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Non-line-of-sight outdoor channel identifcation for wireless sensor networks based on impluse radio ultra wide band

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ABSTRACT

Wireless sensor networks (WSN) have become increasingly popular in a variety of fields in recent years. This is due to the development of their capabilities, which include remote environmental monitoring, process automation, telemedicine, and many other domains. Besides, among the widely used modern WSN radio technologies, we find impluse radio ultra wide band (IR-UWB) that is recognized by their advantages regarding low power consumption, low cost, low complexity and high resistance to multipath fading in outdoor wireless networks. Energy consumption minimization, packet delivery ratio improvement and latency minimization are the main objectives in this work. The chosen performance metrics (energy consumption, packet delivery ratio and latency) are justified by the direct impact of these three parameters on the network's efficiency. Accordingly, we proposed and introduced an outdoor non-line-of-sight (NLOS) packet delivery ratio using broadband radio access network (BRAN) channel to improve WSN's based on IR-UWB performance in terms of energy consumption, packets delivery ratio (PDR) and latency.

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1. INTRODUCTION

In digital communications, minimizing the communication channel influence is one of the most important challenges. A standard way to address this problem is to first estimate the channel impulse response parameter, and then equalize it with an equalizer. This approach strongly relies on the quality of the communication channel's estimation also known as identification. This procedure has been widely investigated by the use of higher order cumulants (HOCs) [1], without increasing the data stream transmission rate, or additive noise color. HOCs are an active subject with great income in many applications such as systems theory, digital signal recognition [2], real signals classification [3], and space-time block code identification [4]. However, HOCs are constrained by their non-convex optimization characteristics and the danger of getting locked in local minima. In recent years, a technique founded on kernel adaptive filtering [5] was used in a great number of applications in the field of telecommunications. One of the most important advantages of this technique is exploited to recast several classic linear methods in high dimensional reproducing kernel Hilbert space (RKHS) [6], [7], and reformulated as an inner product to achieve more robust nonlinear extensions, which has established itself as an important tool for machine learning. Until today, numerous adaptive kernel filtering algorithms have been proposed in the research literature. These include kernel affine projection algorithms (KAPA) [8], kernel principal component analysis (KPCA) [9], kernel least mean squares (KLMS) [10], and kernel recursive least square (KRLS) [11]. To enhance the robustness of adaptive kernel filtering algorithms, some of their subtypes have also been offered for channel identification [12]-[14]. The desire to improve the practical implementation of the presented algorithms has led us to consider the problem of wireless sensor network, using broadband radio access network channels (BRAN). The above mentioned channel models have been approved by the European Telecommunications Standards Institute (ETSI) in the BRAN project [15], [16], which was intended to provide a physical network layer definition and to monitor the HIPERLAN/2 broadband wireless local access network systems.

The wireless communication network [17], [18] technologies have undergone great mutations since their invention both because of scientists and industrialists. The new potential technique is the impulse radio ultra wide band (IR-UWB) [18], [19], which is currently a subject of significant research and development. In general, this technique can do without carriers, and therefore make it possible to remove unnecessary complexity and power consumption of the transmission-reception system. In this paper, we will focus on the IR-UWB technique and show its suitability over practical, i.e., measurable frequency-selective fading BRAN channels (in particular, BRAN C and BRAN E, which are intended for transmission in the outdoor scenario) by using different algorithms based on kernel methods.

Our research methodology is as follows: Firstly, we introduce the channel identification issue in digital ultra wide band receivers by using three algorithms based on kernel hilbert spaces (RKHS) such as the KLMS, kernel normalized LMS (KNLMS) and KRLS. Secondly, while targeting to estimate the outdoor BRAN radio channels parameters, we involve the presented algorithms. Thirdly, we illustrate and confirm the positive impact of using the outdoor non-line-of-sight (NLOS) BRAN E channel with KRLS algorithm compared to the outdoor BRAN C channel with KRLS and CM6 outdoor NLOS channel for the IR-UWB enabled wireless sensor networks (WSNs) in terms of power consumption, packets delivery ratio (PDR), as well as network latency.

