Designing Low Complexity Channel State Indicators for Channel Aware LPWA Networks Using an USRP-based Experimental Platform

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French GNU Radio days 2018

Content

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Context

Current Low Power Wide Area Network (LPWAN) wireless transceivers are designed, or configured at deployment time, to function assuming a worse-case applicative scenario.

The waste of Energy

Most of the time, they waste a significant amount of energy when operated under favourable channel conditions.

Deploy and Forget ⇒ Lifetime Enhancement

Lifetime Enhancement of LPWA nodes by saving energy when they operate under favourable channel conditions.

- Channel-aware : Adaptation of the performance mode of the transceiver (and, therefore of its power consumption) to the channel state.
- Processing, Analysis and classification of the channel states based on Low Complexity Channel State Indicator (LCCSI) for adaptation mode learning.
- Development of energy saving action strategies.

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Channel State Indicator Requirements :

- No probe packets to avoid unnecessary power consumption.
- Low Computational Complexity to avoid power burden.
- Ideally a single value computed per frame.

State of the Art : Link Quality Estimators

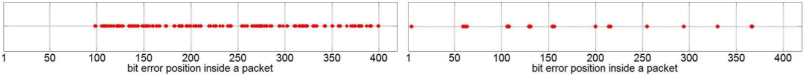
COTS radio transceivers : received signal strength indicator (RSSI) or link quality indicator (LQI), or MAC-level metrics such as packet reception ratio (PRR). ("Baccour et al.,2012")

Problem statement and LCCSI

Problematic and SoA

State of the Art : Symbol Error Density

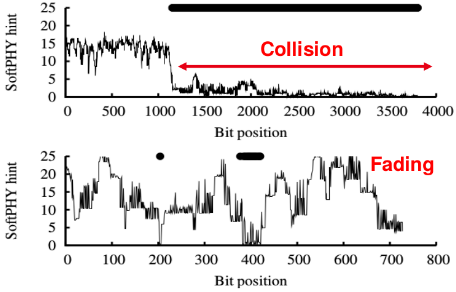
Symbol Error Density is defined as $c/(S_L - S_F + 1)$, where c is the number of detected symbol errors, S_L and S_F are respectively the last error position and the first error position. ("Barac et al.,2014")



- Using channel coding
- To distinguish errors caused by blockers and MFA (Multipath Fading and Attenuation).

State of the Art : SoftPHY hint

SoftPHY hint = the probability that received decoded symbol is correct. ("Vutukuru et al.,2009")



- To distinguish interference from fading

Problem statement and LCCSI

SoA conclusion

Classical LQE

- Not accurate enough (e.g., RSSI)
- Too large time granularity for our application (e.g., PRR)

SED

- Channel coding $\rightarrow$ overhead consumption
- Relevant only at low SNR (low enough to have errors in the frame)

SoftPHY hints

- Used for SNR estimation
- For frame collision identification

Classifier requirements

- The capacity to discriminate between three channel state classes: ‘undisturbed’, ‘fading’, and ‘interference’.
- Accurate enough at Low and Medium SNR situations $\Rightarrow$ to save a maximum of energy without impacting transmission quality.
- Must have a large sensitivity range, from low to high SNR.

Indicator requirements

- Low Complexity
- Clear and simple to use
- Accurate enough for 3 channel state recognition
- Can be generalized to other LPWA standards

Computation

- Based only on the Digital BaseBand with a low computation overhead
- Based on real measurements using USRP-based experimental platform
- Possibility to generate many different Channel Analysis Signals (CAS) and Channel State Indicators (CSI)

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USRP-based Experimental Platform

Experimental Set-up

Since COTS devices do not allow access to DBB algorithms, an SDR platform is needed for experimentation.

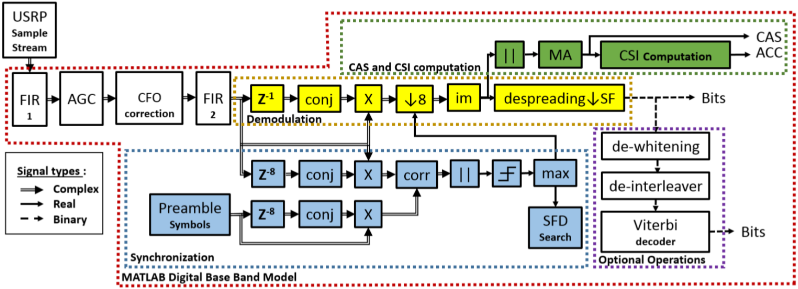
Physicaly

- $5m \times 4m$ experimental room
- 3 N210 USRP from Ettus Research
- 3 WBX [40 MHz- 2200 MHz] daughter-boards
- UHF 900 MHz half-wave dipole antennas

