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A Compressed Sensing Based Direct Sequence Spread Spectrum Communication System

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Abstract: To lower the sampling rate in a spread spectrum communication system, compressive sampling process is applied to take out the received signal. This may cause a decrease within the power consumption or the producing value of wireless receiver's using spread spectrum technology. The most novelty of this paper is that the discovery that in spread spectrum systems it's potential to use compressive sensing with a far easier hardware design than in alternative systems, creating the implementation easier and more energy economical. Our theoretical work is illustrated with a numerical experiment using the IEEE 802.15.4 standard's 2.4 GHz band specification. The numerical results support our theoretical findings and indicate that compressive sensing could also be used with success in spread spectrum communication systems. The results obtained here may also be applicable in alternative spread spectrum technologies, like Code Division Multiple Access (CDMA) systems.

Index Terms: Compressive Sensing, Direct Sequence Spread Spectrum communication System.

I. INTRODUCTION

The idea of compressive sensing is attracting a lot of and a lot of attention within the signal process community. Wherever the classical Shannon-Nyquist sampling theorem needs a symbol to be sampled at double its signal information rate, compressive sensing samples the signal at its data rate, which can be a lot of lower. Compressive sensing is employed to reconstruct a symbol to a full Nyquist rate illustration, however if solely analysis regarding data within the signal is desired, compressive signal process is best suited. Compressive signal process is employed once analysis regarding data during a signal is of interest, instead of the reconstruction of the signal itself. Compressive sensing and compressive signal process samples the signal employing a sampling theme with usually a randomized structure and then exploits sparsity in the signal. In DSSS sparseness is within the choice of a code used for transmission of a given data sequence. During this work, we tend to show however compressive sparseness within the signal to alter sub sampling. In DSSS systems signal process could also be applied to a spread spectrum receiver to lower the rate at the receiver. This could lower the general energy consumption of the device and/or lower the value of the Analog to Digital device (ADC). To show this take into account the following: This work relies on a symbol model employed in the IEEE 802.15.4 standard within which a baseband signal with a Nyquist frequency of 200kHz should be sampled.

To indicate the benefit of lowering the rate, we tend to compare 2 ADCs from Analog Devices: The AD7819 and also theAD7813. The AD7819 is an 8-bit ADC with a most throughput of two hundred kilo samples per second, whereas the AD7813 is an 8- or 10-bit ADC with a most throughput of four hundred kilo samples per second. We tend to aware that 400 kilo samples per second is that the Nyquist rate of the system and also the sampling rate should be beyond this to suits the Shannon-Nyquist sampling theorem. However, we tend to use these 2 ADCs as they are virtually identical in each side apart from the sampling rate, creating them good for comparison. In IEEE 802.15.4 compliant receivers, an ADC like AD7813should be used to suits Shannon-Nyquist, however if compressive signal process is ready to lower the sampling rate by an element of 2, the AD7819 could also be used instead. These two specific ADCs use identical quantity of power thus there are not any energy savings, however wherever the AD7813 prices 2.98$, the AD7819 solely prices 2.29$.

During this work, we tend to apply compressive signal process to a general DSSS system. We tend to show that in a spread spectrum system it is doable to use merely a continual version of the matched filter employed in classic receivers rather than employing a difficult filter structure to accumulate random measurements. This greatly simplifies the implementation and makes compressive sensing possible for implementation in spread spectrum wireless receiver systems. Our approach is not restricted to DSSS however can also be applied in alternative spectrum technologies, like CDMA.

One major obstacle in applying compressive sensing to any wireless system is that the presence of noise folding, that happens as a result of the noise is not measuring noise; however noise additional before measure the signal. This severely impacts the receiver performance that is additionally evident in our numerical experiments.

II. COMPRESSIVE SENSING

CS is a novel sampling scheme, developed to lower the number of samples required to obtain some desired signal.

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At the heart of CS is the linear sampling scheme, called the measurement matrix. In classic receivers the measurement matrix Θ may be modeled as the identity matrix, such that x is sampled at the chip rate of each channel (I and Q). This measurement matrix is then responsible for mapping the N-dimensional signal x to a M dimensional signal. Normally this would make it impossible to recover the original signal, but under the assumption that x is sparse in some basis; it is possible to reconstruct the original signal from the sampled, M-dimensional signal y. Before explaining the reconstruction algorithm, we return to the measurement matrix and introduce a new measurement scheme. This new measurement scheme is easier to implement, but performs almost identically for spread spectrum systems. We call this a Compressive Spread Spectrum (CSS) measurement matrix.

