN statistics, this is called recursive portioning [28].

Here, the decision to subdivide an existing cluster is also based on whether RMSE can be reduced or not. Using this rule in our search and eliminating all other possibilities reduces the number of trials that we conduct from $O(M^{L-1})$ to $O(M)$

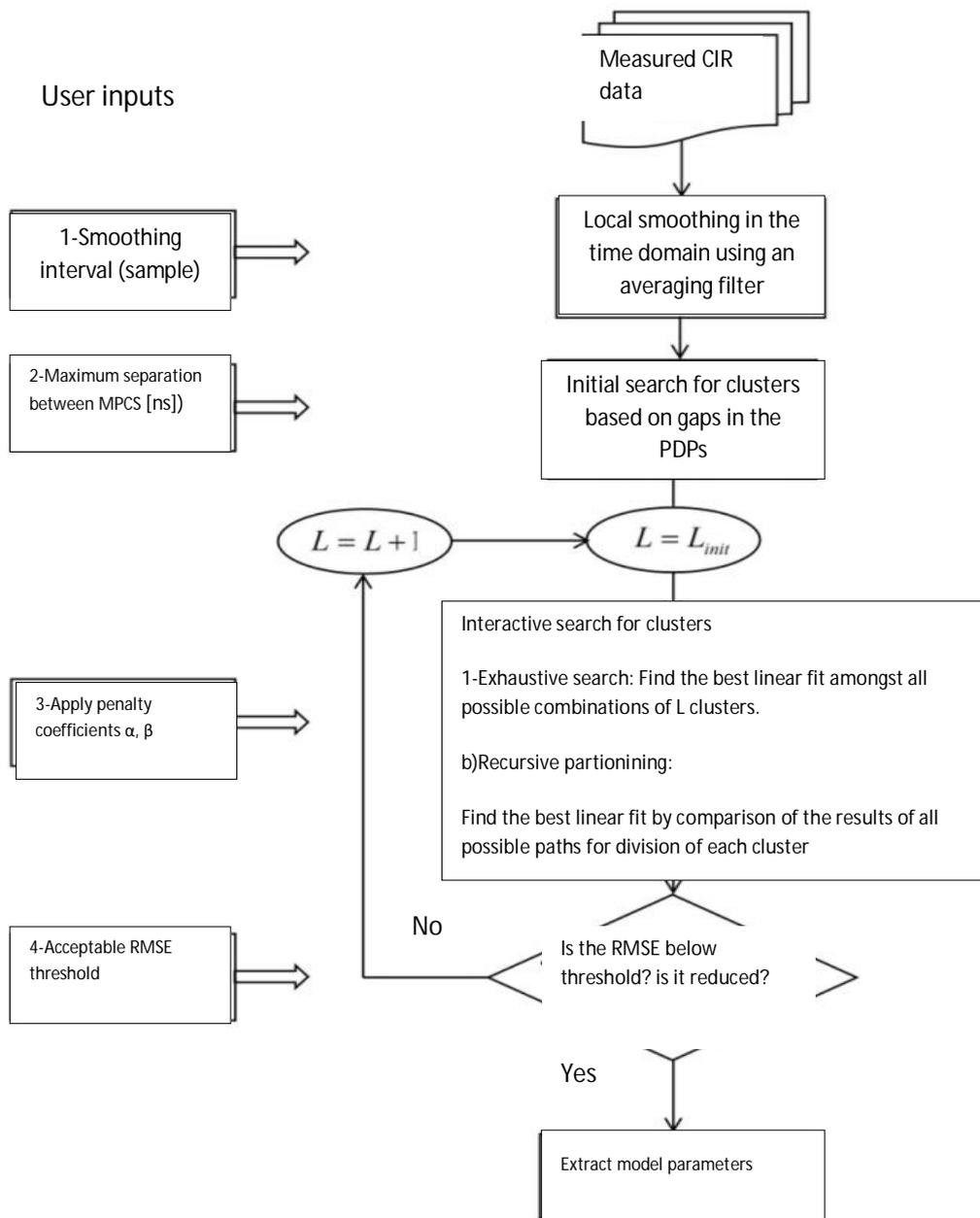


Figure 4- Flowchart of rules based on cluster identification algorithm

II-III THE ROLE OF ANALYSERIN PROPOSEDIDENTIFICATION ALGORITHM

To develop an independent algorithm, there are some problems due to noise and small-scale fading in measurement of UWB channel. To overcome these problems, we can use the previous algorithm by considering lack of fit penalty by the analyzer. Penalty makes algorithm flexible and helps to keep the goals of analyzer. In addition of simple regulation of time of cluster start, it is required that analyzer defines a series of additional rules of weight to improve modified SV model. When additional rules are violated, lack of -fit criterion is used. The increase of this criterion reduces the cluster division in the zones the rules are violated.