USRP-based Experimental Platform

Experimental Set-up

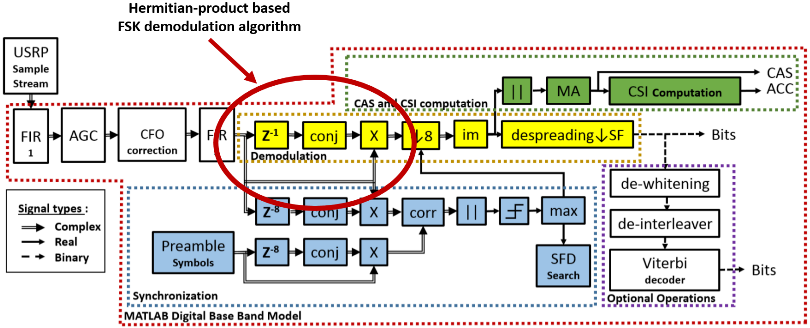
The IEEE.802.15.4k DBB



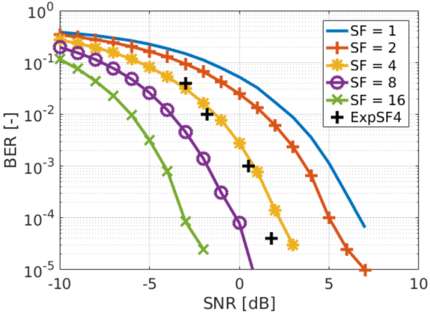
USRP-based Experimental Platform

Experimental Set-up

The IEEE.802.15.4k DBB



USRP-based measurements versus Matlab DBB validation

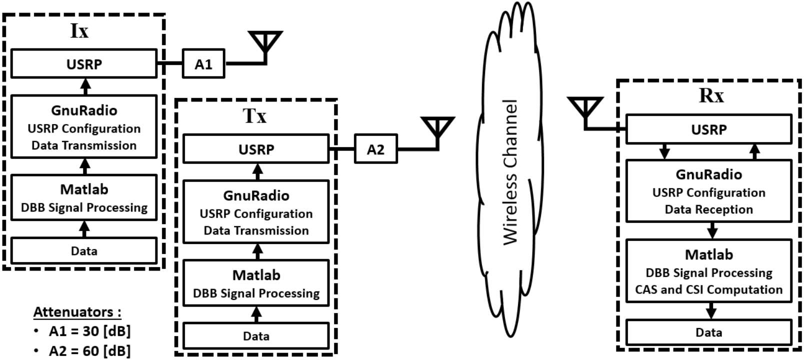


- *SF* is the used Spreading Factor.
- ExpSF4 is the BER values from the USRP-based measurements for $SF = 4$.
- The ExpSF4 points are fitted with Matlab simulated curve for $SF = 4$.

USRP-based Experimental Platform

Experimental Set-up

Set-up



- Ix is emitted in an adjacent channel, the spacing frequency from Tx is 100kHz.

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CAS : Channel Analysis Signal

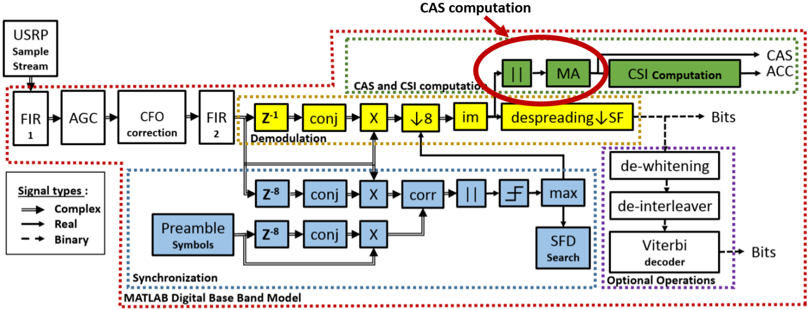
The Channel Analysis Signal carries information about the communication channel variations. The CAS can be computed directly from the DBB blocks (data detection, despreading, soft-decoder, etc.)

CSI : Channel State Indicator

The Channel Sate Indicator is computed from the CAS and gathers CAS information in only one value per frame. The CSI can be used to classify the Channel State into three classes('undisturbed', 'fading' and 'interference').

N.B.: There are many possibilities for CAS and CSI.

An example of CAS



- MA : Moving Average.
- Others CAS can be computed at the despreading or decoding output.

An example of CAS

Let x_k is the imaginary part extraction block output sample. The $\mathbf{CAS} = [CAS_1, ..., CAS_K]$ at the data detection block is defined as :

$$CAS_k = \frac{1}{win} \sum_{i=0}^{win-1} |x_{k-i}| \quad (1)$$

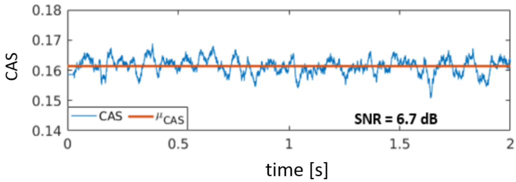
Where :

- win, is the moving average window.
- $k = 1, 2, ..., K$ with K the frame number of sample.