III. CLASSIC TRANSMITTER STRUCTURE

In each the transmitter and the receiver structure we tend to treat the signal symbol-by-symbol, where each symbol may be one little bit of info or a block of bits. Let $B_k \epsilon \{\pm1\}^{N\times1}$ be a binary vector, signifying the symbol to be transmitted and consisting of N information bits. Currently outline a k^{th} binary pseudo-random noise (PRN) sequence as $c_k \epsilon\{\pm1\}^{C\times1}$.These two binary vectors square measure the distinct equivalents of an information signal and a PRN signal, $b_k(t)$ and $c_k(t)$, severally as shown in Fig.1 and outlined as:

$$b_k(t) = \sum_{n=0}^{N-1} b_k[n] rect\left(\frac{t-nT_b}{T_b}\right), 0 \leq t < NT_b \quad (1)$$

$$c_k(t) = \sum_{c=0}^{C-1} c_k[c] rect\left(\frac{t-cT_c}{T_c}\right), 0 \leq t < CT_c \quad (2)$$

Where T_b and T_c are the bit and chip duration respectively, and $NT_b = CT_c$ .we define

$$\text{rect}(t) = \begin{cases} 1 \text{ if} 0 \leq t < 1, \\ 0 \quad \text{oterwise.} \end{cases} \quad (3)$$

When multiplied, they form the spread spectrum data signal, $d_k(t) = b_k(t)c_k(t), 0 \leq t < NT_b$. The notation employed in the above might in some cases be simplified, because the choice of a PRN sequence may well be implemented as a mapping from one bit or a block of bits on to a given sequence of chips, as done in e.g. IEEE 802.15.4.In the following, the signal model we tend to outline relies on the IEEE 802.15.4 standard's 2.4 gigahertz band specification. This suggests the encryption using DSSS could also be written as a matrix vector product, with $M = 2^N$ data signals:

$$d_k(t) = \Psi(t)\alpha_k, \text{ where} \quad (4)$$

$$\Psi(t) = \begin{bmatrix} d_1(t) \\ d_2(t) \\ \vdots \\ \vdots \\ d_M(t) \end{bmatrix}^T, 0 \leq t < NT_b \quad (5)$$

Where Ψ(t) may be a dictionary of data signals and $\alpha_k \in \{0,1\}^{M\times1}$ may be a distributed vector with just one non-zero entry, specifically the entry that selects a given PRN sequence from the dictionary. It may also be considered a symbol vector because it corresponds to the kth symbol being transmitted. The sparsity of α_k is what permits us to use compressive sensing for reception. The sparsity of the signal lies during which PRN sequence is chosen for transmission.

The IEEE 802.15.4 2.4GHz band specification relies on QPSK and thus the output sequence is break up, in order that even-indexed chips in $d_k(t)$ are transmitted within the in section(in-phase) path and odd-indexed chips within the construction section(quadrature-phase) path. Within the following we tend to solely state the equations for the in section path; however similar expressions could also be derived for the construction section path. The resulting data signals are used to modulate some pulse shape function, g (t):

$$g'_k(t) = \Psi'(t)\,\alpha_k, \text{ where} \quad (6)$$

$$\Psi'(t) = \begin{bmatrix} \sum_{c\epsilon S} d_1(t)g(t-cT_c) \\ \sum_{c\epsilon S} d_2(t)g(t-cT_c) \\ \vdots \\ \sum_{c\epsilon S} d_M(t)g(t-cT_c) \end{bmatrix}^T, S = \{0,2,\ldots,C\} \quad (7)$$

Here the dictionary matrix has been recast into an in-phase version, with pulse form enclosed. Notice that g(t) here and as portrayed in Fig.1 is assumed to be a half-sine pulse, that is the pulse shaping function employed in IEEE802.15.4. This pulse form has restricted to support within the time domain that is not true for e.g. a raised cosine pulse form. The equations during this work are outlined for the half-sine pulse form; however they are simply modified to use to different pulse form functions.