To ensure that the fast variations of PDP are not considered as clusters, stopping condition can be more robust by adopting the generalized cross validation criterion as shown in Equation (12) [29]:

$$GCV = \frac{RMSE}{\left[1 - \frac{\alpha B}{M}\right]} \quad (12)$$

Here, B is the number of parameters that we try to estimate; M is the number of smoothed MPCs and α is the user-defined penalty coefficient. Based on GCV criterion, the algorithm will stop if the value of GCV is below the user-defined threshold, or the penalty prevents the value of GCV being reduced.

To be ensuring of the correct operation of the cluster identification algorithm, three additional rules are used. These three additional rules are jointly used during recursive partitioning by applying a multiplicative penalty coefficient, β_i as i denotes the additional rule. The decision to split to an existing cluster is based on LOF criterion as shown in Equation 13:

$$LOF = \beta_1 \beta_2 \beta_3 GCV = \beta_1 \beta_2 \beta_3 \frac{RMSE}{\left[1 - \frac{\alpha B}{M}\right]} \quad (13)$$

Minimum length penalty β_1 : The cluster length should be more than minimum number of MPCs, otherwise β_1 penalty is applied.

Power level increase penalty β_2 : In modified SV model, extra-cluster decay rate is higher than intra-cluster decay rate. Power level at the beginning of a given cluster should be higher than interpolated residual power level of previous clusters. If in separation point of algorithm, interpolated power of the beginning of cluster is less than defined power by user, β_2 penalty is applied.

Positive slope penalty β_3 : In SV model, it is assumed that clusters are decaying and slope of MPCs regression lines should be negative. At some times, due to noise or slow start of dense cluster, algorithm can have a positive slope cluster. We should apply positive slope penalty β_3 at these times.

II-VALIDATION OF CLUSTERIDENTIFICATION ALGORITHM

In this section, at first algorithm validation results are presented by generated CIRs by simulation code 802.15.4a in Matlab and CIR measured data from industrial environments, then by proposed algorithm, the mentioned channel model parameters are obtained.

II-I VALIDATION OF CLUSTERIDENTIFICATION ALGORITHM BY SIMULATERCHANNEL IMPULSE RESPONSE

In this section, algorithm performance is evaluated by generated CIRs by IEEE802.15.4a simulation. Totally, the generated CIRs are equal to 60. TO achieve a fair indication of various environments showing different levels of clustering, two models of standard channel of line of sight (LOS) and non-line of sight (NLOS)-industrial environments (CM1,2) are considered. Each CIR is turned into PDP based on the method in Reference [30].

For penalty, to eliminate small but strong clusters of LOS component $\beta_1 = 1.5(+/- 0.25)$ is used. Sometimes, to eliminate false clusters of small noise fluctuations $\beta_2 = 1.2(+/- 0.1)$ is used. Also, $\beta_3 = 2$ is used when a cluster with positive slope is identified.

After converting each CIR to PDP, number of clusters, amplitude of range of each cluster and arrival time of each identification algorithm for each PDP is estimated. Then, the amplitude and arrival time of clusters and their rays are normalized to estimate Γ, Λ . Also, the process is repeated for MPCs to estimate γ, λ . The details of extraction of mentioned parameters are shown in Reference [30]. The real and estimated values of SV model parameters are shown in Table 1. Even if CIRs are affected mostly by small-scale and random fading of cluster arrival time of Poisson, the estimated parameters are used close to the parameters in simulation.

