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Classification of Radio Channel disturbances for industrial wireless sensor networks☆

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ABSTRACT

The reliability of data transmission in Wireless Sensor Networks (WSN) is always an issue in harsh industrial environments and sets specific challenges for performance optimization. Short-term signal disturbances, in the form of multipath fading and destructive radio interference, are of major concern due to signal path conditions (large concrete and metal surfaces), related line-of-sight (LOS) changes (incoming and outgoing trucks, moving around forklifts and workers), and radio frequency interferences. In this paper we introduce the classification procedure where results of Probability Density Function (PDF) analysis and Spectrogram Analysis are combined to classify the measured radio channel disturbances to a set of predefined disturbance classes. The PDF and Spectrogram analysis methods are used for analyzing the statistical properties of the received signal magnitudes. Tracking the changes of the PDF clearly contributes to recognize and characterize the temporal changes, especially LOS changes in the radio link environment. The spectrogram analysis provides additional information of the radio interferences on co- and adjacent channels.

1. Introduction

The manifold benefits of wireless network technologies have led to their great success in the consumer goods industry. Simple deployment, significant cost savings in installations, lack of cabling, high mobility, and easy rearrangements related to device configuration and sensor locations make the wireless network technologies, especially wireless sensor networks (WSN) appealing also for industrial applications [1–4].

The adaption of wireless technology in industry poses extra challenges since the factory environments are typically harsh for wireless communications in terms of interferences, noise and physical obstacles [5]. Wireless industrial automation has strict requirements for the Quality of Service (QoS), safety and security. The key aspect of QoS for Industrial Wireless Sensor Networks (IWSN) communication is to ensure the transmission of periodic or sporadic messages within pre-defined deadlines and in a reliable fashion [2]. WINA technical committee has undertaken the development of a QoS design and assessment framework for IWSN [6]. The measures of performances that define QoS are throughput, latency, reliability, security, adaptability, and affordability. Within the industrial environment, adaptability is one true advantage of wireless over wired networks meaning the ability to adapt to changes in the environment while maintaining the required levels of QoS attributes [7].

Within the industrial market six different classes of sensor and control applications have been defined varying from critical safety (class 0) to condition monitoring and regulatory compliance (classes 4 and 5) [8]. The main

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difference between the classes is the latency, timing and reliability requirements. In the closed-loop control applications involving mobile subsystems, coordination among mobile robots or autonomous vehicles, health monitoring of machines and tracking of parts, the wireless data communications must satisfy tight real-time and reliability requirements at the same time, otherwise loss of time and money or even physical damage can result [2]. While in monitoring applications the requirements for real-time transmission are generally loose, the reliability is important especially for critical alarm messages.

Several industrial organizations, such as ISA [9], HART [10], and ZigBee [11], have been actively pushing the applications of wireless technologies in industrial automation. ZigBee, WirelessHart, and ISA100 use the same physical level of IEEE 802.15.4, but they differ substantially concerning the medium access control (MAC) level. WirelessHart and ISA100 are mesh solutions adopting frequency agility and power adaption to improve the data transmission reliability [12,13]. WirelessHART introduces channel hopping and channel blacklisting into the MAC layer, while ZigBee can only utilize Direct Sequence Spread Spectrum (DSSS) provided by IEEE 802.15.4. Since ZigBee does not exploit frequency diversity and network shares the same static channel, it makes it highly susceptible to both unintended and intended jamming, and also to frequency selective fading due to the metal-rich propagation environments. ISA100 Wireless is the only industrial wireless network protocol that satisfies the ETSI EN 300.328 v1.8.1 regulation being in effect January 1, 2015. ISA100 Wireless uses CSMA/CA (LBT- Listen Before Talk) CCA (Clear Channel Assessment) technology to detect co-existence with other unmanaged wireless devices using the same 2.4 GHz frequency spectrum, and spectrum monitoring to avoid congested channels by forcing the operation on specific channels [15].

In wireless access systems with terminals equipped with significant power resources, radio and baseband processing chains, different countermeasures against fading can be realized. In WSN's with often simpler and low power sensor nodes, the situation is usually more complicated, and careful design of the overall system given the realization constraints is needed. Due to restricted computing power, signal measurements and further analysis established in sensor nodes cannot be computationally demanding.

In this paper we introduce a novel approach to improve the quality of wireless communication in WSN's. We introduce signal analysis methods and a classification algorithm to identify radio channel disturbances typical for industrial environments in the physical layer. Signal analysis methods based on statistical analysis of the received signal properties help to recognize the temporal disturbances affecting the signal propagation in a radio channel, and have been described in details in our previous work [26,28].

The focus of this work is to introduce the classification procedure; combining the results of signal analysis methods in time and frequency domains we construct a classifier to categorize the radio channel disturbances. We use 2.4 GHz RF transceiver as the transmitter [19] and Software Defined Radio (SDR) [20] as the receiver. Capturing signal with SDR gives us possibilities to analyze the statistical properties of the received signal even in intra-symbol scale. Our channel diagnosis methods are generally applicable to wireless technologies using physical level of IEEE 802.15.4. Our focus is on Layer 1 (PHY), and it applies to all techniques in Layer 2, and above it. The rest of this paper is organized as follows. In Section 2 the overview of reliability of wireless communication is given. In Section 3 we present our signal analysis methods for radio channel disturbance identification. In Section 4 we show the main principles of disturbance classification and in Section 5 test results of the disturbance classification. Finally, the paper is concluded and results discussed in Sections 6 and 7.

2. Reliability of communication in IWSNs

Wireless Local Area Networks (WLANs) based on the IEEE 802.11 specification, cordless telephones and Bluetooth have fully reached the process plant, and when introducing WSN's in the plant, one must accept that the environment is under influence from nearby interference sources. Performance evaluation results on WirelessHART for factory environments have shown that interference from the WLAN will cause increased packet loss rates [14]. Exposing WirelessHART network to attacks from a 2.4 GHz linear chirp jamming device has caused the WirelessHART network braking down completely, with no data reception on the gateway and a resulting reliability of 0% [14]. Zigbee does not have frequency diversity like WirelessHART, and thus is even more exposed to radio channel interferences [15].

The reliability of data transmission in WSNs has been studied from different perspectives. Great amount of research results have been reported on such topics as reliable routing techniques, and reliable transport protocols for WSNs, which aim to overcome the data transmission problems on MAC-, Network- and higher layers. Physical level transmission problems have received less attention though providing feedback of channel disturbances from physical level to upper level could significantly improve the transmission reliability [16]. In channelization, to overcome the problem of spectrum scarcity in a WSN, a new concept of cognitive wireless sensor network (CWSN) has been proposed. The main difference between traditional WSN and CWSN is that in CWSN nodes change their transmission and reception parameters according to the radio environment [17]. Spectrum sensing is a commonly used technique in cellular cognitive radio helping to avoid the most crowded frequency channels, and it considerably improves the radio channel reliability. However radio interference is not the only concern in the industrial environment. The signal strength can be severely affected in factory environments due to multipath fading, originating from large objects blocking the signal path, and reflections from walls and floors.

A common approach for the physical layer measurements is to rely on the Received Signal Strength Indication (RSSI) values provided by the chipset. The main attraction to RSSI as a metric is that the measurements and calculations involved with RSSI are less complicated, and RSSI values are easily available from the chipsets [18]. The drawbacks of using RSSI values are the differences between the RSSI values reported by the individual chips which may originate from differences in antenna design, hardware design, or driver, and accuracy of time resolution. The RSSI is neither measured over the whole received packet [27]. In some cases, the RSSI reported from a packet reception, represented the signal strength only during reception of the PCLP (Physical Layer Convergence Preamble) and PLCP header (IEEE 802.11) [27]. Thus, if the interference affects only the average received signal strength, the effect of interference will not be captured in the RSSI measurements [27]. Nor can the RSSI value provide any information on what kind of disturbance is affecting the signal. However, identification of a physical phenomenon that is behind the transmission problems will help to predict and successfully solve these problems by providing channel condition information to the upper layers. Depending on the interference type (fading or radio interference), specific adaption algorithms must be applied, like power control (PHY layer) or route diversity (Network layer) to overcome the transmission problems.