IV. NYQUIST SAMPLING RECEIVER STRUCTURE

Before introducing our compressive sensing receiver structure, we have a tendency to first define a classic Nyquist sampling receiver structure. At the receiver, the received signal is

$$r_k(t) = s_k + n(t) \quad (8)$$

Where n(t) is additive white Gaussian noise. The in-phase Associate Quadrature-phase analog signals sampled consistent with the chip rate employing a matched filter to the pulse shape used at the transmitter and an ADC. Here, we have a tendency to assume a coherent receiver with good synchronization, performed before information coding using e.g. a pilot sequence. The sampling could also be defined by employing a measurement matrix, Θ1(t):are

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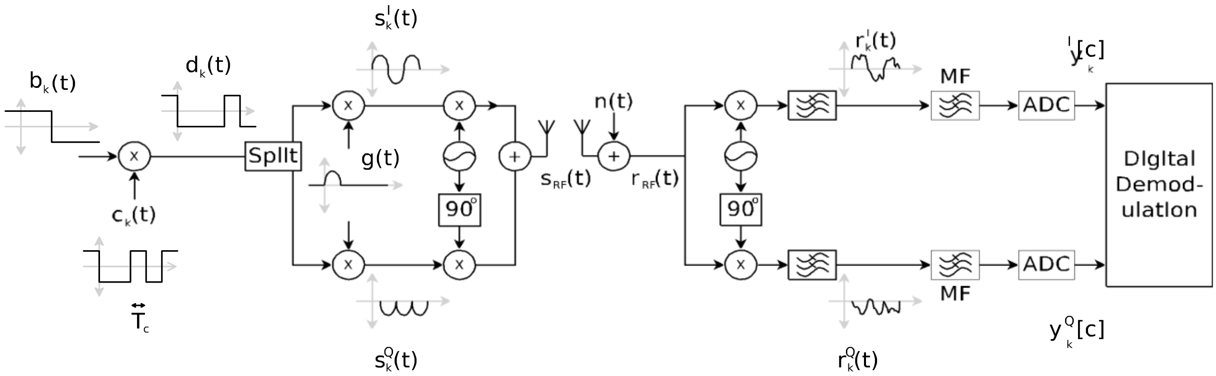

Fig.1. Transmitter and receiver structure for QPSK modulation/demodulation. The items drawn using dotted lines are hardware components that must be modified to enable compressive sensing.

$$y_k^I(t) = \int_{lT_c}^{(l+1)T_c} \theta_l(t) r_k^I(t) dt \qquad (9)$$

$$\Theta_1(t) = \begin{bmatrix} \theta_0(t) \\ \theta_1(t) \\ \vdots \\ \theta_{C-1}(t) \end{bmatrix}, \theta_i(t) = g(t - iT_c), 0 \le t < CT_c \quad (10)$$

The measurement matrix is denoted Θ1 as a result of it samples each Tc/1, i.e. at nyquist sampling rate.

This means that for each received symbol 2C samples should be taken for the in-phase and quadrature-phase signals in total. These samples then form the received signal vectors, Y_k^I and Y_k^Q ,are used to demodulate the signal and find an estimate of the transmitted symbol, represented as αk, employing a method of least squares estimator.

Thanks to the easy style of this signaling scheme and therefore the matched filter, it is attainable to perform the reception method as a method of least squares estimation with straightforward strictly binary versions of the analog dictionary and measurement matrices, $\psi^I(t)$,$\psi^Q(t)$ and$\Theta_1(t)$ respectively.

outline $y_k = y_k^I + jy_k^Q$ and outline M signal candidates as $s_m = \Phi_1(\Psi^I \propto_m + j\Psi^Q \propto_m)$, wherever Θ_1= I is now simply the C×C unit matrix and $\Psi^I \in \{\pm1\}^{C\times M}$ and $\Psi^Q \in \{\pm1\}^{C\times M}$ are the discrete in-phase and quadrature-phase dictionary matrices with every entry signifying either a positive (1) or negative (−1) pulse within the analog versions of the dictionary matrices. With these definitions so as the least amount squares estimate will be found as:

$$\propto_{k,idx} = arg_m \min (y_k - s_m)^H (y_k - s_m) \qquad (11)$$

Where (•) H denotes Hermitian transpose, $\propto_{k,idx}$ is that the estimate of the index within the α_k vector that is non-zero, i.e. the index comparable to the symbol that has been transmitted.