The structure of the paper is the following: Section 2 introduces the WSN. Then, section 3 illustrates the essential idea of Kernel-based radio channel identification with a description of kernel adaptation methods, including KLMS, KNLMS and KRLS algorithms. The results and discussion are presented in section 4. Finally, section 5 concludes the paper.

2. WIRELESS SENSOR NETWORK

As shown in Figure 1, WSN is defined as a collection of wireless intelligent devices known as sensoand rs that can detect and distribute some information about the environment in which they are installed. These devices typically collect data from users who want to monitor and control a specific phenomenon and send it to a central location known as a sink node. The latter delivers the data information to either local or a remote control via a bridge that users can connect to over the network. In order to get the required information, the users are using applications that contact the network by means of requests [20].

WSN technology has known a considerable enhancement over the last few years thanks to the development of additional studies that contributed to this field. The infrastructure-less capability of a sensor network enabled the deployment of limited resource sensor units close to or distant from the investigation process. A sensor network consists of many sensor nodes that include sensing, information handling, energy supply, and components for communication. Because of this capability, sensor nodes detected in any location should be able to give the end-user information and a better comprehension of the situation in which they are located. The WSN applications contain health monitoring [21], monitoring of environmental [22], multimedia [23], agriculture [24], internet of thinks (IoT) [25], and intelligent vehicular systems [26].

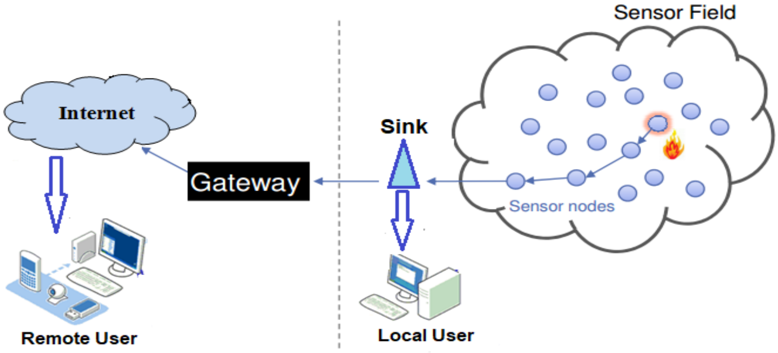

Figure 1. Sensor network architecture

3. KERNEL-BASED RADIO CHANNEL IDENTIFICATION

This section will start with a brief overview of the essential idea of adaptive kernel filtering, followed by a description of kernel adaptation methods. Many adaptive algorithms have evolved thanks to the reproducing kernel theory. The adaptive ability of these algorithms is based on the principle of error correction learning. The basic idea of kernel adaptive filtering is to project the input space data $u \in \mathrm{U}$ into a high-dimensional vector space $(\mathcal{H}, <.,.>)$, called a reproducing kernel Hilbert space (RKHS), in which linear methods can be implemented from a positive definite kernel $\kappa(.,.): \mathrm{U} \times \mathrm{U} \rightarrow \mathbb{R}$. Here, symbol $<.,.>$: $\mathcal{H} \times \mathcal{H} \rightarrow \mathbb{R}$ denotes an inner product in the RKHS.

To implement the kernels methods on a measured input U, it is practically enough to have kernel values for all pairs in this data input. These values are usually memorized in a square matrix that called the Gram matrix. This matrix is given by (1).

$$K_{ij} = \kappa\left(u_i, u_j\right), for\ i, j = 1, \dots, N \tag{1}$$

In particular, if $\kappa : \mathrm{U} \times \mathrm{U} \rightarrow \mathbb{R}$ is defined positive, then it can be represented as a scalar product in a vector space where the data are projected, which is known as feature space. The expansion associated with a kernel is a function ϕ: $\mathrm{U} \rightarrow \mathcal{H}$ such that (2).

$$\kappa\left(u, u'\right) = \phi(u)^T \phi(u'), \quad \forall\left(u, u'\right) \in \mathrm{U}^2 \tag{2}$$

The Gaussian kernel is used in this work, which is generally a default choice because of its good generalization product and statistical stability, to create the reproducing kernel Hilbert spaces concept:

$$\kappa\left(u_i, u_j\right) = \exp\left(-\frac{\left\|u_i - u_j\right\|^2}{2\sigma^2}\right), \ \forall\left(u_i, u_j\right) \in \mathrm{U}^2 \tag{3}$$

Where $\sigma > 0$ represents the kernel width.