3. Signal analysis for interference detection

The complexity of real environments causes time and space dependent signal magnitude variations (i.e. fading) that are difficult to define in a deterministic way. To characterize the fading effects the statistics of the observed fading is approximated with probability models that fit the data. Temporal fading can be defined as the variability of received power over time at a fixed location in the radio propagation environment. Measurements performed in industrial environments indicate that temporal fading caused by frequently moving trucks or other heavy machines may cause deep fades in radio signal, and require 20 or 30 dBm more transmitter power to achieve lower bit error rates.

Observing the statistics of the received signal in frequency domain contributes to detect and define the radio interferences disturbing the signal propagation of sensor nodes in IWSNs. The WSN nodes use very low transmit power (<0 dBm), while typical transmit power, for example, for Wireless LAN is about 20 dBm. The detection of co-channel interference overlapping with our signal transmission will provide us additional information on the channel state, and thus help us to classify the transmission problem.

In this work the signals transmitted by wireless sensor nodes is captured using SDR, see Fig. 1. We used SDR (USPR N210, ETTUS) as an independent tool. Here, the SDR is connected to the WSN gateway (GW) through Ethernet which gives us an opportunity to analyze the same data which is captured by the GW. The digitized IQ data (inphase and quadrature) returned by the SDR is transferred to the host CPU (here laptop), processed and analyzed. The results of signal analysis are used to the interference classification, and wireless connectivity improvement.

3.1. PDF analysis of the received signal

The Probability Density Function (PDF) analysis is based on the idea that changes in statistical properties of the received signal are strongly correlated with the transitions of the channel states. It has been shown that temporal fading in the industrial environment exhibits Rician fading properties [21–23]. Thus, matching the PDF of the received signals to the theoretical Rician distribution and deriving the PDF's shape parameters, we can numerically characterize the effects of environment disturbances, i.e., obstacles to the channel state. The PDF shape parameters (noncentrality/shape parameter a and scale parameter *sigma* ("σ") are estimated from sample data by fitting a probability distribution object, here a Rician Distribution Object, to the data. To estimate the distribution parameters from the sample data the Maximum likelihood estimation (MLE) is used.

In literature, there are two probability models that are commonly used to characterize the propagation channels with fast and/or temporal fading [24]. One is the Rayleigh model, which corresponds to situations where no line-of-sight (NLOS) path is present between the transmitter and the receiver. The PDF of the received signal magnitude in the case of Rayleigh distributed fading is defined by Eq. 1. The other probability model is the Rician model, which corresponds to situations where one strongly dominant

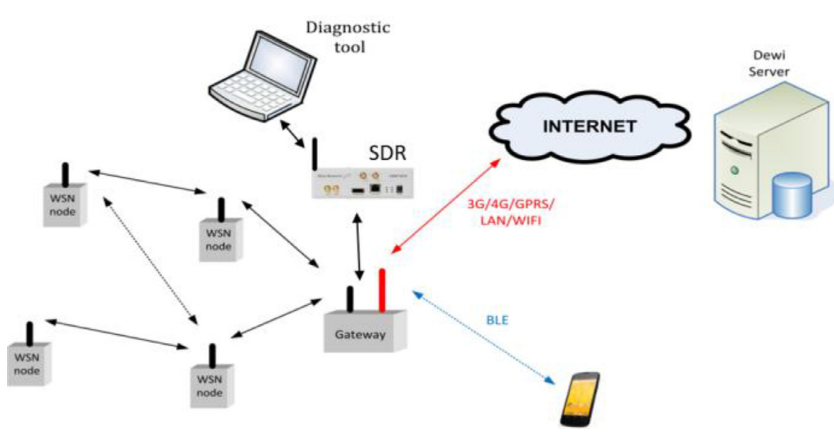

Fig. 1. The basic WSN architecture with the Network Diagnostic tool.

path exists. In this case the probability density function of the magnitude is given by Eq. 2.

$$f_\rho(\rho|a,\sigma) = \frac{\rho}{\sigma^2}\exp\left(-\frac{\rho^2}{2\sigma^2}\right) \tag{1}$$

$$f_\rho(\rho|a,\sigma) = \frac{\rho}{\sigma^2}\exp\left(-\frac{\rho^2+a^2}{2\sigma^2}\right)I_u\left(\frac{a\rho}{\sigma^2}\right) \tag{2}$$

where

- I_u modified zeroth-order Bessel function of the first kind;
- ρ denotes the magnitude value measured at the receiver;
- a corresponds to the signal amplitude due to the LOS path in the absence of all other multipath components;
- σ standard deviation of the real part of the time-harmonic multipath component.

Furthermore, ρ is given by Eq. 3.

$$\rho(t) = \sqrt{I^2(t)+Q^2(t)} \tag{3}$$

where I is the inphase and Q the quadrature components of the received signal.

Environmental changes in radio channel (e.g. trucks, other radio transmissions) cause fluctuations in strength of the received signal and consequently in the PDF of the received signal. Shape and scale parameters, '*a*' and 'σ' (Eq. 1), are used to characterize the shape of the PDF. The PDF is calculated from the received signal magnitude samples and matched with theoretical Rician PDFs. The shape and scale parameters are derived from the theoretical Rician PDF which best matches the PDF calculated form the received signal. In the Rician distribution the '*a*' value reflects the amount of the specular power of the received signal while the *sigma* value is related to the amount of the scattered power of the received signal.

In our earlier work [25,28] we studied correlation of the temporal fading caused by large objects to a-, and *sigma*-parameters variations. During our measurements a vehicle (a car, a van and a truck) was approaching the line-of-sight between two radios and stopping for a moment to block the direct signal, and then drove away. The situation where no vehicle is blocking the signal, we call LOS channel state, meaning that the signal with shortest propagation path is not blocked or disturbed. And again, the situation where vehicle drives between the radios and blocks the signal, we call NLOS channels state, meaning that the signal with shortest propagation path is blocked or disturbed. The drops of both a- and sigma values are detected while the channel state changes from LOS to NLOS, and increases again while changing from NLOS to LOS.

In this work we investigate the behavior of "*a*" and "*sigma*" parameters in situations of strong radio interference. Here, the "*a*" –value is not altered, but "*sigma*" –value changes dramatically due to effect of two signals summing up, see Figs. 2 and 3. The *sigma* value increases (=peaks) while the channel state changes from LOS to LOS+H, and drops while changing from LOS+H back to LOS. Here, "H" stands for radio interference (=WLAN 802.11b). The peaks of sigma values during LOS+H channel state means that these received packets were disturbed by the WLAN 802.11b signal.

PDF parameters are calculated from the raw 16–bit I and Q samples provided by the SDR, and are not scaled.