V. COMPRESSIVE SAMPLING RECEIVER STRUCTURE

In hardware compressive sensing sampling structures, such as the Random Demodulator, a PRN sequence is mixed with the received signal followed by low-pass filtering.

Because of the presence of a PRN sequence in a spread spectrum transmitter, which spreads the information signal, a compressive sensing-enabled receiver might just use a recurrent version of its matched filter, subsample the received signal and still extract the data. Before sampling, the matched filter should be changed to contain not solely one chip pulse form however as several chip pulse shapes as shall be contained per sample. This received signal vector might then be written as:

$$y_k^I = \int_{lT_{c/k}}^{(l+1)T_{c/k}} \theta_l \; r_k^I \, dt \qquad (12)$$

$$\varphi_{1/k}(t) = \begin{bmatrix} \theta_0(t) \\ \theta_1(t) \\ \vdots \\ \theta_{L-1}(t) \end{bmatrix}, \theta_j(t) = \sum_{c=j/k}^{(j-1)/k} g(t - CT_c) \; 0 \le t \le CT_c \qquad (13)$$

Here every value of ℓ = 0, 1, …..,L signifies a set of chips because of the sub sampling wherever L = C_k is that the range of samples taken per symbol. $\kappa = \frac{L}{C} \in [0, 1]$ is the under sampling ratio in the compressive sensing system and signifies the magnitude relation between taken samples and Nyquist samples. During this work we tend to limit ourselves to eventualities wherever 1/k is an integer number, i.e., solely an integer number of Nyquist samples are compressed along into one sample.

To verify that employment of an extra PRN sequence at the receiver makes no sense, we tend to might inspect the end result of the sub sampling ADC in Fig. 1. Assuming a noise-free setting (n(t) = 0), the end result becomes:

$$y_k^I[l] = \sum_{c=l/k}^{(l+1)/k} \int_{CT_c}^{(C+1)T_c} r_{k P_{PRN}}^I(t)\, dt$$

$$= \sum_{C=l/k}^{(l+1)/k} \int_{CT_c}^{(c+1)T_c} \sum_{c^1=0}^{c/2-1} b_k(t + C^1 T_c) C_k(t + C^1 T_c).$$

$$g(t - nT_c) P_{PRN}(t)\, dt \qquad (14)$$

Notice that the up and down-conversions are assumed good and P_{PRN} (t) may be a new PRN sequence, added at the receiver as is done within the Random Demodulator

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receiver structure. The symbol c′ denotes a chip picked get into $d_k(t)$ at the transmitter and used to avoid confusion with c, the chips added along into a sample at the receiver. The special classification with Tc in reference to b_k (t) and c_k (t) is to pick out the chips within the in-phase path solely. As a result of everything is multiplicative, it is seen that $c_k(t + n\,Tc)$ and $P_{PRN}(t)$ are synchronized and have a similar chip rate, i.e. they will be viewed as one PRN sequence. It follows that the multiplication of a PRN sequence at the receiver makes no sense here.

Because we have a tendency to demodulate a signal, that is equivalent to a classification problem, it is not necessary for us to reconstruct the total original signal as is done in compressive sensing. Instead we have a tendency to use the recently introduced construct of compressive signal process to perform classification within the compressed domain. By classification, we have a tendency to mean to classify that of the signal candidates within the dictionary Ψ^I and Ψ^Q has been transmitted. This does not need reconstruction of the signal itself and should thus be finished less procedure quality by using compressive signal process, instead of classic compressive sensing algorithms, that reconstruct the total signal.

To extract the data at the receiver using the 2 sub-sampled chip sequences, y_K^I and y_K^Q, the classification rule (11) is employed once more with $\Theta_{1/\kappa} \in \{0, 1\}^{L\times C}$ rather than $\Theta 1 \in \{0,1\}^{C\times C}$. In [3] a pre-whitening matrix, W is introduced to counter noise coloring by the activity matrix. However, as our projected activity matrix, $\Theta_{1/\kappa}$, has no overlapping rows, the noise remains white in our case. This pre-whitening matrix is thus not necessary here, but if e.g. a mathematician or Bernoulli measurement matrix is employed instead, it must be included.

