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Design of a Low Complexity Interference Detector for LPWA Networks

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Abstract—Many Internet of Things applications are deployed over shared ISM (Industrial, Scientific, Medical) radiofrequency spectrum bands. With the recent development of Low Power Wide Area (LPWA) wireless networks, the probability of interference and frame collisions has significantly increased. In this context, real-time interference monitoring is essential to provide precise information for network planning, base-station installation site selection, congested area detection, etc. This work presents a novel, low complexity interference detector for mobile LPWA nodes that is designed using a set of experimental data acquisitions. A first classifier is used to detect the presence of interference and shows a detection accuracy of 94%. If interference is detected, a second classifier is used to classify the interference’s relative strength into ten classes with a correct classification rate up to 97%. The detector also provides an estimation of the interference’s duration with an average relative error of 2% for medium to strong interference levels.

Index Terms—Internet of Things (IoT), Low Power Wide Area (LPWA), Interference Detection, Classification, Channel State Information, Channel Analysis Signal, Interference Presence Indicator, Ultra-Low Power Transceivers.

I. INTRODUCTION

The massive deployment of Internet of Things (IoT) applications requires an efficient use of the scarce radiofrequency (RF) spectrum. Current IoT wireless communication protocols are deployed either over cellular networks, using e.g. the NB-IoT protocol, or in shared ISM (Industrial, Scientific, Medical) frequency bands. While cellular systems offer spectrum availability guarantees, spectrum sharing in ISM bands is only enforced through coexistence rules. Historically, ISM bands were used for short-range communication systems with inherently low mutual disturbance probability. The recent development of Low Power Wide Area (LPWA) wireless networks deployed over these same ISM bands has significantly increased the probability of interference for two reasons: First, the order of magnitude greater range increases the probability of co-located networks. This is true for both same-type and for different-type co-located LPWA communication systems (e.g. networks such as LoRa, Sigfox, IEEE 802.15.4/g/k, MYOTY, and so on, that are all deployed in the same ISM bands). Second, the increase in range implies that extremely low payload bit-rates must be used. Thus, the resulting very long frame on-air times increase the probability of collisions [1]. For example, recent research has shown that LoRa networks based on an ALOHA medium access protocol quickly become interference limited when node density increases, thus necessitating new interference-related performance metrics [2].

The present work focuses on the design of a low complexity, real-time interference detector for LPWA transceivers. Our objective is that, every time the transceiver correctly receives a frame, the detector simultaneously outputs information on the presence or absence of interference, and, if applicable, information concerning the interference’s relative strength and duration. This interference-related information gathered by the wireless node can be used in many ways. An obvious application is network planning and selection of base station installation sites. Indeed, since the information is gathered by the nodes themselves, the network installer will dispose of very precise information concerning congested areas and be able to optimize the base station placement accordingly. Alternatively, interference-related information can be used by adaptive transmission protocols that aim to optimize the physical layer signalling rate in view of either improving throughput or saving energy when favourable RF propagation conditions have been detected. Detailed per-frame interference-related information can be exploited to fine-tune channel adaptation strategies.

This paper focuses on the design of an information-rich interference detector for ultra-low power transceivers typically employed in LPWA IoT applications. To comply with the extremely tight energy budget of these applications, our detection mechanism avoids the transmission of dedicated frames or symbols and avoids burdening the wireless node’s processing capacity with algorithms that require high computational complexity. In addition, to ease the development of new MAC or network-level adaptive communication protocols, the information delivered by the detector is clear, simple to use, precise, and reflects the instantaneous propagation conditions.

To address this challenge, our strategy is to exploit channel-related information contained within the received signal itself. To this end, a channel analysis signal (CAS) is defined in the digital base-band (DBB) processing part of the wireless receiver. The CAS is then processed to calculate two features per frame and which are used as inputs to classifiers. For each correctly received frame, the proposed detector is able to detect the presence or absence of interference, and if required
provide an indication of the relative strength and duration of the interference. While the work described below is based on the LECIM FSK physical layer of the IEEE 802.15.4-2015 standard, the approach can easily be generalized to other LPWA communication standards.