3.1. KRLS algorithm

This part of the article introduces the kernel RLS algorithm [10]. It's an algorithm that falls under the recursive least squares category. The fundamental concept is to create the input data by running the linear RLS algorithm in the Hilbert space, which is connected to a reproducing kernel, mostly via feature map ϕ given by (4).

$$\{\left(\phi\left(u_1\right), s_1\right), \left(\phi\left(u_2\right), s_2\right), \dots, \left(\phi\left(u_n\right), s_n\right), \dots.\} \tag{4}$$

The KRLS algorithm's problem formulation can be written as (5).

$$\min_{\phi \in \mathcal{H}} \sum_{k=0}^{n-1} \lambda^{n-k} \left|s_k - \phi(u_k)\right|^2 + \lambda^k \|\phi\|_{\mathcal{H}}^2 \tag{5}$$

Where λ stands for a standard positive smoothing parameter, s_k denotes the desired system response, and $\phi(u_k)$ denotes the system's corresponding output value for u_k.,

The representation theorem [27] states that the answer to the problem (5) can be expressed as (6).

$$\phi(.)_n = \sum_{i=1}^{m} \theta_{n,k}\ \kappa\left(., u_k\right) \tag{6}$$

Where $\theta_n = \left(\theta_{n,1}, \theta_{n,2}, \dots, \theta_{n,n}\right)^T$ is the vector of the parameter model. The best answer to the issue results from integrating (6) into (5) as continues to (7).

$$\min_{\theta} \Lambda \left\|s_k - H_k \theta\right\|^2 + \lambda^n\ \theta^T K_k \theta \tag{7}$$

Where $H_k = \kappa\left(u_k, u_i\right)$, for k,i=1,2,...,n, Λ is a size (n,n) diagonal matrix in which the (k,k) th component would be λ^{n-k} , and $K_k = \left(\kappa\left(u_1, u_n\right), \kappa\left(u_2, u_n\right), \dots, \kappa\left(u_m, u_n\right)\right)^T$,

If is assumed to be invertible, the answer to the problem (7) would be:

$$\theta_n = P_n H_k^T \Lambda_n s_n \tag{8}$$

With:

$$P_n = (H_k^T \Lambda_n H_k + \lambda^n K_k)^{-1} \quad (9)$$

We update H_{n+1} and s_{n+1} by (10) and (11), respectively, at the instant n + 1, a new u_{n+1} observation is observed at the system's input.

$$H_{n+1} = \begin{pmatrix} H_n \\ h_{n+1}^T \end{pmatrix} \quad (10)$$

$$S_{n+1} = (s_0, s_1, \dots, s_n) \quad (11)$$

With $h_{n+1} = (\kappa\,(u_{n+1}, u_1), \kappa\,(u_{n+1}, u_2), \dots, \kappa\,(u_{n+1}, u_m))^T$. And after that, the KRLS algorithm's equations are updated using:

$$G_{n+1} = \frac{\lambda^{-1} P_{n+1} h_{n+1}}{1 + \lambda^{-1} h_{n+1}^T P_{n+1} h_{n+1}} \quad (12)$$

$$\theta_{n+1} = \theta_n + G_{n+1}\,(s_{n+1} - \theta_n h_{n+1}^T) \quad (13)$$

$$P_{n+1} = \lambda^{-1} P_n\,[1 - G_{n+1} h_{n+1}^T] \quad (14)$$

Where the term $s_{n+1} - \theta_n h_{n+1}^T$ represents the estimation error.

