Low-cost spectrum sensor for ultra-narrowband transmissions

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Abstract. Growing interest in wireless sensors and actuators for the Internet of things has recently prompted development of wireless protocols employing ultra-narrowband transmissions at the physical layer. These transmissions present new challenges for spectrum sensing, both in the context of technology coexistence and in supporting dense ultra-narrowband networks through collision avoidance. In this paper we present a custom designed, low-cost spectrum sensor hardware designed from off-the-shelf integrated circuits and associated software implementing covariance based-detection. We also show results of a table-top experiment where we tested the sensor's detection performance with ultra-narrowband signals in the UHF frequency range.

Keywords: ultra-narrowband, spectrum sensing, covariance-based detection, hardware, internet of things

1 Introduction

Recently there has been growing interest in small autonomous interconnected sensors and actuators. Some predictions for the growth of the so-called Internet of things now tell of trillions of deployed wireless devices by 2020 in densities up to 100 devices per m^2 [1]. Existing, widely deployed wireless technologies, like LTE and IEEE 802.11 WLAN are ill-suited for such use: they have been optimized for low-latency, high-throughput applications typical for laptop computers and smartphones. Their low spectral efficiency and high preamble overhead become significant burdens when faced with high density of devices that only need to infrequently transfer a few bytes of data at a time, with very relaxed requirements regarding latency and bitrate.

A number of technologies and standards employing so-called ultra-narrowband transmissions have emerged recently specifically to address such use cases: Sigfox [2], Weightless [3], 3GPP Cooperative Ultra-Narrowband (C-UNB) [4]. These technologies employ very low bit-rate transmissions (on the order of 100 to 1000 bits/s) using binary phase-shift keying (BPSK) or Gaussian frequency-shift keying (GFSK) modulations with bandwidths on the order of 100 Hz to 1 kHz. Hence they exhibit high spectral efficiency and low preamble overhead with short payloads [5].

Narrow bandwidth allows for demodulation at low signal-to-noise ratios. Combined with use of sub-1 GHz bands with good propagation properties, these technologies enable long range with relatively low transmit powers, which makes them suitable for battery operated devices. 868 MHz European Short-range devices (SRD) band is most often used at the moment. Extension to TV whitespaces as well as dedicated spectrum in the 694 - 790 MHz range [6] is possible in the future.

Using a spectrum sensor for detecting whether a frequency channel is occupied by an ultra-narrowband transmitter has several applications. In general, reliable sensing of other users of radio spectrum is seen as an important component of future smart radios that will be able to intelligently optimize their operation. It is highly likely that currently emerging standards will be still in use when such radios will be commonplace. If ultra-narrowband devices will reach predicted deployment numbers and densities, other technologies sharing same frequency bands will have to rely on spectrum sensing to avoid interference with them.

Apart from coexistence concerns, spectrum sensing is also interesting for increasing the density of ultra-narrowband devices that can be supported in a cell. Currently, most devices choose transmission time and channel pseudo-randomly. Beyond a certain device density, such a scheme leads to high collision rate and requires a high number of packet retransmissions. Detecting channel occupancy opens the possibility of media-access protocols with collision avoidance.

Properties of ultra-narrowband that make it convenient for the described use cases also make it problematic for spectrum sensing. Large cell sizes and low signal-to-noise ratios mean that traditional energy detectors will not be able to reliably detect many transmissions [7]. Hence, energy detection carrier sense, like for instance employed in IEEE 802.11 CS-MAC, becomes impractical. Detecting signals buried in noise typically requires advanced, computationally complex sensing methods and high-performance software-defined radio front-ends. This is in stark contrast to simple, low-cost transceivers employed on ultra-narrowband devices.

In this paper we present a simple spectrum sensing setup that we believe is well suited for ultra-narrowband applications – both from the standpoint of performance as well as required hardware and software complexity.

2 Hardware

VESNA SNE-ESHTER is a low-cost compact spectrum sensor. The device consists of two parts: the SNE-ESHTER analog front-end and the VESNA low-power sensor node core (SNC) [8]. A simplified block diagram is presented in Fig. 1. Device without an antenna measures approximately 70 x 50 x 20 mm.

The analog front-end performs the frequency down-conversion and signal conditioning before analog-to-digital conversion. The front-end is a custom designed single-conversion, low-intermediate frequency (IF) receiver based on the off-the-shelf NXP TDA18219HN integrated circuit. The specified input frequency range is between 42 MHz and 870 MHz. The local oscillator (LO) signal is generated by a FRAC-N phase-locked loop (PLL) from a 16 MHz crystal oscillator.