Table 1- Comparison of estimated and real parameters for industrial environment

Industrial		Algorithm parameters	
CM2	CM1		
NLOS	LOS		
1	4.75	Real	L_{mean}
1	4.4	Estimated	
N/A	13.5	Real	Γ
N/A	13.2	Estimated	
N/A	0.071	Real	
N/A	0.06	Estimated	
85.36	0.65	Real	γ
95.32	0.54	Estimated	

In Figure 5, CIR of UWB model for CM2 is depicted. Also, Figure 6 shows PDP of channel impulse response by 9 rays. By comparison of real PDP changes in Figure 5 and estimated PDP changes in Figure 6, we can find that proposed clustering algorithm presented good performance.

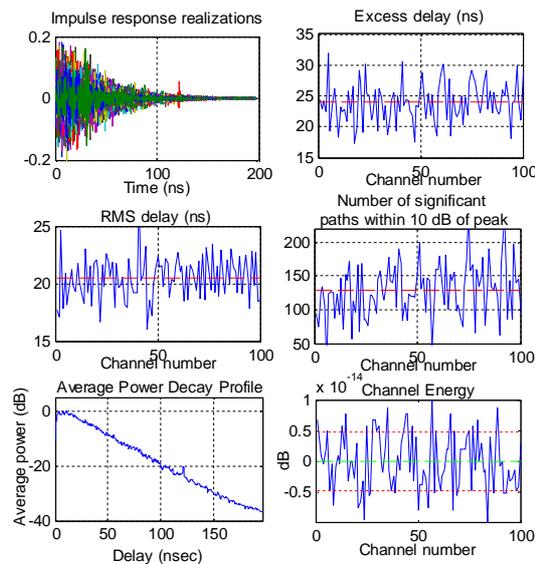


Figure 5- CIR and features of UWB model for CM2

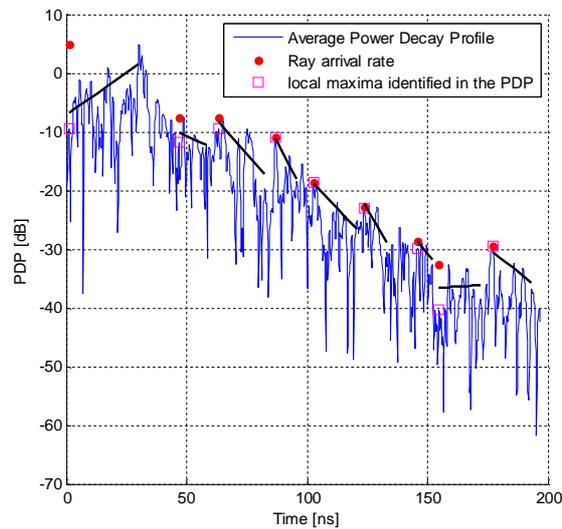


Figure 6- Identification of CM2 channel impulse response by 9 ray clusters

III. VALIDATION OF CLUSTER IDENTIFICATION ALGORITHM

III-II VALIDATION OF CLUSTER IDENTIFICATION ALGORITHM BY SIMULATED CHANNEL IMPULSE RESPONSE

As it was said, empirical data are used as comparison based. This measure is done in 1995 by MovayVien in California lab. The measured data and the method are free [31]. A block diagram of test conditions is shown in Figure 7.

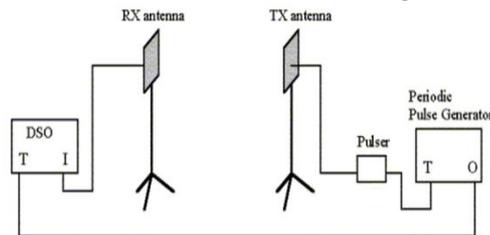


Figure 7- Block of general diagram of measurement model [31]

Image 8 shows above view of lab. LOS of tests is performed in a laboratory with dimensions 2.7m×13.5m×8.5m (length× width× height). The transmitter is at the distance 165cm from the floor and 105cm from ceiling in the proximity of southern wall of lab. LOS receiver as W is located around the eastern angle of building with the distance 9m from transmitter. The distance of receiver antenna from ceiling is 150cm and from floor as 120cm.