3.2. KLMS algorithm

In this section, we will introduce the LMS algorithm of the kernel [11]. The KLMS algorithm is a member of the stochastic gradient algorithm class. The fundamental idea is to implement the linear LMS algorithm in the Hilbert space. Now assume that the function map ϕ was used to successfully transform the sequence of samples, and then applied the LMS algorithm to the transformed data that is defined in (4), we will get the LMS kernel algorithm:

$$e_n = s_n - \theta_{n-1}^T \phi(u_n) \quad (15)$$

$$\theta_n = \theta_{n-1} + \mu e_n \phi(u_n) \quad (16)$$

In (16) differs significantly from LMS in that it is located in a space with characteristics that may have an infinite number of dimensions, making direct updating nearly impossible. As an alternative, we'll make use of each θ_n of them to relate to their initialization θ_0 :

$$\theta_n = \theta_0 + \mu \textstyle\sum_{i=1}^{n} e_i\,\phi(u_i) \quad (17)$$

$$\theta_n = \mu \textstyle\sum_{i=1}^{n} e_i\,\phi(u_i) \qquad \text{(if we suppose that } \theta_0 = \theta\ (0) = 0) \quad (18)$$

The model prediction solution is obtained by means of the kernel trick:

$$\langle \theta_n, \phi(u_i) \rangle_{\mathcal{H}} = \mu \textstyle\sum_{i=1}^{n} e_i\,\langle \phi(u_i), \phi(u_n) \rangle = \mu \sum_{i=1}^{n} e_i\ \kappa\,(u_i, u_n) \quad (19)$$

Where n represents the total of training samples and $\kappa\,(u_i, u_n)$ is a Mercer kernel.

3.3. KNLMS algorithm

The KNLMS algorithm is usually more efficient than the KLMS algorithm. The update rule of kernel NLMS is written as (20) [28]:

$$\theta_n = \theta_{n-1} + \frac{\mu \phi(u_n)}{\varepsilon + \kappa\,(u_n, u_n)}\,[s_n - \phi(u_n)^T\ \theta_{n-1}] \quad (20)$$

Where, ε is the check value.

4. RESULTS AND DISCUSSION

In this section, firstly, we conduct Monte Carlo simulations to investigate the performance of the KRLS algorithm in outdoor non-line-of-sight (NLOS) BRAN channels identification compared to KLMS and KNLMS. Secondly, we developed our own class BranPhyLayer under MiXiM platform on OMNet++ to test and evaluate the performance of the selected channel in the first simulation step.

Consider the NLOS BRAN channels (C and E) models of fading radio channels. These models' data is collected in an outdoor setting. The impulse response of the BRAN (C and E) radio channels is described by the (21).

$$h(n) = \sum_{i=0}^{p-1} m_i \delta(n - \tau_i)\,,\ p = 18. \quad (21)$$

Where $\delta(n)$, τ_i and $m_i \in N(0,1)$ respectively, stand for the function of Dirac, the path's i time delay, and the path's i magnitude.

In this case, we present an experimental comparison of different kernel algorithms (KRLS, KNLMS and KLMS). The Table 1 summarize the measured impulse response parameters of the ETSI BRAN C and ETSI BRAN E radio channels, respectively.

Table 1. Delay vs. magnitudes of BRAN C and BRAN E channels

BRAN C				BRAN E			
Delay. τ_i [ns]	Magn. m_i [dB]	Delay. τ_i [ns]	Magn. m_i [dB]	Delay. τ_i [ns]	Magn. m_i [dB]	Delay. τ_i [ns]	Magn. m_i [dB]
0	-3.3	230	-3.0	0	-4.9	320	0
10	-3.6	280	-4.4	10	-5.1	430	-1.9
20	-3.9	330	-5.3	20	-5.2	560	-2.8
30	-4.2	400	-5.9	40	-0.8	710	-5.4
50	0	490	-7.9	70	-1.3	880	-7.3
80	-9.2	600	-9.7	100	-1.9	1070	-10.6
110	-1.7	730	-13.2	140	-0.3	1280	-13.4
140	-2.6	880	-16.3	190	-1.2	1510	-17.4
180	-1.5	1050	-21.2	240	-2.1	1760	-20.9