3.2. Spectrum analysis of received signal

The spectrum analysis is based on calculation the spectrograms of the received signal magnitude and obtaining the statistical information of the radio interferences with image analysis methods. Spectrogram is a visual representation of the spectrum of frequencies, and it is calculated from the time space signal using the Fast Fourier Transformation (FFT). The horizontal axis of spectrogram represents time and the vertical axis frequency; a third dimension indicating the magnitude of a particular frequency at a particular time is represented by the intensity or color of each point in the image. The spectrograms can be used to extract distinctive features of the received signals and to identify the modulation of the signals. The instantaneous

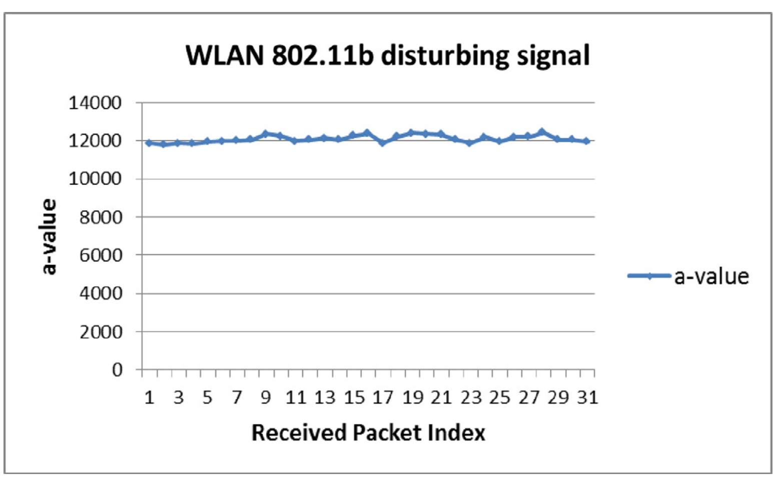

Fig. 2. Received signal behavior in LOS – LOS+Interference – LOS scenario: Rician 'a' value.

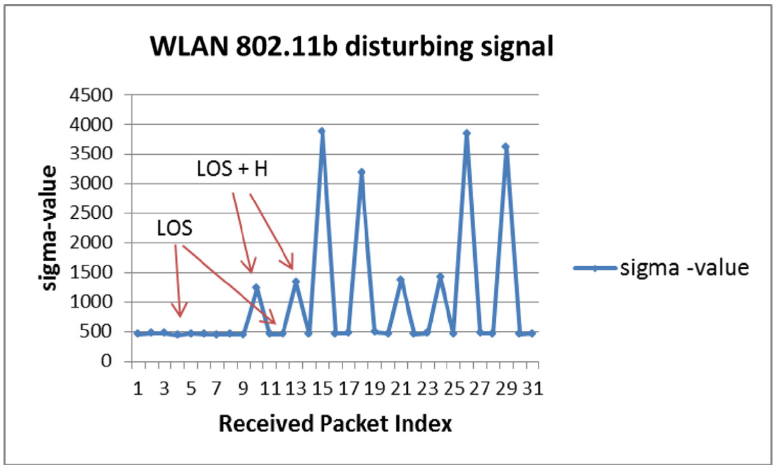

Fig. 3. Received signal behavior in LOS – LOS+Interference – LOS scenario: Rician 'sigma' value.

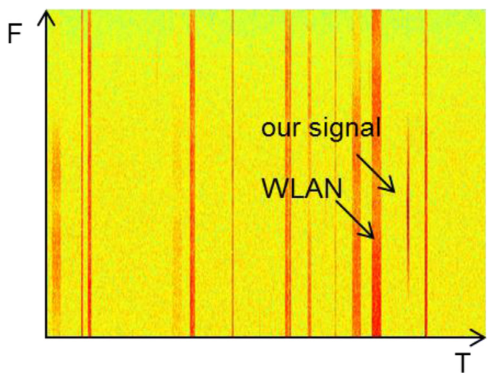

Fig. 4. Exemplary spectrogram for industrial environment; our signal is not disturbed.

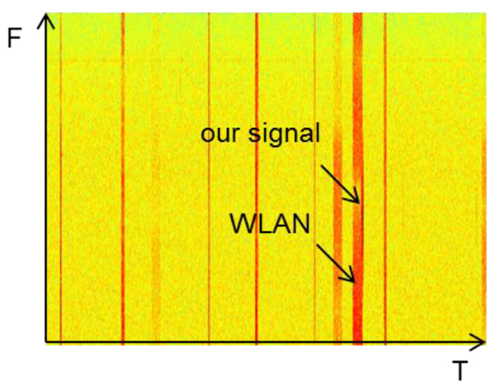

Fig. 5. Exemplary spectrogram from industrial environment: our signal is disturbed.

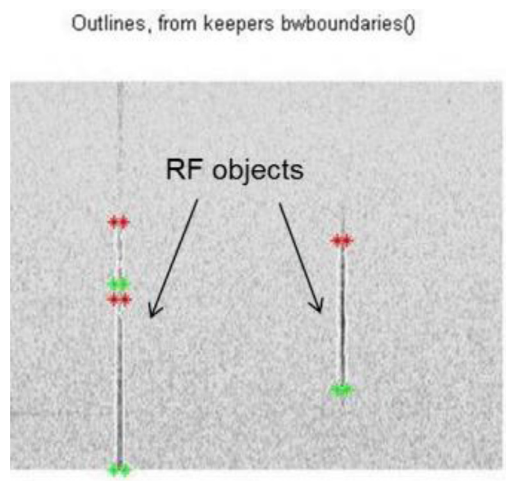

Fig. 6. Radio interferences detection process performed using image analysis techniques.

amplitude, phase and frequency transitions of the different types of modulated signals will have different spectral characteristics in the time-frequency domain [12]. In our work we will focus on extracting the frequency and time related features of the received signals to detect and characterize the radio interference.

Figs. 4 and 5 presents the example spectrograms recorded with the SDR in the industrial environment. In Fig. 5 our signal is not disturbed by other radio transmissions (mostly WLAN), and the spectral trace is easily observed (indicated with arrow). In Fig. 6 the situation is more complicated; here, our signal was strongly disturbed by other radio transmitting (WLAN) on the same frequency channel.

RF spectrograms are processed with image analysis tools to find transmission or disturbance entities, which we call RF objects, see Fig. 6. RF objects are transmissions or disturbances having a frequency band and duration time. After the objects are detected, they are transformed to the numerical representation by obtaining the frequency (y axis), time and duration information (x axis) of each object.

4. Classification of the signal disturbances

The recognition and identification of the radio disturbance is based on fusion of the signal magnitude analysis and spectrogram analysis with a classifier. We follow

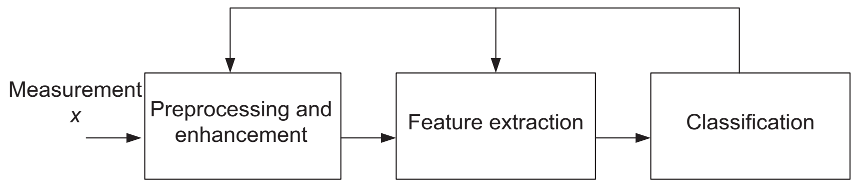

Fig. 7. General pattern for classification procedure.

the typical pattern for classification algorithms, presented in Fig. 7.

The algorithm includes following phases: pre-processing of measured data, feature extraction from the measured data and classification. In addition, the already classified data can be used to train the system to improve the performance of classifier. The features are arranged in an n-dimensional feature vector, which yields a multidimensional measurement feature space. The classification is accomplished by portioning the feature space into class-labeled decision regions, and assigning the measured feature vector to the nearest region.

In our work, the received digitized I(n) and Q(n) samples are pre-processed and analyzed both in time and frequency domains. For each received packet, the PDF of the signal magnitude is estimated as a signal magnitude histogram, and matched to the theoretical Rician PDFs, see Fig. 8. In parallel, the spectrogram is created from the received signal magnitude values, and the RF objects extracted from the spectrogram with image analysis tools. The RF objects compare to the transmitted packets (own or interference), and are shown as ridges, plains or otherwise distinguishable forms of the spectrogram. The parameters of the detected RF objects and related Rician parameters compose features which are used in channel state classification. The feature extraction mechanism and classification algorithm are described in details below.