The contributions of this paper are:
- A low complexity single-frame interference presence indicator (IPI) for LPWA transceivers based on a mono-feature classifier and with 94% accuracy;
- A 10-level interference relative-strength classifier with an accuracy up to 97% built upon two minimal complexity features;
- An interference duration estimator;
- An experimentation-based classifier design methodology.

This paper is structured as follows: relative work is discussed in Section II, followed by a presentation of the experimental platform and data collection in Section III. The design methodology for our interference detector and interference strength estimator is proposed in Sections IV and V, respectively. Finally, experimental results are discussed in Section VI.

II. RELATED WORK

Interference detection mechanisms have been developed and employed in the field of wireless communications for many different applications and in many differing contexts. In particular, blind interference detection techniques have been extensively investigated for cognitive radios (CR) where transceivers must compete for spectrum use while avoiding the interference caused by other communication systems sharing the same frequency band. For example, a pilot-aided interference detection method was proposed in [3] to allow robust orthogonal frequency division multiplexing (OFDM) signal detection in the presence of in-band interference. A pilot-free interference estimation technique was proposed in [4] for similar OFDM-based cognitive radios. More generally, many different spectrum sensing techniques have been developed in the cognitive radio context, for example using hidden Markov modeling [5].

Interference detection techniques have also been proposed for ISM radio communications where many different propagation schemes share the same spectrum. For example, for the 2.4 GHz ISM band, an approach to detect and minimize the impact of interference caused by Bluetooth packets to IEEE 802.11g OFDM-based transmissions is proposed in [6]. The authors exploit the OFDM demodulation algorithm to extract useful information from the symbol magnitude for each sub-carrier obtained after the demodulation FFT. In [7] and [8], the authors propose a PHY-independent interference detection mechanism based on the detection of abrupt changes in a BER estimate calculated for each received symbol. While very efficient, this approach requires that a large number of per-symbol confidence data, gathered within the DBB, be transferred to the upper-layer protocol layers for processing. Alternatively, the authors in [9] propose a very simple interference detection mechanism based on the analysis of the distribution of coded bit errors within a frame. Unfortunately, this approach implies that frame data be necessarily encoded and limits interference detection to frames received at low SNR, since bit errors must absolutely be present.

Finally, in [10], demodulated chip error patterns of 2.4 GHZ IEEE 802.15.4 transmissions are analyzed to infer the wireless link conditions, both to uncover the reasons for frame loss and also to determine whether interference is present, even when no frame is dropped. The extensive experiments performed by the authors focus on the transitional region of a wireless link which is characterized by highly volatile link conditions and thus in which received signal power is barely above the receiver’s sensitivity. While a channel classification heuristic is proposed by the authors, little effort is committed to the explanation of observed error patterns with respect to the channel conditions. Compared to the above related work, our work focuses on LPWA transmission schemes which, with respect to OFDM signalling schemes, are generally of lower complexity. Consequently, we focus on low complexity interference detection mechanisms.

III. EXPERIMENTAL PLATFORM AND DATA COLLECTION

Since commercial off the shelf (COTS) devices do not allow access to DBB algorithms, a software defined radio is necessary for experimentation. The aim of the experiments is to gather realistic data for channel analysis, IPI choice, and
data-set collection for classifier training and validation. After
the presentation of the SDR-based experimental platform, a
brief description of the IEEE 802.15.4-2015 LECIM FSK PHY
standard is given, and the labelled data-set collection
procedure is described.

A. SDR-Based Experimental Platform

The SDR platform is composed of three universal software
radio peripherals (USRP) located in a 5 m × 4 m room. The
three USRP are programmed to support the LECIM (Low
Energy Critical Infrastructure Monitoring) FSK PHY of
the IEEE 802.15.42015 standard [11]. The first USRP is used
as transmitter (Tx), the second as interference source (Ix)
and the last as receiver (Rx). The USRP are N210 models
[12] from Ettus Research with WBX [40 MHz - 2200 MHz]
daughter-board. All experiments employ a carrier within the
869.3-869.4 MHz ISM band which is not limited by duty
cycle in France if transmissions are below 10 mW. Attenuators
are inserted between each emitting USRP output SMA port
and the half-wave dipole antenna which allows us to limit
the transmission range to approximately two meters which is
necessary for leading controlled experiments. Each USRP is an
RF front-end which performs up/down frequency conversion,
analog filtering and DA/AD conversion. The USRPs are driven
by GnuRadio through a Gbit Ethernet connection to a PC. The
transmission and reception DBB algorithms are implemented
in MATLAB which provides/receives complex baseband data
at a sample rate of 300 kHz to/from GnuRadio.