4.1. BRAN channel impulse response estimation

The BRAN C and BRAN E channels parameters estimations by using the methods based on kernel adaptive filtering (KLMS, KNLMS, and KRLS) for SNR = 15dB, data input N = 1024 and 50 Monte Carlo iterations are presented in Figures 2 and 3 respectively. These models represent different transmission scenarios with the objective to exploit the opportunity offered by the combination of broadband radio and the local network technology in a fixed access radio to meet the needs of future multimedia applications as well as services. Each model consists of 18 paths with exponentially decreasing delay amplitudes and a transmitter-to-receiver distance of 50 to 150 meters.

The estimated parameters presented in Figures 2 and 3 show clearly that the KRLS algorithm achieved a higher prediction accuracy than the KNLMS and KLMS algorithms. In the meantime, KNLMS outperformed KLMS by a small margin. The good results were achieved by using of a very quickly fading channel.

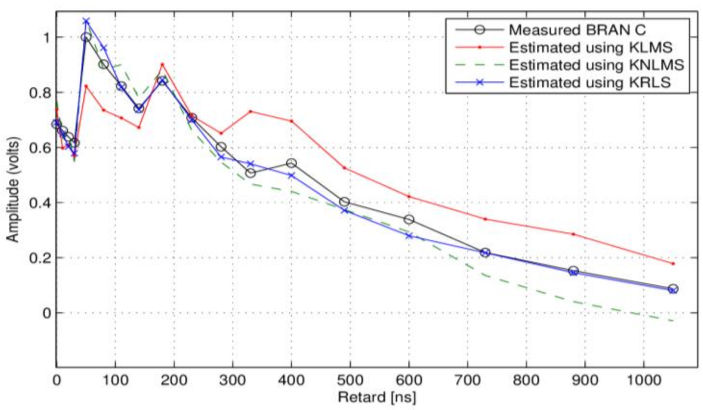

Figure 2. ETSI BRAN C channel impulse response estimation, for SNR = 15dB and N = 1024

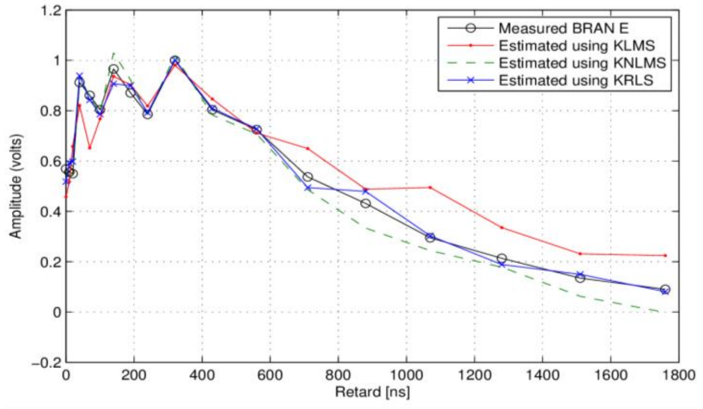

Figure 3. ETSI BRAN E channel impulse response estimation, for SNR = 15dB and N = 1024

4.2. Choosing the channel

In this subsection, we will study the robustness of the KRLS algorithm on two channels (BRAN C and E) in order to know which of the two channels is the best. In the following Figure 4, we present the mean square error (MSE) simulation results for various SNR obtained using the estimated parameters of the BRAN C and BRAN E channels, and the identification is executed using the KRLS algorithm. We observe that the accuracy of the KRLS algorithm is important in the case of the BRAN E channel. From this result Figure 4, we can observe that: if SNR = 30dB, the MSE value is near to −20 in the specific case of the estimated ETSI BRAN C channel, but by using the estimated amplitude of ETSI BRAN E channel, we have an MSE value equal to −20 when the SNR value is equal to 12.5dB. This difference may be due to larger fluctuations in BRAN E Channel. A normal thing since, for a fixed N value, the channel identification is proportional to SNR: the SNR value is bigger the more our system becomes able to identify the BRAN channel.