4.1. Feature extraction

The feature vector comprises seven parameters:

$$F = \begin{bmatrix} a \\ sigma \\ a_{err} \\ sigma_{err} \\ f \\ \Delta f \\ \Delta t \end{bmatrix}$$

where

a	amount of the specular power;
$sigma$	amount of the scattered power;
a_{err}	standard error of a-value;
$sigma_{err}$	standard error of sigma-value;
f	center frequency of the signal;
Δf	width of the frequency band;
Δt	duration of the signal.

To reduce computation, the parameters are calculated only to the estimated time slots of our own signal. The parameter values for *a* and *sigma* are derived by matching the histogram calculated from the magnitude values of the received signal (=one packet) to the simulated Rician PDF, see Fig. 9.

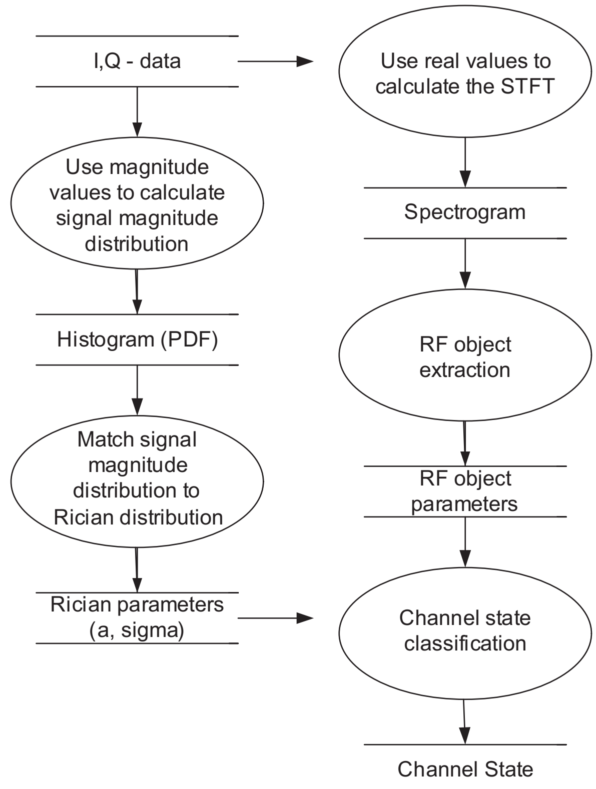

Fig. 8. Fusing results of PDF analysis and spectrogram analysis to classify radio disturbances.

The goodness of this fit is defined by the *a_err* and *sigma_err* parameters which are the standard error of the estimated shape parameters *a* and *sigma*. Our observations have shown that the less the histogram of the received packet resembles the simulated Rician PDF, for example in case if other radio disturbance, the larger is the standard error of estimated parameters, see Fig. 10.

The last three parameters f, Δf and Δt are obtained as characteristics of the RF object from the spectrogram of the received signal; f defines the mean of the frequency band, Δf the width of the frequency band and Δt the duration of the signal, see Fig. 11.

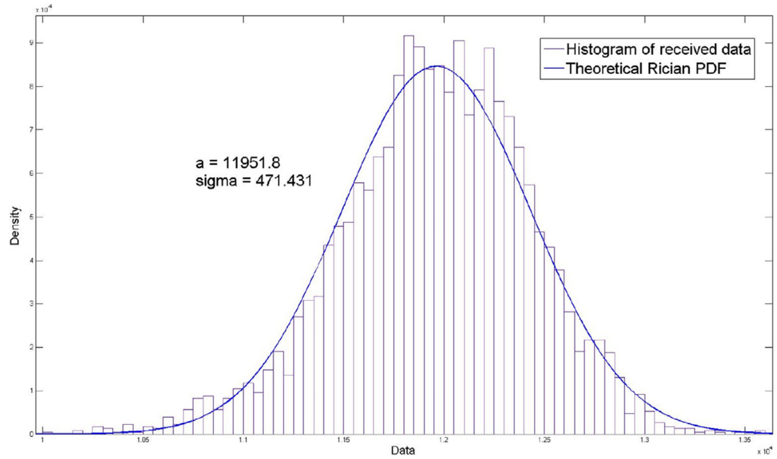

Fig. 9. Received signal magnitude PDF and matching theoretical Rician PDF.

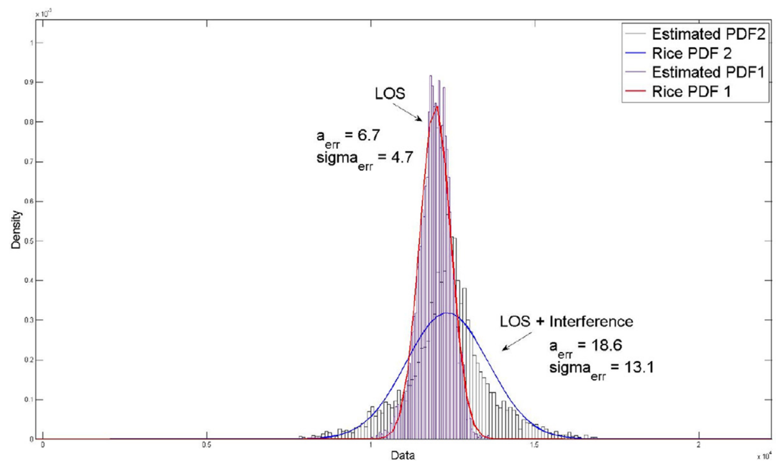

Fig. 10. Received signal magnitude PDF and theoretical Rician PDF with a clear matching error for the interference signal.

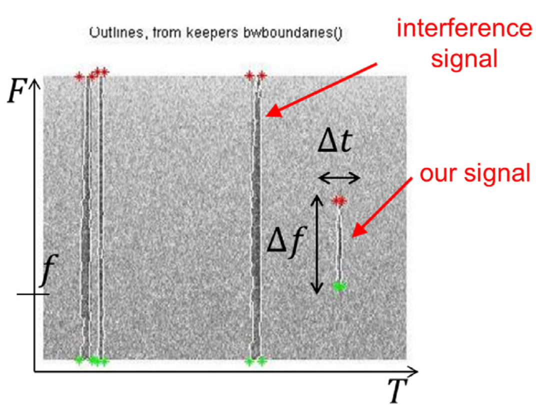

Fig. 11. Spectrogram of the received signal.

4.2. Reference classes and the classification procedure

We use a practical and simple approach for the classification – Nearest Neighbor Rule (NNR). The underlying idea is quite simple: samples that are ‘close’ in feature space likely belong to the same class. The NNR uses a training set directly to implement a classifier. Classification capability is achieved by considering samples in training set to be typical representations of each class and employing similarity measure. The determination of good and suitable similarity measure is a one of the difficult problems in classification procedure. In this work, we chose the minimum Euclidean distance in order to minimize the computation expense. A training set will be different in different environments, and thus need to be obtained for each case individually. This phase of classification we call calibration, and it is need to be performed only once during the WSN installation in the new environment. In Fig. 12 the classification procedure is presented.

The reference feature vectors represent class-labeled decision regions where we want the measured feature vector calculated from each received data packet to assign. The reference feature values are the mean values per training set. Thus, a feature vector representing a class is a set of measured mean feature values. Both the feature vector calculated from a received data packet and reference feature vectors are normalized to a nominal feature vector.