B. IEEE 802.15.4-2015 LECIM FSK PHY

Since FSK-based modulations are extremely common in
ultra-low power communication systems, the experiments
described in this work are based on the IEEE 802.15.4-2015
LECIM FSK PHY which extends the range of conventional
IEEE 802.15.4 physical layers through spread spectrum tech-
niques [13]. This physical layer employs the GMSK modula-
tion at 37.5 kchip/s with optional direct-sequence modulation
spreading factors of 2, 4, 8 or 16. The frames generated
for the experiments are composed of a 4-byte preamble, 3-
byte start of frame delimiter (SFD), 2-byte header, 1250-
byte payload and 2-byte cyclic redundancy check (CRC)
code. The 2-byte CRC is based on the generator polynomial
\( G(x) = x^{16} + x^{15} + x^2 + 1 \). Convolutional 1/2 rate forward error
code with constraint length \( K = 7 \), optional in the standard,
is used in all of our experiments along with a spreading factor
of 4. Including coding and frame synchronization overheads,
the resulting frames have an on-air time of 2.15 seconds.

A digital baseband receiver able to detect FSK-modulated
frames was designed and is presented in Fig. 1. Indeed, with
\( A[k] \) defined as the complex output of the channel filter (FIR2),
it can be shown that \( x[k] = 3(A[k] \times A^*[k-1]) \) is a good ap-
proximation of the instantaneous frequency. Synchronization
and SFD detection is handled by blocks in blue which perform
a correlation with the known preamble sequence. These blocks
calculate the optimal decimation moment thus allowing the
sample stream to be decimated by a factor 8. Demodulation
is performed by yellow blocks while green blocks compute
the channel analysis signal (CAS) as well as the features
used by our interference detector (DDSL and ADA) which
are described below.

C. Labelled Data Collection

The \( Tx \) power is chosen such that the received signal is
approximately 15 dB above the \( Rx \) sensitivity. This relatively
high SNR level is typical of real-world deployments since
it allows for a comfortable fading margin. Labelled data-
data-sets are produced by two experiments. In the first one, 300
frames are acquired in an undisturbed RF environment and
labelled accordingly. In the second experiment, an interference
environment is generated using \( Ix \) as an interference source.
The interference is an IEEE 802.15.4-2015 LECIM FSK PHY
signal emitted in the same frequency band as that of \( Tx \). The
emission duration of \( Ix \) is randomly selected in the range
[30; 1700] ms. To account for variable interference levels, ten
interference environment data-sets are collected, each obtained
using a different baseband signal amplitude ‘a’ applied to the
samples transmitted by \( Ix \). Values of ‘a’ are selected from 0.1
to 1 with a step of 0.1 in order to cover a 20 dB dynamic
range for received interference power. Thus, values of ‘a’ close
to 0.1 and 1 respectively correspond to low and high levels
of interference. The \( Ix \) USRP gain is configured such that,
when \( a = 1 \), frames received by \( Rx \) contain bit errors
which are corrected by the forward error correction decoding
process. In this configuration, the measured signal to co-
channel interference ratio (CIR) is approximately 4 dB, which
is consistent with the expected sensitivity of an FSK-based
spread-spectrum receiver. In all of these experiments, only
CRC-valid frames were analyzed and collected for feeding
the classifier training and evaluation steps. For each value of
‘a’, a set of 100 frames was acquired to which was assigned
the label ‘disturbed’ as well as the label ‘l’, with \( l = 10 \times a \). Thus
a total of 1000 frames was collected in this second experiment.