Results

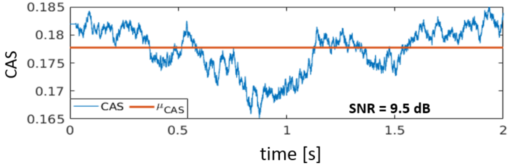
CAS and CIS computation

CAS for an ‘undisturbed’ channel



- μ_{CAS} is the average value of CAS.
- The variation around the average value seems to correspond to the noise.

CAS for a 'fading' channel

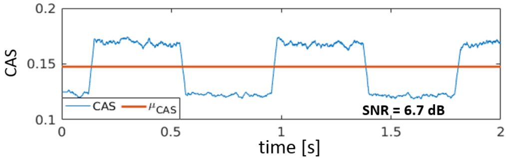


- μ_{CAS} is the average value of CAS.
- The variation around the average value is due to human mobilities next to the Tx.
- The variation 'trend' is slow regarding the frame duration.

Results

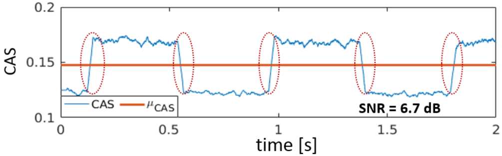
CAS and CIS computation

CAS for an ‘interference’ channel



- μ_{CAS} is the average value of CAS.

CAS for an ‘interference’ channel

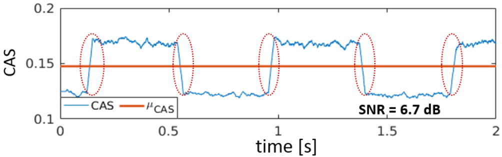


- μ_{CAS} is the average value of CAS.

Results

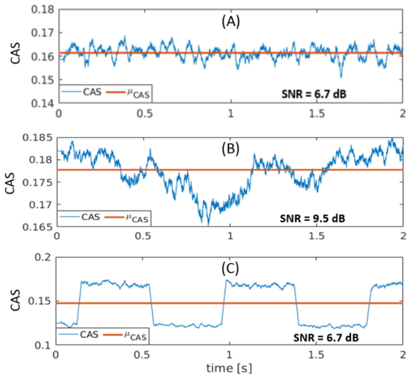
CAS and CIS computation

CAS for an ‘interference’ channel



- μ_{CAS} is the average value of CAS.
- Abrupt transitions across the average value.

CAS comparison



- How can the information contained in the CAS be gathered into only one CSI value for 3 class classification ?

An example of CSI : The ACC

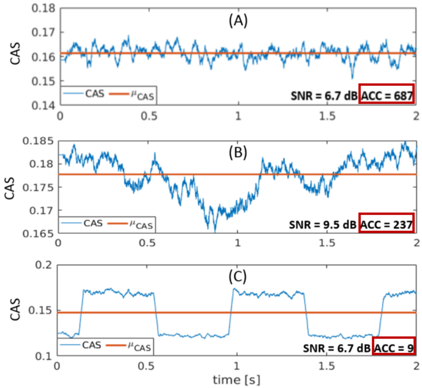
The ACC (Average Crossing Count) is a CSI which merges the channel state information contained in the CAS to a channel state recognition indicator. The ACC is defined as :

$$ACC = \frac{1}{2}\sum_{k=2}^{K} \mid S_k - S_{k-1} \mid \quad , \quad k = 2, 3, ..., K \tag{2}$$

Where :

- $S_k = \mathrm{sgn}(CAS_k - \mu_{CAS}) \quad , \quad k = 1, 2, ..., K$
- $sgn(y)$ is the sign function of y

An example of CSI : The ACC

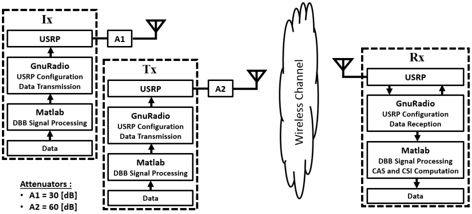


- Computed ACC value provides an indicator to distinguish 'undisturbed'(A), 'fading'(B) and 'interference'(C) channel state.

Results

Channel State Recognition

Labeled frames from USRP-based platform

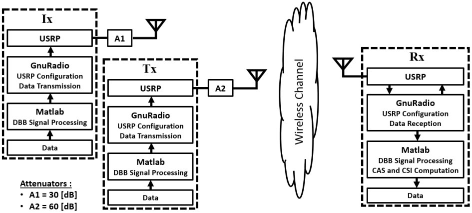


- 'undisturbed' frames : In undisturbed radio frequency environment.