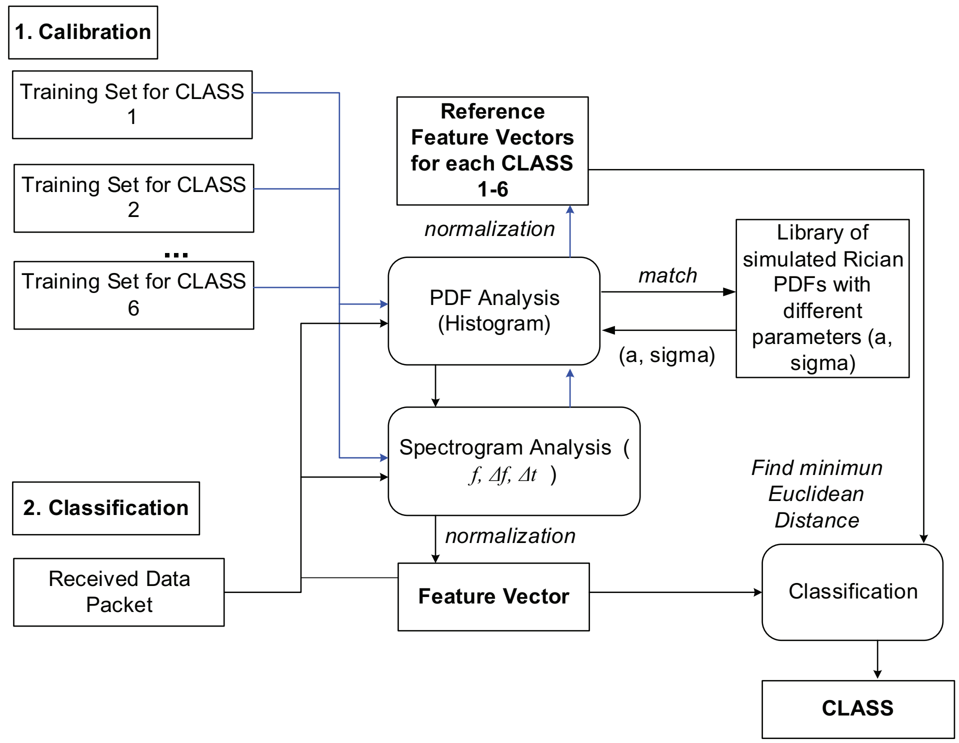

Fig. 12. Classification and Calibration phases.

The normalization is needed because otherwise some feature values will have larger variance than others, and thus dominate the classification results.

$$F_{norm} = \begin{bmatrix} a/a_n \\ sigma/sigma_n \\ a_{err}/a_{err_n} \\ sigma_{err}/sigma_{err_n} \\ f/f_n \\ \Delta f/\Delta f_n \\ \Delta t/\Delta t_n \end{bmatrix}$$

where

a_n	normalized a-value;
$sigma_n$	normalized sigma-value;
a_{errn}	normalized value of standard error of a-value;
$sigma_{errn}$	normalized value of standard error of sigma-value;
f_n	normalized value of center frequency of the signal;
Δf_n	normalized value of frequency bandwidth of the signal;
Δt_n	normalized value of signal duration.

The nominal feature vector $[a_n\ sigma_n\ a_{errn}\ sigma_{errn}\ f_n\ \Delta f_n\ \Delta t_n]$ is acquired from a training set in the absence of any kind of disturbances (Class 1: LOS). The nominal feature vector is dependable on the transmission settings (transmit power) and the environment (industrial or office), and need to be trained for the specific case (industrial or office). In this work, the analysis is performed assuming that distance between the transmitter and receiver is known and it is static. The distance dependency will be avoided by scaling the signal magnitude values to a predefined magnitude interval. The absolute distance between the sensor nodes is not important for classification procedure, only the relative changes of the magnitude values comparing to the nominal case matter. However, this is part of our future work.

In our work we wanted to focus on classifying the dominant radio channel disturbances; active disturbances such as electromagnetic interference (co-channel interference) and passive disturbances such as trucks or other large objects blocking the signal partly or totally. Investigation of the real-life measurements results led us to formation of six reference classes, see Table 1.

Classes 1–6 represent different channel states. Our goal is to identify the actual channel state, and provide this information to network controller (gateway). This will reveal the sources for the transmission problems and also allow the sensor network to adapt to changing conditions by reconfiguring the network parameters, like power control or routing.

Table 1
Reference classes.

CLASS/Disturbance	Passive disturbance	Co-channel Interference
CLASS 1	LOS	Non
CLASS 2	LOS	Weak
CLASS 3	LOS	Strong
CLASS 4	NLOS	Non
CLASS 5	NLOS	Weak
CLASS 6	NLOS	Strong

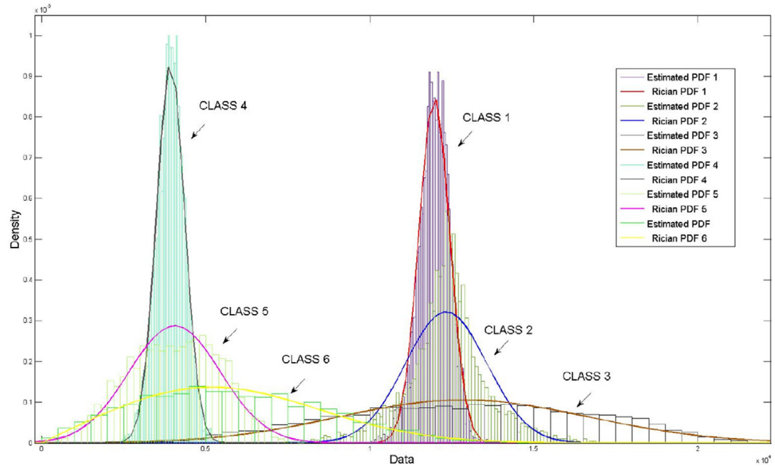

Fig. 13. Reference histograms with matching Rician PDFs.

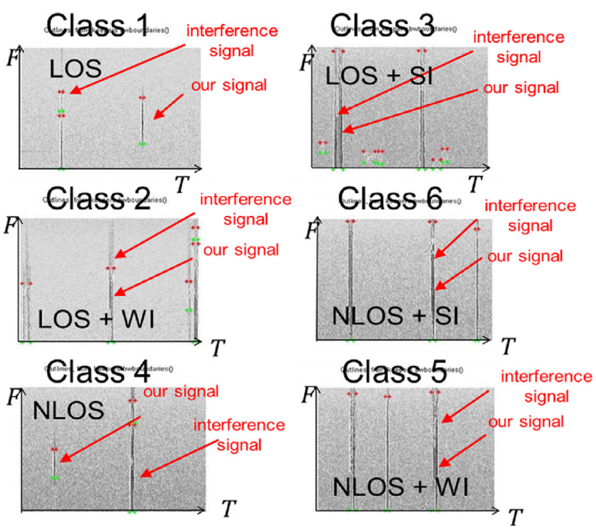

Fig. 14. Reference spectrograms and RF objects.

In Fig. 13 the reference PDFs from different classes are presented. The estimated PDFs were acquired during the measurements under different channel conditions in an orderly manner. The shape of PDF of the received signal varies depending on the channel state (=class). The a –parameter is the most affected in case of transforming from LOS channel state (=class 1) to NLOS (=class 4) since it reflects the magnitude of the LOS component of the received signal. Then again, the more signal is distorted, the more the PDF shape is scattered and the larger *sigma* parameter is.

In Fig. 14 the reference spectrograms of the received signal under different propagation conditions are presented. The spectrogram provides us additional information on whether there is an overlapping transmission on the same channel at the same time or not. In some cases, our signal is badly disturbed by the interference signal and cannot be recognized, but it can be discovered since we know the time windows of our signal transmissions. If needed, the interference signals can also be detected and their frequency parameters (f, Δf and Δt) obtained and analyzed. This will increase our awareness of the frequency band occupancy.