IV. INTERFERENCE DETECTOR DESIGN METHODOLOGY

In this section, the proposed channel analysis signal (CAS)
and interference presence indicator (IPI) are presented. Then,
the methodology for designing the interference detector and
interference duration estimator is detailed.

A. Channel Analysis Signal (CAS)

In [7], [10] and [8], the receiver’s digital baseband (DBB)
is instrumented to compute channel analysis signals (CAS) for
channel diagnostics. Similarly, the CAS proposed in this work
is extracted directly from the receiver’s DBB. In our case,
the CAS corresponds to the (averaged) absolute value of the
input signal of the soft de-spreading block, \( x[k] \). The CAS is
thus proportional to the probability that the received symbol
is correct. More formally, the CAS is defined as:

\[
CAS_k = \frac{1}{\text{win}} \sum_{j=0}^{\text{win}-1} |x[k - j]|.
\]  

(1)
In order to smooth the signal $|x[k]|$ and to highlight the interference footprint, a moving average (MA) over a computation window of $\text{win}$ samples is used. The choice of $\text{win}$ must be compatible with the shortest detectable interference duration. For the given $37.5$ kHz decimated sample rate, a value of $\text{win} = 1000$, corresponding to $T_{\text{win}} = 26.6$ ms, is selected. Finally, we define $\text{CAS} = [\text{CAS}_1, ..., \text{CAS}_N]$ as the channel analysis signal, where $N$ is the total number of samples in the frame. Fig. 2 shows an example of the CAS calculated for a frame received in the presence of interference. In this figure, we can easily recognize the temporal footprint of the disturbance corresponding to the presence of a strong interference. The computation of the CAS signal only requires a modulus operation and a moving average filter allowing this approach to be easily generalized to all FSK-based IoT standards (e.g. Sigfox, Bluetooth). Other signalling schemes can similarly be addressed by reusing the soft demodulator input signal of the corresponding DDB receiver.

B. Interference Presence Indicator (IPI)

Our aim is to find a single-value, low complexity IPI that is able to accurately extract the interference footprint information from the CAS. To this end, we propose to use the DDSL which measures the Difference between the averaged Disturbance and Signal Levels. The DDSL summarizes into one numerical measures the Difference between the averaged Disturbance and Signal Levels. The DDSL summarizes into one numerical measure the Difference between the averaged Disturbance and Signal Levels. The DDSL summarizes into one numerical measure the Difference between the averaged Disturbance and Signal Levels. The DDSL summarizes into one numerical measure the Difference between the averaged Disturbance and Signal Levels. The DDSL summarizes into one numerical measure the Difference between the averaged Disturbance and Signal Levels. The DDSL summarizes into one numerical measure the Difference between the averaged Disturbance and Signal Levels. To this end, we propose to use the DDSL, which is defined as an undisturbed frame wrongly classified as 'disturbed'. A true positive is defined as a frame with interference correctly classified as 'disturbed'. A false positive is defined as an undisturbed frame wrongly classified as 'disturbed'. The performance of an ideal detector is determined by a $100\%$ TP and a $0\%$ FP, corresponding to the point $\{\text{FPR}(\lambda), \text{TPR}(\lambda)\} = \{0, 1\}$. The optimum value of $\lambda$ is found by choosing the point on the ROC curve with the minimum distance from the ideal point $(0,1)$. The minimizing equation is described by (3).

$$
\lambda_{opt} = \arg \min_{\lambda} \left\{ \left( \text{FPR}(\lambda)^2 + (1 - \text{TPR}(\lambda))^2 \right)^{1/2} \right\} \quad (3)
$$

D. Interference Duration Estimator

Once a frame is detected as ‘disturbed’, the duration of the interference can be calculated from the CAS signal. The estimated interference duration $\hat{\tau}$ is equal to the number of samples contained in the $I\text{CAS}_k$ set, $P$, divided by the decimated sample rate ($F_{s,d}$). $\hat{\tau}$ is computed by (4).

$$
\hat{\tau} = \frac{P}{F_{s,d}} \quad (4)
$$

Alternatively, an estimation of the relative interference duration, defined as $P/N$, could also be calculated. Depending on how the interference detector data is exploited (e.g. network planning or adaptive protocol design), one or the other information might be more useful.