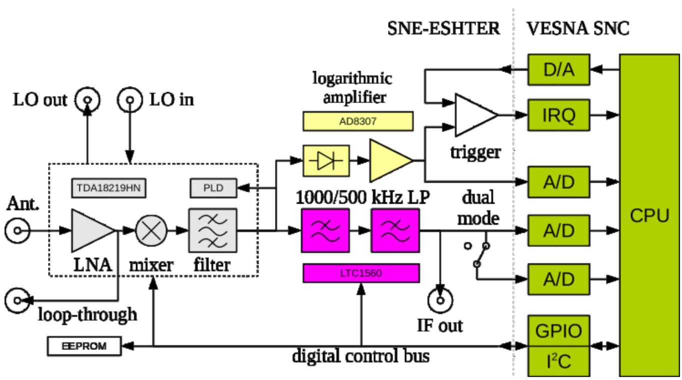

Figure 1: Block diagram of VESNA SNE-ESHTER

The raido-frequency (RF) signal from the antenna is amplified in a low-noise amplifier (LNA) and mixed with the LO in an image-rejection mixer to produce a signal at IF. Several stages of automatic gain control are used to minimize non-linear distortion and maximize signal-to-noise ratio of the signal. The signal passes through one tracking RF and two IF band-pass filters with software-selectable bandwidth. The final stage is a 10th order elliptic anti-aliasing filter with two settings: 500 kHz and 1000 kHz, corresponding to 1 Msample/s and 2 Msample/s sampling rates. After the anti-aliasing filter, the IF signal is routed to the SNC to be sampled by an analog-to-digital converter (ADC).

VESNA SNC contains three 12-bit successive approximation ADCs with up to 2 Msample/s sample rates. ADCs are driven by a DMA controller and store samples directly into a sample buffer in SRAM without any intervention from the CPU. The sample buffer has space for up to 25000 real samples (up to 12.5 ms of continuous reception at 2 Msample/s sample rate).

SNC is driven by an integrated microcontroller with an ARM Cortex M3 CPU core with a 56 MHz clock and 64 KB of SRAM. The microcontroller also contains an RS-232 interface with a 576 kbit/s maximum bitrate that can be used to connect the device to a PC. The software on the microcontroller controls the front-end through an I^2C bus and several GPIO lines.

3 Software and sensing algorithm

Microcontroller on the SNC was programmed to calculate elements of the covariance matrix σ_l from the signal samples x_n in the ADC sample buffer using the following equation:

$$\sigma_l = \frac{1}{N_s} \sum_{n=0}^{N_s - 1} x_n \cdot x_{n-l} \qquad l \in [0, L-1] \tag{1}$$

where N_s is the length of the ADC sample buffer and L is size of the covariance matrix $\mathbf{R}$.

$$\mathbf{R} = [r_{ij}] = \begin{bmatrix} \sigma_0 & \sigma_1 & \cdots & \sigma_{L-1} \\ \sigma_1 & \sigma_0 & \cdots & \sigma_{L-2} \\ \vdots & \vdots & \ddots & \vdots \\ \sigma_{L-1} & \sigma_{L-2} & \cdots & \sigma_0 \end{bmatrix} \tag{2}$$

The ARM Cortex M3 core does not support floating point arithmetic instructions. To achieve high performance and still retain sufficient resolution of covariance estimates, fixed point arithmetic was used instead of software floating point implementation or integer arithmetic. We found the ARM architecture especially convenient for the fixed point implementation because the barrel shifter allows correction of the scaling factor in multiplications without consuming additional CPU cycles. We used scaling factor 8 (3 bits), which allowed multiplication of two 12 bit ADC samples in Equation 1 to be performed in a single 32 bit CPU register.

In our experiment, the resulting L covariance values were sent over the RS-232 line to a laptop computer where a Python script implemented the rest of the signal detection. We chose to implement part of the detection outside of the device to simplify development and experimentation. Since the most computationally intensive task, the covariance estimation, was performed on the device itself, we believe our results are comparable to the case where the complete detector would be implemented on the device. Implementation of the remaining parts of the detectors on the SNC itself would be trivial.

We implemented three detector test statistics based on the estimated sample covariance matrix:

$$\gamma_{ED} = r_{11} \tag{3}$$

$$\gamma_{CAV} = \frac{\sum_{i=1}^{L} \sum_{j=1}^{L} |r_{ij}|}{\sum_{i=1}^{L} |r_{ii}|} \tag{4}$$

$$\gamma_{MAC} = \frac{\max_{i,j} |r_{ij}|}{|r_{11}|} \tag{4}$$

γ_{ED} is identical to the common energy detection test statistic. γ_{CAV} is the "covariance absolute value" statistic [9]. γ_{MAC} is the "maximum auto-correlation" statistic [10].