VI. NUMERICAL RESULTS

To show the performance of our estimated receiver structure, we have performed a numerical experiment within which we have a tendency to compare the Bit Error Rate (BER) of a classical receiver to it of a compressive sensing-enabled receiver. This can be done for a variety of Signal-to-Noise-Ratio (SNR) levels. The system used for this experiment is our MATLAB implementation of the physical layer of the IEEE802.15.4 2450 MHz OQPSK radio band specification. Each block of 4 bits is mapped into one among 32 binary chip sequences. The chip sequence is then modulated using Offset Quadrature Phase Shift Keying (OQPSK).

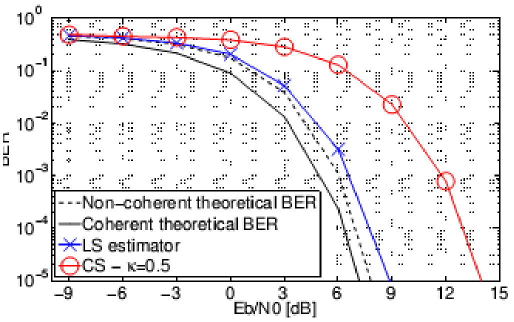

Fig.2. The BER versus Eb/N0 for a classical receiver implementation using least squares compared to that of a compressive sensing enabled receiver with κ = 0.5. The full black curve signifies theoretical BER per Eb/N0 for coherent MFSK and the dashed curve is theoretical BER per Eb/N0 for non-coherent MFSK.

This standard has been chosen due to its widespread use, having been deployed already in several applications round the world and since it is a legendary standard to several scientists and engineers. The experiment is repeated for a variety of SNRs or a lot of specifically energy per bit per noise spectral density (Eb/N0).The noise is added in a bandwidth corresponding to that of the baseband signal, i.e.,2 MHz Our experiment is conducted by sending randomly generated data packets of length 127 × 8 = 1016 bits every (the maximum size of an IEEE 802.15.4 data packet). For each of 2 tested ways and for every Eb/N0 level, bits are transmitted till at least1000 bits are received in error.

To validate the implementation of the compressive sensing framework, we have conducted a numerical experiment within which we have a tendency to add a constant to the transmitted signal, instead of additive white Gaussian noise (AWGN). The results for each the classical method of least squares and the compressive Sensing implementation follow the expected results as found through mathematical calculations, thereby indicating that the implementation performs obviously.

The results of the BER versus Eb/N0 experiment with AWGN are shown in Fig. 2. Additionally shown that the theoretical BER versus Eb/N0 for coherent MFSK, numerically evaluated

$$P_b = \frac{8}{15}\frac{1}{\sqrt{2\pi}}\int_{-\infty}^{\infty}[1-(1-Q(x))^{15}]\,e^{-\frac{\left(x-\sqrt{8\frac{E_b}{N_0}}\right)^2}{2}} \quad (15)$$

We have additionally enclosed the theoretical curve for non-coherent MFSK, because it is expressed within the IEEE 802.15.4:

$$P_b = \frac{8}{15}\frac{1}{16}\sum_{m=2}^{16}(-1)^m\binom{16}{m}e^{\frac{E_b}{N_0}\left(\frac{1}{m}-1\right)} \quad (16)$$

The classical implementation does not follow the theoretical bound specifically as a result the PRN sequences are not orthogonal and because of the short code lengths. For κ = 0.5 the compressive sensing receiver performs worse than a classical receiver by ≈ 4-5dB.

VII. CONCLUSION

We have shown that compressive sensing permits sub sampling of a DSSS signal. This has been demonstrated by means that of IEEE 802.15.4 2.4GHz OQPSK signals, that we have successfully sub sampled with half the Nyquist rate. This sub-sampling could cause a decrease in energy consumption or a lowering of the producing value. The penalty is that the expected decrease in performance

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because of noise folding. This penalty has not been more treated during this work.

An under sampling of k=0.5 is not a large under sampling rate. This is because of the impact of noise folding and since the IEEE 802.15.4 standard spread spectrum codes are solely 16 chips long in every channel (I and Q). For additional complicated spread spectrum systems with longer chipping sequences (and thus additional potential sparsity) and multiple users and if quantization is enclosed within the signal model, we have a tendency to powerfully believe there are cases wherever the sampling rate may be decreased, whereas still attaining an equivalent or higher BER performance than a classical receiver.

The main results of this paper is that the observation that in a spread spectrum receiver it is possible to use compressive sensing without generating a PRN sequence and compounding it with the received signal. This can be achievable as a result of a spread spectrum signal has already been spread by the transmitter.

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