V. Interference Strength Estimator

In this section, each frame previously classified as ‘disturbed’ is further classified into one of ten classes, $C = 1, 2, ..., 10$, corresponding to the previously defined labels $l = 1, 2, ..., 10$ related to the interference strength.

A. Average of the Disturbance Area

While only DDSL is needed for the interference detector, the 10-level classification requires the use of an additional feature, the average of the disturbance area (ADA), to perform at its best. ADA gathers additional details concerning the temporal footprint of the interference. ADA is defined as the area between the $I\text{CAS}_k$ and the $\mu_{\text{CAS}}$ curves (cf. Fig. 2) divided by the number of times the average, $\mu_{\text{CAS}}$, is intersected by the CAS$_k$ signal. The computation of ADA is described by (6). The calculation of ADA requires only a few mathematical operations since $\frac{1}{P} \sum_{k=1}^{P} I\text{CAS}_k$ and $\mu_{\text{CAS}}$ have been previously computed. Also, the comparisons used previously to separate the $I\text{CAS}_k$ and $U\text{CAS}_k$ sets can be simultaneously used to compute the denominator of (6).

The DDSL is used to classify each frame into two classes: ‘undisturbed’ and ‘disturbed’, with a detection threshold, $\lambda$. The ‘disturbed’ class is selected when DDSL is higher than $\lambda$. The value of $\lambda$ is learned using a training data set from an empirical ROC curve. The ROC curve displays the true positive rate as a function of the false positive rate for all possible values of $\lambda$. A true positive is defined as a frame with interference correctly classified as ‘disturbed’. A false positive is defined as an undisturbed frame wrongly classified as ‘disturbed’. The calculations of ADA are performed for each frame.

$$
S_k = \text{sgn}(\text{CAS}_k - \mu_{\text{CAS}}) \quad (5)
$$

$$
\text{ADA} = \frac{2P(\mu_{\text{CAS}} - \frac{1}{P} \sum_{k=1}^{P} I\text{CAS}_k)}{\sum_{k=2}^{N} |S_k - S_{k-1}|} \quad (6)
$$

As an example, the temporal footprint of the interference caused by the emission of $I_x$ in Fig. 2, corresponds to the previously defined label $I_x$. ADA is defined as the average of the distance area (ADA), to perform at its best. ADA gathers additional details concerning the temporal footprint of the interference. ADA is defined as the area between the $I\text{CAS}_k$ and the $\mu_{\text{CAS}}$ curves (cf. Fig. 2) divided by the number of times the average, $\mu_{\text{CAS}}$, is intersected by the CAS$_k$ signal. The computation of ADA is described by (6). The calculation of ADA requires only a few mathematical operations since $\frac{1}{P} \sum_{k=1}^{P} I\text{CAS}_k$ and $\mu_{\text{CAS}}$ have been previously computed. Also, the comparisons used previously to separate the $I\text{CAS}_k$ and $U\text{CAS}_k$ sets can be simultaneously used to compute the denominator of (6).
B. 10-Level Interference Classification

The ten-level interference classifier uses ten multidimensional centroids. Each frame $i$ is represented by a set of 2 features $f_i = [DDSL_i, ADA_i]$. In the feature space, each class $C$ is represented by its centroid and dispersion. The centroid is defined as $\mu_C = [DDSL\mu_C, ADA\mu_C]$ corresponding to the mean values of DDSL and ADA for each class. The dispersion of each class is represented by $V_C = [DDSL\sigma_C^2, ADA\sigma_C^2]$, the variance values of DDSL and ADA. The values $\mu_C$ and $V_C$ are learned for each class using its corresponding learning data set. For a test frame $f_i$, the Mahalanobis squared distance between $f_i$ and the centroid of class $C$, $D_{i,C}$, is calculated for each class using (7). The covariance matrix of each class is considered to be diagonal.

$$D_{i,C} = (f_i - \mu_C)(\text{diag}(V_C))^{-1}(f_i - \mu_C)^T$$

(7)

$$\mathcal{C}_i = \arg\min_{C} \{D_{i,C}\}$$

(8)

The class assigned to $f_i$, $\mathcal{C}_i$, where $\mathcal{C} \in \mathbb{N}^{[1,10]}$, is the class whose $D_{i,C}$ is the smallest of the ten computed. Note that, for each class, the computation of (7) requires only 2 subtractions, multiplications and divisions and one sum.