Results

Channel State Recognition

Labeled frames from USRP-based platform



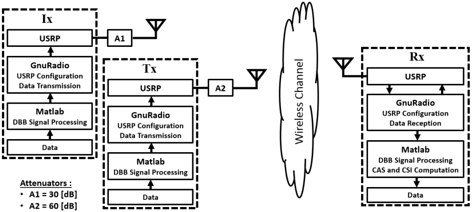
- 'undisturbed' frames : In undisturbed radio frequency environment.

- 'Fading' frames : Environment with mobility next to the Rx (pedestrian motion next to the USRP, arm or object moving trough the direct transmission path between Tx and Rx).

Results

Channel State Recognition

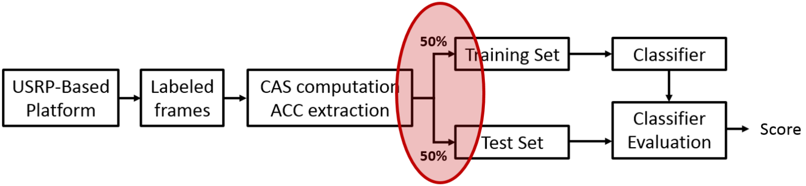
Labeled frames from USRP-based platform



- 'undisturbed' frames : In undisturbed radio frequency environment.
- 'Fading' frames : Environment with mobility next to the Rx (pedestrian motion next to the USRP, arm or object moving trough the direct transmission path between Tx and Rx).
- 'Interference' frames : The interference environment is generated using Ix.
- 120 frames are collected for each scenario.

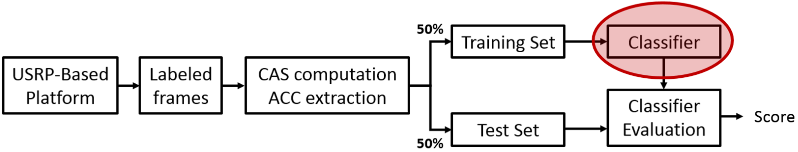
The mono-feature classifier

The used classifier is a mono-feature classifier based on threshold values.



- The labeled ACC values are splitted into 2 sets :
  - Training set : $60 + 60 + 60 = 180$
  - Test set : $60 + 60 + 60 = 180$

The mono-feature classifier

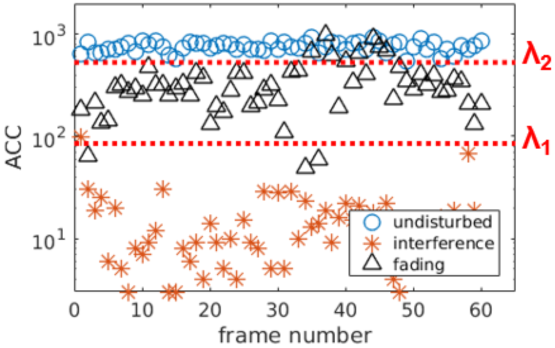


- The classifier training step aims to find two thresholds, λ_1 and λ_2 to discriminate between three channel state classes : ‘undisturbed’, ‘fading’ and ‘interference’.

Results

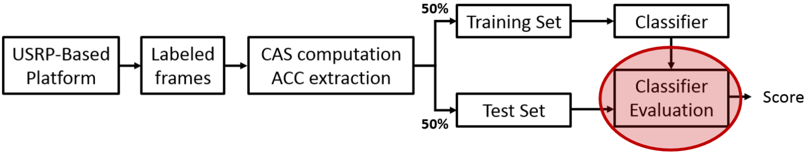
Channel State Recognition

The mono-feature classifier



- λ_1 and λ_2 are optimized using ROC (Receiver operating characteristic) curves.

The mono-feature classifier



- The test set is used to evaluate the classification score.
- Obtained classification score reaches 96%.
- Nota : Acquisitions are relatively ideal (interference and fading are strong enough).

More diverse data set generation

- To master the SNR and the CIR and to ensure the right labeling step.
- Diversifying the data set by varying the SNR, the CIR, interference duration, desired signal duration, etc.
- Diversifying the data set by randomizing the behaviour of the interference

Content

Future Work

- Enrichment of the classification to identify other types of disturbances (shadowing, electromagnetic noise, ...).
- Measurement with envelop modulated interference (e.,g. Sigfox).
- Measurement with in-band interference.
- Algorithm complexity study

Conclusion

- Platform = USRP + GnuRadio + Matlab
- To provide signal from real world
- To design realistic and reliable Low Complexity Channel State Indicators
- To feed realistic classification algorithm
- To recognize the current channel state between : ‘undisturbed’, ‘fading’ and ‘interference’
- To aid the development of energy saving strategies for lifetime enhancement of radiofrequency systems for LPWA networks.

Thank you !

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