For each of these test statistics we determined a threshold γ_0 that resulted in the chosen constant false alarm rate (P_{fa}) according to the complementary cumulative distribution function method described in [11]. The detector performed a binary decision: if $\gamma > \gamma_0$ then the detector considered the channel occupied by a transmission. Otherwise, the channel was considered vacant.

4 Experiment setup

To generate the ultra-narrowband signal we used a Rohde & Schwarz SMBV100A vector signal generator. We used the arbitrary wave form generator function (ARB) to generate a BPSK signal at 160 bits/s. Sequence length was 324 bits. Bit values were pseudo-randomly generated. ARB sample rate was 1600 Hz. These settings correspond to a C-UNB packet with 12 bytes of payload. Central frequency was set to 700 MHz.

The generator was connected to 30 dB attenuator using 60 cm of LMR-195 coaxial cable. Before starting the experiment, all devices were left turned on for 2 hours to reach their temperature equilibriums. Total signal attenuation A at the attenuator connector, including cable loss, was measured using the average channel power measurement mode on a Rohde & Schwarz FSV signal analyser. True input power P_{in} was calculated by subtracting A from signal generator output power level.

$$A = 33.2 \text{ dBm}$$

During the experiment, attenuator output was connected to the SNE-ESHTER antenna input connector. Receiver was tuned to 700 MHz. Receiver filter bandwidth was set to 1 MHz. Sampling rate was 2 Msamples/s. Detector was programmed to operate in a continuous loop: collect the full buffer of N_s signal samples, calculate L covariances and send them to the laptop computer over RS-232 for final processing.

For $N_s = 25000$ and $L = 20$, our implementation took approximately 280 ms to obtain one detector decision (including signal sampling, covariance estimation and test statistic calculation). Since this time was shorter than C-UNB packet transmission time (approximately 2 s), no special provisions were necessary to synchronize detection with the packet transmission. Hence ARB trigger on SMBVA100A was set to "automatic".

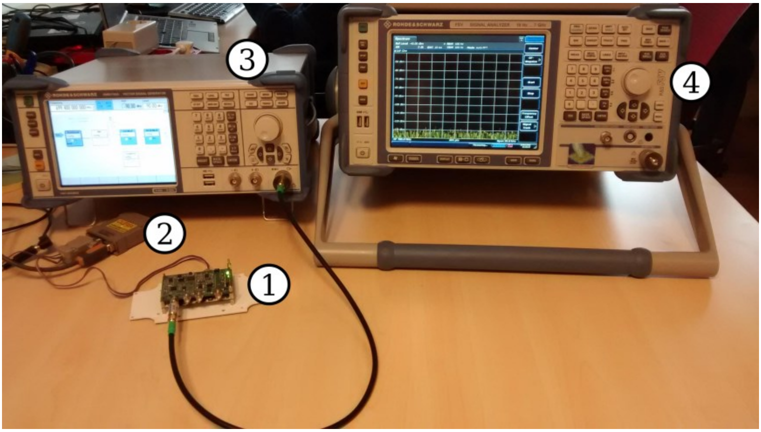

Figure 2: Experimental setup. (1) VESNA SNE-ESHTER sensor, (2) RS-232 interface, (3) vector signal generator, (4) signal analyser.

Detector thresholds were set for P_{fa} = 0.05. Two separate measurement campaigns were performed: To estimate the lowest detectable signal power, the generator output power was swept from -100 dBm to -75 dBm in increments of 1 dBm. For each generator setting, 500 binary decisions for each of detector were recorded. To estimate the frequency range of the detector, the generator central frequency was swept from 699.00 MHz to 700.60 MHz in increments of 0.05 MHz, while the receiver was kept tuned to 700 MHz. Generator output power was kept constant at -90 dBm. Again, 500 binary decisions for each detector were recorded.

5 Results

From the recorded binary decisions for each campaign, the probability of detection was estimated for each of the three detectors. Results of the two measurement campaigns are shown in Fig. 3. Lines show maximum likelihood estimate for P_d. Shaded areas show 1-10^{-5} confidence interval.

Minimum input power required to reach probability of detection P_d = 0.99 for energy detector was -119.2 dBm, for CAV (at L = 20) it was -123.4 dBm and for MAC (at L = 5) it was -122.4 dBm. Same minimum *Pd* was reached in a 392 kHz wide band for CAV and 107 kHz wide band for MAC at -123.2 dBm input power.