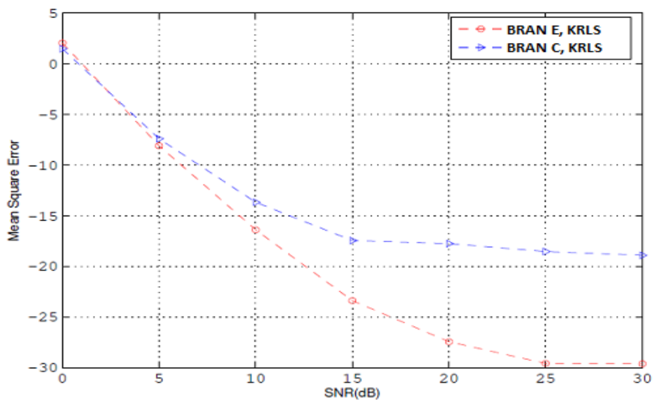

Figure 4. MSE vs. SNR of the estimated BRAN channels (C and E), using KRLS algorithm for N = 1024

4.3. Energy consumption

Optimizing power consumption in order to improve the WSN lifetime is a challenging issue that has been investigated in different aspects. But, the majority of studies have excluded the impact of the channels, such as the finite bandwidth, the mean square error, and the SNR. As the data source rate of sensor nodes becomes higher, throughput patterns that optimally trade-off power loss may require considerably more bandwidth than is available. As a result, disregarding the channel's bandwidth restrictions could result in impractical solutions. In this subsection, we show the good impact by introducing the Broadband channel in the area of IR-UWB based WSN. The low power consumption of the nodes network in the case of BRAN E by using the KRLS algorithm is realized by the performance presented in Figure 5. It demonstrates that the power consumption by using the outdoor BRAN E channel with KRLS is remarkably less than the case of the outdoor BRAN C channel with KRLS and CM6 outdoor NLOS channel due to retransmission packets generated by the collision in the last towing channel. By increasing the nodes' number in the network, this figure also illustrates the linear relationship between power consumption and this number.

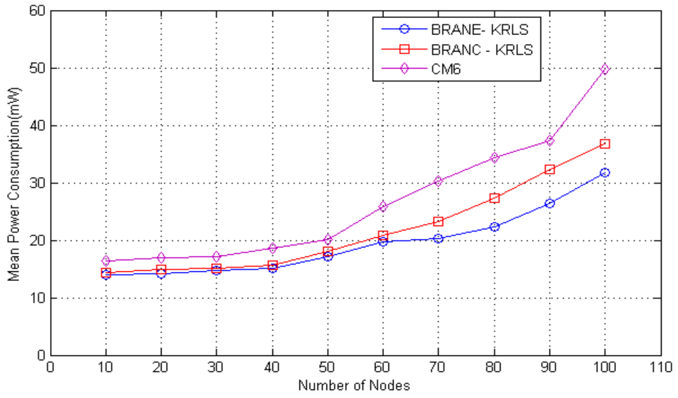

Figure 5. Nodes' power consumption average

4.4. Packets delivery ratio (PDR)

PDR is considered as the main parameter that affects directly the quality of service (QoS). It is defined by the number of received packets by destinations split by the number of sent packets by the sources. In any physical layer, in order to provide an adequate QoS, we had to investigate the PDR parameter as it is a practical consequence of the effectiveness of the channel used and of the packet losses caused by the generated error observed at the time of the mode transmission. Figure 6 illustrates the considerable improvement in terms of PDR by using the outdoor NLOS BRAN E channel with KRLS compared to the outdoor NLOS BRAN C channel using KRLS and CM6 outdoor NLOS channel. These experiments prove the benefits of low MSE obtained in the case of outdoor NLOS BRAN E channel using KRLS Figure 4.