C. Classifier Performance

To evaluate the performance of this classifier, a correct classification rate can be computed for different requirement levels. The $\gamma$-correct classification rate, $R_{\pm\gamma}$, is given by (9), counting as correct any frame classified into the $\gamma$ adjacent classes. In (9), $[\ldots]$ are the Iverson brackets, $[B]$ is defined to be 1 if $B$ is true, and 0 if it is false and $N_T$ is the number of frames contained within the test set.

$$R_{\pm\gamma} = \frac{1}{N_T} \sum_{i=1}^{N_T} \left\lvert \left\lfloor \mathcal{C}_i - l_i \right\rfloor \leq \gamma \right\rceil$$

(9)

VI. RESULTS

A. Disturbed versus Undisturbed Classifier

A learning set made of 150 ‘undisturbed’ frames and 150 ‘disturbed’ (i.e., ‘interference’) frames randomly chosen among the 1000 samples labelled as ‘interference’ (cf. section III-C) is created. This set is used to build the ROC curve displayed in Fig. 3. Using (3), the optimum operating point (FPR=0.04, TPR=0.82) is found with $\lambda_{opt} = 3.4 \times 10^{-3}$. Fig. 4 shows clearly that it is possible to use DDSL to discriminate ‘disturbed’ frames from ‘undisturbed’ ones, with $\lambda_{opt}$ as a good boundary. The presence of some error points in the DDSL distribution is explained by the fact that the ROC curve never reaches the ideal point (0,1) meaning that the classifier is not flawless. Next, classifier performance is evaluated from a test set consisting of 300 labelled frames (150 frames per class) different from those contained in the learning set. The detector satisfies a correct detection rate of 94%.

B. Interference Duration Estimator

To validate and compute the interference duration estimator performance, an additional 400 frames are collected, this time with controlled interference duration. In order to generate a correct validation data-set, frames transmitted by $Ix$ are set to have on-air times of 0.4 s separated by 0.4 s pauses while $Tx$ transmits 2 second frames separated by 2 second pauses. In this way, we are certain that each acquired frame is impacted by at least 0.8 seconds of interference. The extraction of the $CAS_k$ set is slightly modified to include only samples corresponding to a complete interference signal. To emulate various levels of interference, randomly generated values of $\alpha$ between 0.2 and 1 are applied to $Ix$. The interference duration estimator accuracy is evaluated computing the root mean square error (RMSE) and the average relative error ($\delta_{\alpha}$) between the estimated duration value $\hat{\tau}$ and the preset value $\tau$. Fig. 5 shows the evolution of the RMSE and the average relative error $\delta_{\alpha}$ for different values of the interference’s complex signal amplitude $a$ (cf. section III-C). The proposed interference duration estimator is very accurate for $a > 0.5$, corresponding to medium to strong interference with a RMSE $< 0.044$ s and a $\delta_{\alpha} < 2\%$. Even if the precision of the estimator is less accurate for lower-level interference, the estimator can still provide valuable information that can be used by an adaptive protocol that attempts to improve communication link by modifying frame length.

C. Interference Strength Classifier

The interference strength classifier is trained using a training set of 500 samples (50 samples per class). Next, the classifier
signal (CAS) extracted directly from the receiver DBB, two novel feature extractors (DDSL and ADA) and two classifiers. Low computational complexity is an important requirement for all elements of the detector. The first classifier is able to detect the presence of interference with 94% accuracy. The second is able to discriminate between low, medium and strong interference levels with 97% accuracy. A reliable estimation of the interference duration, with an average 2% relative error when the level of interference is medium to strong is also proposed. The approach presented in this work can be easily generalized to other LPWAN standards. Future work will include experimentation with other types of interference sources (e.g. LoRa, Sigfox) to validate the classifier performance in generalized scenarios.

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