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Implementation of a Distributed Compressed Sensing Algorithm on USRP2 Platforms

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Abstract - It has been recently demonstrated that the challenging implementation of the signal detectors can be facilitated by using the compressive sampling theory. In this paper, we consider a network of secondary nodes that cooperate to detect the primary signals by sampling the overall bandwidth periodically at a rate much smaller than the Nyquist rate. The delays inherent to the propagation channel are used to implement a periodic non-uniform sampling detector when the secondary nodes combine their observations. We demonstrate that the proposed detector can efficiently detect the primary user signal, and implement the algorithm on a USRP2 platforms network.

I. Introduction

The theory of compressed sampling (CS) has recently received an increasing attention as it may help in relaxing the constraints on the system design [1] : sparse signals may be sampled at a rate significantly lower than the Nyquist rate without losing information. In the CS framework, signal recovery is classically achieved through expensive algorithms, whether in a single user scenario [2,3] or a distributed scenario [7]. However signal reconstruction is not necessary in many inference problems [5,6].

We have recently extended [5] to the optimal Maximum Likelihood (ML) detection of linearly modulated signals of unknown parameters in a set of predetermined subchannels [6]. In this paper, we focus on the detection of primary signals directly in the compressive domain (as in [6]).
We demonstrate that the CS architecture can advantageously be implemented by a sensor network, where each node subsample the signal with a different propagation delay. The system can be viewed as a periodic non-uniform sampling architecture when the signals are combined at the coordinator node.

II. System model and frequency estimator

A primary user is transmitting a finite sequence of i.i.d complex symbols $I[n]$ (of length N, period T_{symb} and variance σ_I^2) in one of the M available subbands. This sequence of symbols is lowpass filtered by the pulse-shaping filter $g(t)$, then shifted to the frequency Δf. The secondary system is a set of Q sensing nodes that send their observations to a coordinator node. Each received signal is affected by a different propagation delay τ_i, a phase shift φ_i and a Rayleigh coefficient α_i modeling the fading channel. Before sampling, the signal is lowpass-filtered with an ideal filter $f(t)$ of bandwidth $1/T_s$ where $T_s = T_{\text{symb}}/M$ is the Nyquist sampling period. The signal is corrupted by an additive white Gaussian noise (AWGN)

$w_i(t)$ of variance σ_w^2. The signal received at node i is:

$$r_i(t) = \left[\alpha_i e^{j\varphi_i} x(t-\tau_i) + w_i(t)\right] * f(t) \qquad (1)$$

where $x(t) = \sum_{n=1}^{N} I[n] g(t - nT_{symb}) e^{j2\pi\Delta f t}$

We assume that it is periodically sampled at the symbol rate $1/T_{\text{symb}}$ (not the Nyquist rate $1/T_s$). We demonstrated that the signal detector reduces to a matched filter applied independently at each sensing node at the symbol rate. The estimated occupied frequency band is given by:

$$\overline{\Delta f} = \arg\max_{\Delta f} \sum_{n=1}^{N} \left| \sum_{i=1}^{Q} y_i[n] \right|^2 \qquad (2)$$

where $y_i[n] = \alpha_i^* e^{-j(2\pi\Delta f(nT_{symb}-\tau_i)+\varphi_i)} \sum_m r_i[m] g_i^*[m-n]$

The results are transmitted to the coordinator node where the sum is taken to obtain the final metric based on which the occupied band is estimated.

III. Implementation

The subchannel estimation error probability is assessed numerically for 5000 realizations. A 100 MHz bandwidth is uniformly divided in 20 subchannels. A sequence of 50 symbols is transmitted at the rate 5 Msps on each subchannel.

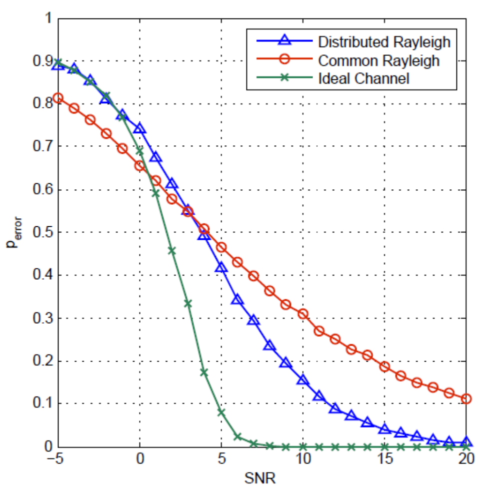

Fig. 1. Error probability as a function of the SNR for ideal, Rayleigh, distributed Rayleigh channels (Q = 5).

Fig. 1 illustrates the probability of error as a function of the SNR in three scenarios. Rayleigh fading incurs a performance loss compared to the ideal channel but the system benefits from spatial diversity in a distributed sensing network.

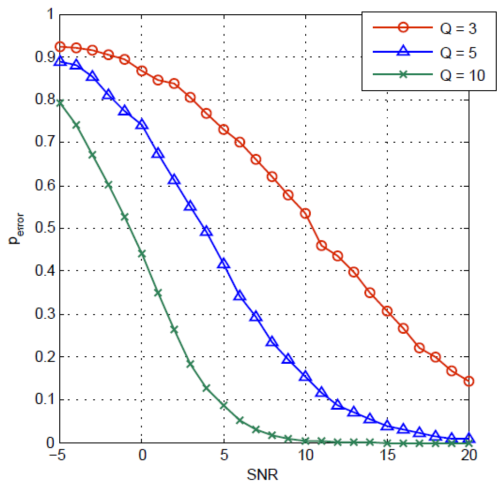

Fig. 2. Error probability as a function of the SNR. Impact of the number of sensing nodes.

Fig. 2 illustrates that the performance improves with the number of sensing nodes thanks to the increasing average sampling frequency and the additional source of diversity.

We demonstrated the efficiency of this estimator with a software defined radios sensor network, by implementing the algorithm on USRP2 platforms. Our system currently works for $Q = 2$ secondary users and is being extended to $Q = 4$.

IV. Conclusion

Contrary to state-of-the-art solutions, the proposed signal detector works directly in the compressive domain and therefore does not require the reconstruction of the received signal. Performance results show that the system benefits from the spatial diversity present in the distributed network. We were also able to fully demonstrate the algorithm efficiency on a USRP2 sensor network.

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