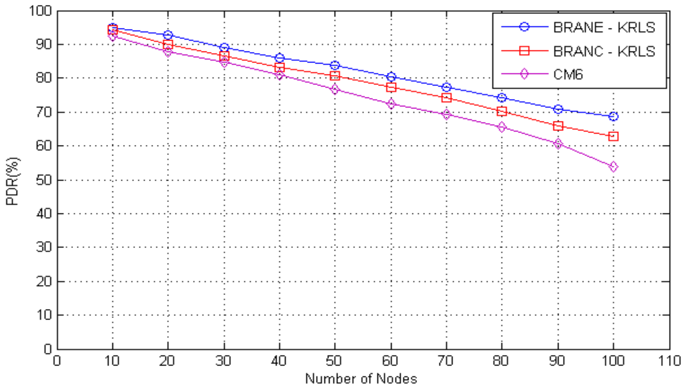

Figure 6. Packets delivery ratio (PDR)

4.5. Latency

The packet arrival delays (Latency) in IR-UWB based WSN is a key measure especially for timesensitive applications. This latency depends derectly the channel's quality and the distance or number of hops between the start and end nodes. Figure 7 depicts a deep analysis of the latency parameter for different values of nodes' number varie from 10 nodes to 100 nodes. It shows an arrival delays average of the node in the case of outdoor NLOS BRAN E channel using KRLS between 8.91 and 29.79 ms and from 9.53 and 10.37 to 35.93 and 43.87 ms for outdoor NLOS BRAN C channel using KRLS and CM6 outdoor NLOS channel respectively. Furthermore, this means is near the smallest values in three situations, signifying that practically all the nodes' packet delay times are going to reach these mean values. Consequently, it demonstrates clearly the successful results that have been achieved by the node in the case of outdoor NLOS BRAN E channel using KRLS compared tooutdoor NLOS BRAN C channel using KRLS and CM6 outdoor NLOS channel.

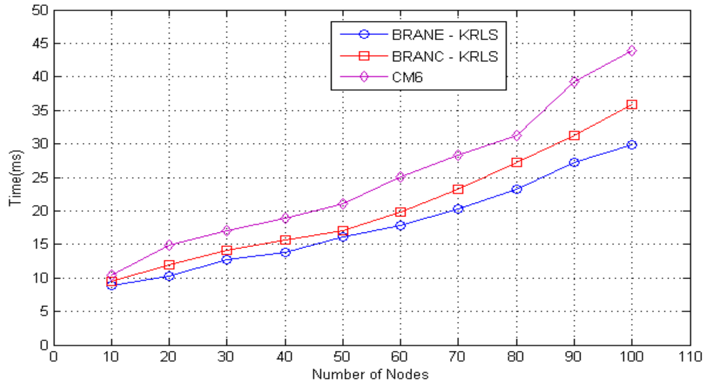

Figure 7. End-to-end packets delay average

5. CONCLUSION

An Outdoor WSN based on IR-UWB was investigated and analyzed in this paper where the BRAN channels are introduced. Our studies focused on the CM6 outdoor NLOS channel and outdoor NLOS BRAN channels such as BRAN C and BRAN E using the KRLS algorithm. The selection of the KRLS algorithm for the outdoor NLOS BRAN channels identification can be understood thanks to the obtained good results in the BRAN channel response estimation subsection. This work also demonstrates the important results in terms of Power consumption, PDR and Latency in the case of the outdoor NLOS BRAN E channel using KRLS algorithm compared to the outdoor BRAN C channel using KRLS and CM6 outdoor NLOS channel. These achievements are attained due to it main features as well as the attained low MSE. To exploit the main features of the outdoor NLOS BRAN E channel using KRLS, we intend as a future work to propose a new MAC protocol that can be efficiently paired with this channel.

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