5. Test results

Field tests were carried out to demonstrate the feasibility of our approach. Test measurements were performed to collect data for the reference feature vectors, and to test the performance of classifier. Measurements were performed outdoors in a parking area. The environment of parking area is easy to control; it includes no obstacles close to transceivers and no active radio interference sources which may disturb the experiment results. During the measurement we aimed to create disturbances typical for industrial environment such as metal machinery and strong radio interference. In the tests both transmitter and receiver antennas were placed on the camera stands on such height that the line-of-sight signal would hit a metal part of the car.

During the tests a car was used to create the blocking effect, and WLAN 802.11b base station was used to create an interference signal. The measurements data were recorded by the SDR and analyzed with Matlab tools. The goal of the measurements was to collect typical data set for each class.

5.1. Measurements results

All six data sets recorded with SDR are first statistically analyzed to find the mean, min, max and standard deviation range of the recorded raw samples, see Table 2. The more complicated the situation is, such as in CLASS 6, the larger the variance of the values is. Though, the testing results show that the large variance of a single feature vector value does not affect the classification results. Comparing the feature values of LOS and NLOS channel states (CLASS 1 and CLASS 4), the most significant difference is in a -values; the a –value in NLOS case in only one third of the

Table 2
Feature vector characteristics in the training sets.

CLASS 1: LOS	Mean	Min	Max	Std
a	11973	11806	12348	154.19
sigma	463.7	448	476	8.99
a_std_err	6.71	6.5	6.9	0.13
sigma_std_err	4.76	4.6	4.9	0.09
f1	1.38	1.08	1.61	0.17
ΔF	1.48	1.1	2.03	0.4
ΔT	0.001426	0.001426	0.001426	0
CLASS 2: LOS + WI	mean	min	max	std
a	12242	12133	12331	100.5
sigma	1321.7	1242	1383	72.3
a_std_err	19.3	18.2	20	0.9
sigma_std_err	13.7	12.8	14.3	0.8
f1	1.2	0.5	1.63	0.6
ΔF	1.68	1.37	2.22	0.4
ΔT	0.0022	0.0016	0.0025	0.0005
CLASS 3: LOS + SI	mean	min	max	std
a	12196	12063	12281	94.07
sigma	3638	3189	3874	318.7
a_std_err	55.8	48	60	5.6
sigma_std_err	39.5	34	42.5	3.9
f1	0.54	0.53	0.55	0.008
ΔF	2.9	2.34	4.12	0.9
ΔT	0.0032	0.0014	0.0053	0.0017
CLASS 4: NLOS	mean	min	max	std
a	3730	3520	3940	162.7
sigma	417.5	402	436	10.2
a_std_err	6.13	5.9	6.4	0.16
sigma_std_err	4.3	4.1	4.5	0.11
f1	1.6	1.43	1.84	0.13
ΔF	1.09	0.8	1.5	0.2
ΔT	0.001426	0.001426	0.001426	0
CLASS 5: NLOS + WI	mean	min	max	std
a	3768	3629	3909	106.3
sigma	1607	1459	1752	146.5
a_std_err	28.7	23.6	33.7	4.3
sigma_std_err	20.7	17.1	24.4	3.1
f1	0.65	0.53	0.9	0.17
ΔF	3.4	2.82	3.96	0.4
ΔT	0.0025	0.002	0.003	0.0005
CLASS 6: NLOS + SI	mean	min	max	std
a	3981	3630	4297	335
sigma	2736	2380	3400	576
a_std_err	71.8	53	104	28.4
sigma_std_err	46.7	38.3	63.6	14.6
f1	0.54	0.53	0.54	0.006
ΔF	3.8	3.15	4.15	0.5
ΔT	0.0028	0.0027	0.00303	0.0002

a-value in LOS case. Then again in the presence of the interference both in LOS and NLOS cases (CLASSES 2-3 and CLASSES 5-6), the *sigma* value increases considerably; the stronger the interference is the more the *sigma* –value escalates. The changes of the feature values obtained from the frequency domain (f, Δf and Δt) are not so obvious. The Δf value is smaller in the NLOS case than in the LOS case due to the decreased power of the received signal. The Δt value is the same in the LOS and NLOS cases, because the decreased power of the signal does not affect the duration of the received signal, but in cases of interference the Δt value grows due to the interference signal overlapping with our signal, which can be seen in the spectrogram as two RF objects overlying. The f value is also altered in the case of interference for the same reasons as the Δt value; the stronger is the interference the more is the RF object of our signal in the spectrogram is affected by the RF object of the interference signal. The mean values of measurement data are used as a training set for each class to compose the reference classes. The feature vectors of each class are normalized to the nominal feature vector. For example, the normalized feature vector of Class 2 is

$$F_{class2} = \begin{bmatrix} a/a_n \\ \sigma/\sigma_n \\ a_{err}/a_{errn} \\ \sigma_{err}/\sigma_{errn} \\ f/f_n \\ \Delta f/\Delta f_n \\ \Delta t/\Delta t_n \end{bmatrix} = \begin{bmatrix} 12242/11973 \\ 1322/464 \\ 19.3/6.7 \\ 13.7/4.8 \\ 1.2/1.38 \\ 1.68/1.48 \\ 0.0022/0.001426 \end{bmatrix} \approx \begin{bmatrix} 1 \\ 2.9 \\ 2.9 \\ 2.9 \\ 0.9 \\ 1.1 \\ 1.5 \end{bmatrix}$$

The normalized feature vectors for all classes are presented in Table 3. The CLASS 1 is the nominal case; the data transmission link is not affected by any disturbance. The CLASSES 2-3 and CLASSES 5-6 represent the cases, where the data transmission is disturbed by the weak or strong interference signal. Here, weak means that the interference source is relatively distant from our radio receiver, and strong that it is close to our radio receiver. The overlapping interference signal is causing strong changes in sigma, a_err and sigma_err -values as well as in f, Δf and Δt –values. The track of feature values changes during the channel state transition is straightforward to deduce (increases/decreases), but the relative volume of the change is dependable on the transmission parameters and environment, and need to be calibrated either by performing real tests or by deriving them mathematically, or both. In this work the reference feature vectors for each class were obtained from the training measurements results.

Table 3
Normalized feature vectors of reference classes.

Feature/CLASS	CLASS 1	CLASS 2	CLASS 3	CLASS 4	CLASS 5	CLASS 6
a	1.0	1.0	1.0	0.3	0.3	0.3
sigma	1.0	2.9	7.8	0.9	3.5	5.9
a_err	1.0	2.9	8.3	0.9	4.3	10.7
sigma_err	1.0	2.9	8.2	0.9	4.3	9.7
F	1.0	0.9	0.4	1.2	0.5	0.4
ΔF	1.0	1.1	2.0	0.7	2.3	2.6
ΔT	1.0	1.5	2.2	1.0	1.8	2.0

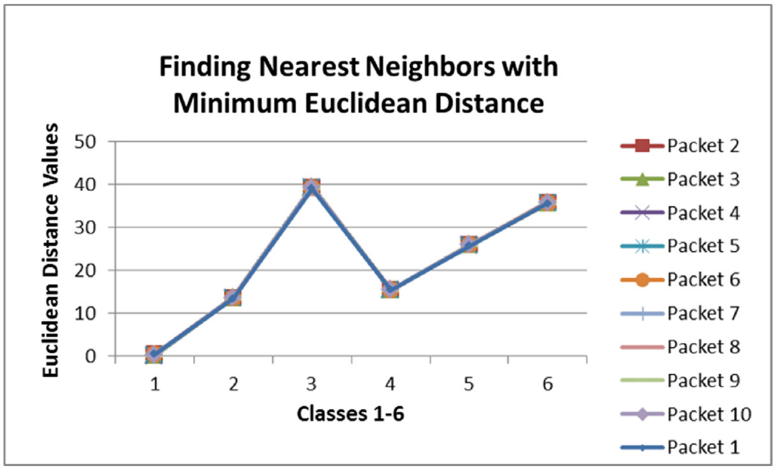

Fig. 15. Graphical results of classification of the received data packet: LOS case (CLASS 1).