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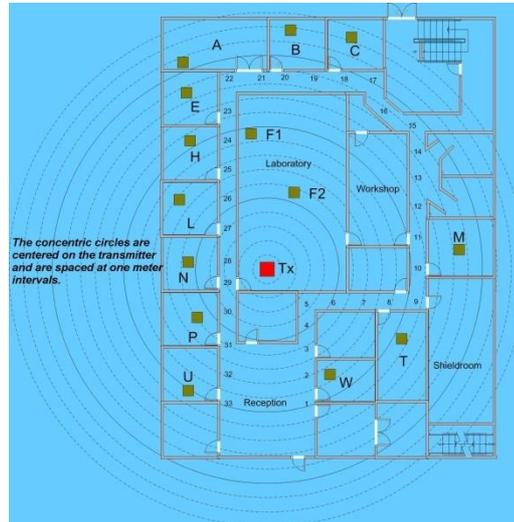


Figure 8-Above view of building for LOS state [31]

In receiver location, a square environment as 90cm is considered. This square as shown in Figure 4-6 is partitioned to some areas. The distance of each point from another one is 15cm. Each point is denoted by (I,j), I denotes row and j column. Then, for each of the points, measurement is done and the response with time length 300ns is registered [20]. There are 49 registered measured response in receiver.

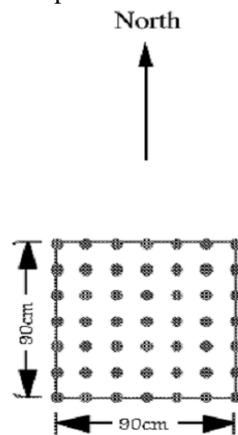


Figure 9-Matrix of measurement place in receiver location [61]

Among 49 measured impulse responses, 14 first clusters are shown in Figure 10. For validation, proposed clustering algorithm is used. As shown in Figure 11, proposed algorithm can estimate PDP of channel impulse response by 18 clusters as well.

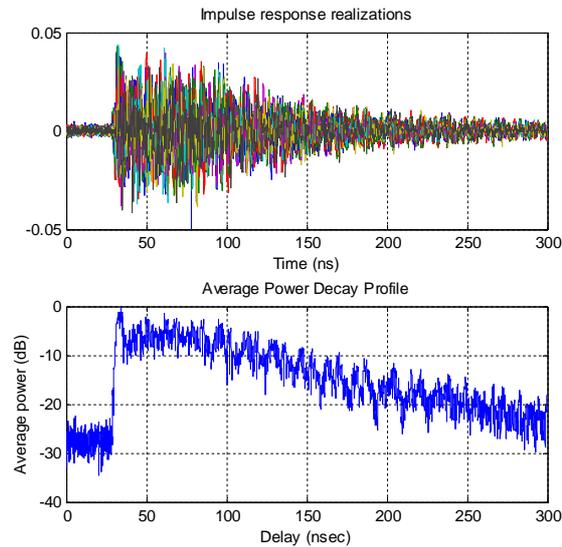


Figure 10- Impulse response and PDP of measured channel

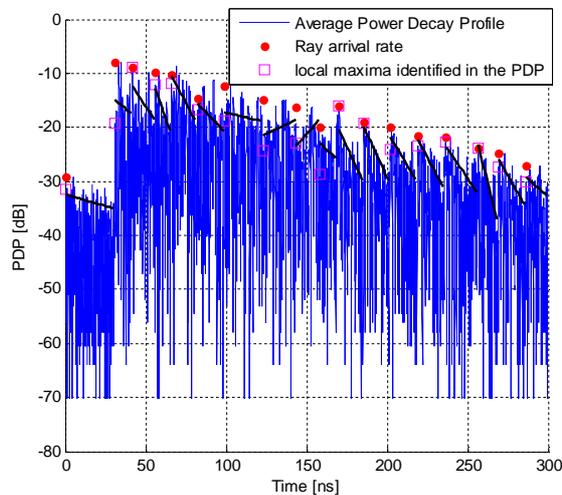


Figure 11: Identification of measured channel impulse response by 18 ray clusters

IV. CONCLUSION

In this paper to evaluate the validity of proposed clustering algorithms, two approaches are proposed: 1) Using simulated channel impulse responses IEEE802.15.14a, 2) Using measured impulse responses of channel. Although some limitations as the number of clusters of each CIR or clusters density in CIR were effective on performance of proposed clustering algorithms, the results of implementation were optimistic and showed good efficiency of algorithm.

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