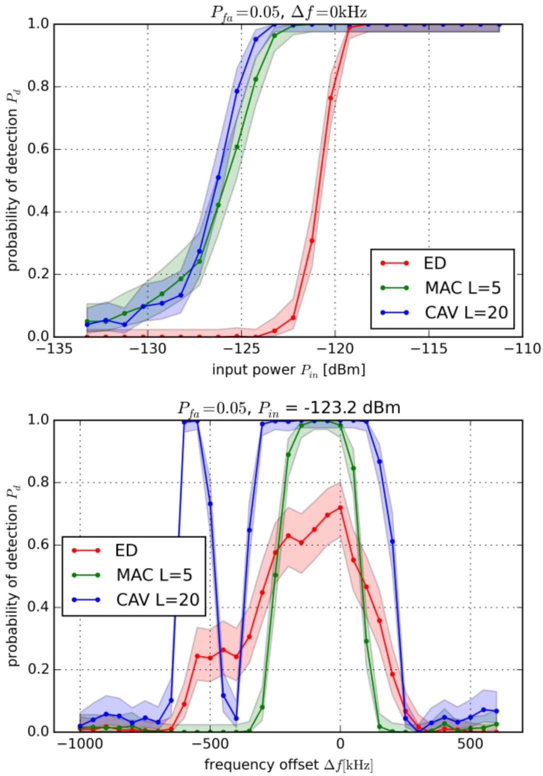

Figure 3: Probability of detection versus power (top) and frequency offset (bottom).

6 Discussion

Our results show that covariance-based detection can be successfully applied for sensing of ultra-narrowband transmissions. They achieve 99% probability of detection at 3 dB lower signal power than an energy detector. We can also see that the lowest detectable power of the MAC detector is only 1 dB worse than that of CAV detector, with significantly lower L. This is important since number of required multiplications in the detection algorithm scales linearly with L.

Another interesting property of these detectors is their frequency dependency. We can see that the width of the frequency band with reliable detection differs significantly between the three tested detectors. Even though MAC detector is sensitive to a significantly narrower range of frequencies than the width of the receiver's 1 MHz channel, it would still be capable of detecting transmissions with 99% probability over approximately half of the C-UNB 200 kHz uplink band.

A limitation of our approach is the fact that the detector only produces a binary decision for the complete reception bandwidth. It does not provide information on the exact frequency of the transmission. This means that such a detector would be most useful for other users that wish to avoid interference with ultra-narrowband transmissions. On the other hand, inability to distinguish individual channels would make it less useful for use in an ultra-narrowband CS-MAC implementation.

Channel information could be obtained by implementing additional signal filtering in software before detection. However filtering would likely add significantly to processing time required to arrive at the binary decision. Considering inherent frequency selectivity of covariance methods itself, another interesting possibility would be exploring possible ways of adjusting frequency selectivity of the detector itself without the need for additional filtering.

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For wider interest

There is only a limited amount of useful radio frequencies that can be used for wireless communications. Rapid increase in demand for wireless technologies in recent years has made this limitation evident. Ultra-narrowband is a new technology that is optimized for sensors and other devices that only occasionally transmit small amounts of data. Compared to existing mobile networks or Wi-Fi it is capable of accommodating many more devices in the same amount of radio spectrum.

Spectrum sensing is a special method of radio reception where instead of extracting information being sent by a transmitter we are only interested in the fact that a transmission exists. The most basic and widely used method is detecting the energy emitted into the electromagnetic field. However physical laws impose limits on how weak a signal can be reliably detected with energy detection. More sophisticated methods, like those based on statistical covariances, can reliably detect transmitters even when their signals are many times weaker than noise.

Spectrum sensing can be used to provide real-time information on which radio frequencies in an area are in use and which are vacant, independent of the radio technology. This can help network planners in manually optimizing their wireless networks. More interestingly, it opens a possibility for intelligent devices that can autonomously and dynamically adapt to environment, avoiding interference from other devices. Early application of this technology can be seen for example in automatic channel selection in modern Wi-Fi routers.

Spectrum sensors were traditionally complex devices. Just as new radio technologies continuously decrease the cost of wireless devices, to the point where billions of are now predicted to be in use in the near future, so must spectrum sensors follow this trend if they are to be included on such devices. In this paper we present a custom designed spectrum sensor that was developed using off-the-shelf components intended for use in TV receivers. We show that advanced spectrum sensing algorithms can be implemented on low-cost hardware and that they are effective in detecting the kind of radio transmissions that will likely be widely used in the future by smart wireless sensors and other devices in the future Internet of things.