5.2. Classification results

During classification of the channel state, the received packet captured by SDR is processed, and features are extracted. The data set used for testing the performance of classifier is not the same as the data set which was used to compose the reference classes; both data sets were recorded in the same environment, but then divided for different purposes. For example, feature vector of one received random data packet is:

$$F_{data} = \begin{bmatrix} 3715 \\ 410 \\ 6 \\ 4.2 \\ 1.82 \\ 0.93 \\ 0.001426 \end{bmatrix}$$

The first four values of the feature vector were obtained from the PDF of the received signal (*a, sigma, a_err, sigma_err*), and the last three parameters from the spectrogram analysis (f, Δf and Δt). The formed feature vector is then normalized to the nominal feature vector:

$$F_{data_n} = \begin{bmatrix} a/a_n \\ \sigma/\sigma_n \\ a_{err}/a_{err\,n} \\ \sigma_{err}/\sigma_{err\,n} \\ f/f_n \\ \Delta f/\Delta f_n \\ \Delta t/\Delta t_n \end{bmatrix} = \begin{bmatrix} 3715/11973 \\ 410/464 \\ 6/6.7 \\ 4.2/4.8 \\ 1.82/1.38 \\ 0.93/1.48 \\ 0.001426/0.001426 \end{bmatrix} \approx \begin{bmatrix} 0.3 \\ 0.9 \\ 0.9 \\ 0.9 \\ 1.3 \\ 0.6 \\ 1 \end{bmatrix}$$

Classification is achieved by employing the similarity measure between the vector F_{data_n} obtained from the received data and a training set $CLASS_i$ ($i=1;2;3;4;5;6$). Figs. 15–20 illustrate the results of application of nearest neighbor classification. The feature vectors calculated from the received packets are compared with the reference vectors and the Minimum Euclidean Distance is calculated. The weight vector was used during the calculations to emphasize the meaning of the a-value changes, and thus highlight the transitions from the LOS to NLOS channel state, and otherwise.

The test results of classification of data packets recorded during the LOS channel state are shown in Fig. 15. The Euclidean distance was calculcated for the features vectors obtained from the ten random received data packets and reference feature vectors which represent the Classes 1–6. The results show that minimum distance is achieved between the feature vectors and CLASS 1 for all packets. These particular data packets were disturbed neither by the blocking objects nor by the radio interferences.

In Fig. 16 the results of classification of data packets recorded under the LOS channel state in the presence of the weak radio interference (WLAN 802.11b) in four different situations are shown. In all situations the WLAN signal was disturbing the received data packet, but the strength of the disturbing signal varied from very weak to weak (30–50% of the received signal strength). Here, the minimum classification distance is achieved between the feature vectors and CLASS 2 for all packets. To decrease the bit-error-rate and prevent the packets loss due to radio interference the algorithm for adaptively increasing the transmission power or changing the frequency channel could be applied in this case [26].

In Fig. 17 the results of classification of data packets recorded under the LOS channel state affected by a strong radio interference (WLAN 802.11b) in four different situations are presented. Also here, in all situations the strength of the disturbing signal varied (from 50–80%), but was classified as strong. The results show that minimum classification distance is achieved between the feature vectors and CLASS 3 for all packets.

The results of classification of data packets recorded under the NLOS channel conditions is shown in Fig. 18. The Euclidean distance was calculcated for the features vectors obtained from the ten random received data packets and reference feature vectors which represent the Classes 1–6. The results show that minimum distance is achieved between the feature vectors and CLASS 4 for all packets.

In Fig. 19 the results of classification of data packets recorded under the NLOS channel state disturbed by the weak radio interference (WLAN 802.11b) in four different situations are presented. In all situations the WLAN signal

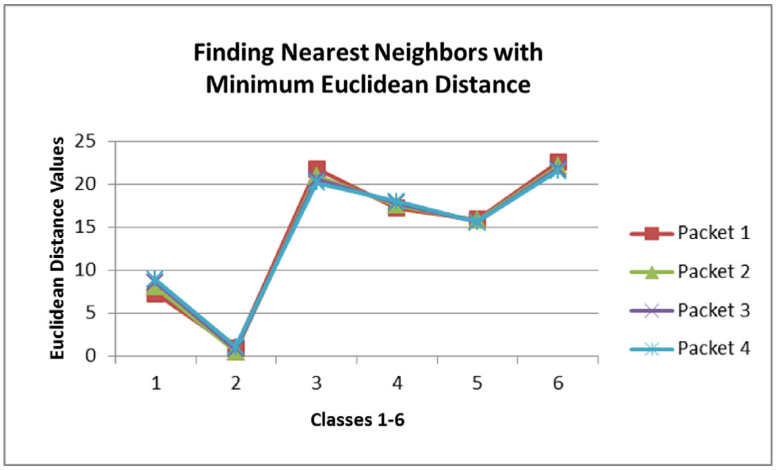

Fig. 16. Graphical results of classification of the received data packet: LOS+Weak Interference case (CLASS 2).

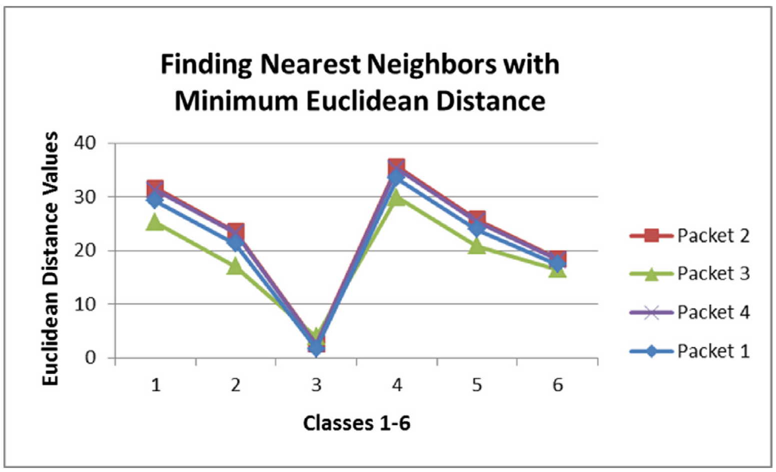

Fig. 17. Graphical results of classification of the received data packet: LOS+Strong Interference case (CLASS 3).

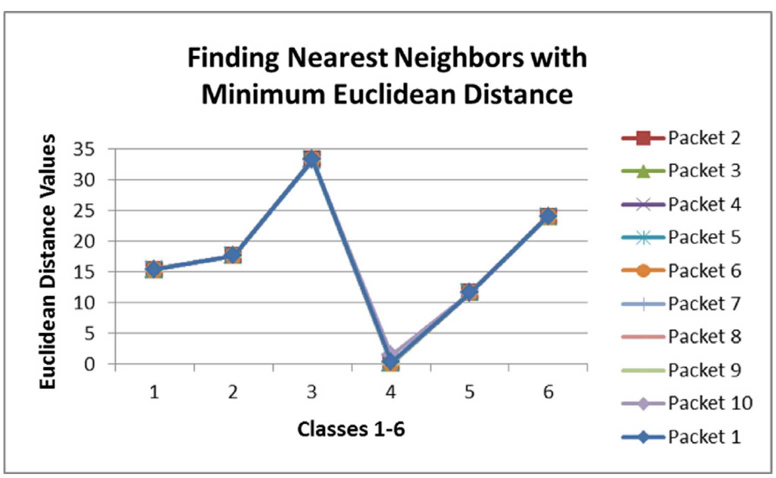

Fig. 18. Graphical results of classification of the received data packet: NLOS case (CLASS 4).

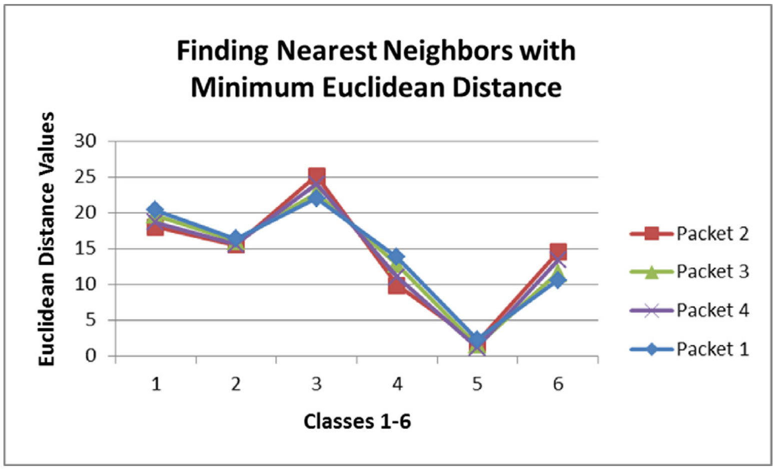

Fig. 19. Graphical results of classification of the received data packet: NLOS + Weak Interference case (CLASS 5).

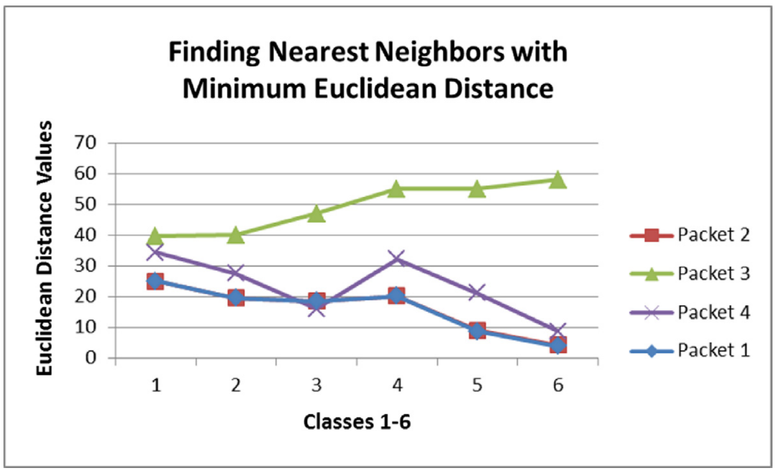

Fig. 20. Graphical results of classification of the received data packet: NLOS + Strong Interference case (CLASS 6).

was disturbing the received data packet, but the strength of the disturbing signal varied from very weak to weak (30–50% of the received signal strength). The results show that minimum distance is achieved between the feature vectors and CLASS 5 for all packets.

In Fig. 20 the results of classification of data packets recorded under the NLOS channel state disturbed by the strong radio interference (WLAN 802.11b) in four different situations are shown. In all situations the WLAN signal was disturbing the received data packet, but the strength of the disturbing signal varied from strong to vary strong (50–120% of the received signal strength). This CLASS is the most challenging to classify since the data packets are strongly disturbed, and some of them are barely recognizable. The results show that Packet 3 could not be classified, but with other data packets, the minimum distance was achieved between the feature vectors and CLASS 6. In case of Packet 3, the interference signal was stronger that in all other cases. Here, the strength of our signal was less that the interference signal and thus, the feature vector was obtained for the interference signal and not for our data packet. In cases of the interference signal is being stronger that our signal, our data packet cannot be classified, but with spectrogram analysis we are still aware of the situation, and the problem can be resolved by increasing the transmitting power, or by changing the transmitting channel.

6. Discussion and future work

The transmission links between the nodes in wireless sensor networks should be reliable and secure even in extreme conditions. Changes in external environmental factors and radio conditions along with the multipath propagation phenomena lead to unpredictable signal fading and may cause poor performance in a communication system. Identification of transmission problem will help us to choose the right actions to overcome the degradation of link quality.

We have described a signal analysis and classification procedure to detect and identify radio disturbances. Our main focus is on industrial environments or other similar

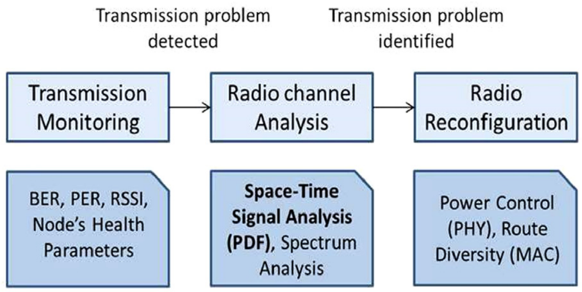

Fig. 21. WIreless SEnsor NEtwork MOnitoring & management tool WISE-NEMO.

challenging environments like machine maintenance halls in facilities. The PDF based radio channel analysis method can be used to detect passive radio disturbances, also when RSSI and BER data are not available. The spectrum analysis brings for the disturbance classification additional valuable information on the radio frequency channel congestion state. The performed tests showed that our analysis methods are applicable for the radio disturbance detection, identification and classification. Next step of our work is to verify the functionality of our approach by performing more extensive tests in real industrial environments. This disturbance classification is planned to be the basis of the Wireless Sensor Network monitoring and management tool, WISE-NEMO, which is being developed to improve the reliability of radio transmission in harsh environments. The system functionality is shown in Fig. 21.

The Monitoring Tool will be used to monitor the link quality between the nodes, the health parameters of each node, and RSSI value if needed. The Radio Channel Analysis Tool aims to predict and identify radio transmission problems and provide channel condition information to the upper layers. The Radio Reconfiguration Tool is used to manage the wireless network parameters based on the information received from the Radio Channel Analysis Tool, which is in turn activated by Monitoring Tool in case of transmission problems.

The WISE_NEMO diagnostic tool is planned to be integrated with the normal functionality of a WSN network and provide additional intelligence to manage the WSN network and improve the performance. Our goal is to implement the WISE-NEMO tool as independent software package which can be ported to any sensor node. The next step in our work will be implementing the Radio Analysis Tool on the Linux machine abandoning the Matlab environment. This will require the optimization of the code and algorithm's lightening which in turn will get us closer to our final goal; porting all code to the sensor nodes. Not all sensor nodes in a network will need the Radio Channel Analysis Tool to be ported, only the ones responsible for reliable data transmission (=sink nodes).

7. Conclusions

In this paper we presented the effects of environmental disturbances on the quality of the transmitted signals in wireless sensor network. The harsh signal propagation conditions in such environments as factory, machine maintenance halls, market halls etc., may cause the substantial degradation of wireless link performance, and lead to loss of time and money. We studied the physical phenomena behind the transmission problems, and came up with signal analysis methods that help to identify the radio channel disturbances; PDF based method and Spectrogram based method.

The Probability Density Function (PDF) channel state analysis method is based on the idea that changes in statistical properties of the received signal are strongly correlated with the transitions of the channel states. Especially for the cases when the errors are too severe for successful demodulation of the signal, and RSSI or BER values cannot be accessed due to the lost packets, the PDF parameters can provide the needed information on the current channel state and possible disturbance objects. The spectral analysis is based on calculation the spectrograms of the received signal and obtaining the statistical information of the radio interferences with image analysis tools. Combining the results of signal analysis in time and frequency domains we constructed a classifier to classify the radio channel disturbances. Our final goal is to develop a solution which will not include calculations requiring much computing power since the energy consumption of the low-powered sensor nodes must be considered.

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