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On the suitability of compressive sampling for the implementation of low-cost multi-channels synchronous data acquisition system

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***Abstract*-**Nowadays the most of the technical applications require the acquisition and the processing of signals coming from many sensors disseminated in the measurement field. Typically, to reduce the cost of the overall measurement process, the above-mentioned tasks are performed by devices as microcontroller, low cost Data Acquisition Systems (DAS), Field Gate Programmable arrays (FPGA), and so on. This is even more true when smart-sensors, or wireless sensor networks, applications are considered. These devices are characterized by some main limitations concerning with the reduced quantity of internal memory, and the use of multiplexer devices to share the same Analog to Digital Converter (ADC) over different physical channels. The former limitation influences the maximum observation time these devices are able to collect with a single shot acquisition, the latter imposes unwanted phase shifting on the acquired signals. The use of modern acquisition and processing techniques might overcame some of these issues. One of these is the Compressive Sampling (CS) that promise the capability of signal reconstruction starting from very low acquired samples. To this aim the paper deals with the design of this technique on a few cost multi-channel data acquisition systems (DASs) as that of low cost devices such as 8 or 16-bit microcontrollers. Aim of the paper is the analysis of the accuracy of reconstructed data and phase shifting recovery.

I. Introduction

The acquisition of signals coming from several sensors proves to be a fundamental issue in a number of application fields, such as the wireless sensor networks [1]-[4], the analysis and assessment of electrical power quality [5],[6], survey and control of environmental quantities of interest [7]-[9], control and monitoring of complex production process[10]-[13], detection of life signs [14-[16], systems and devices characterization [17]-[19], and so on [20]-[25]. In the most of these applications the development of cost-effective measurement systems is a very important task that has to be accomplished for. To give an idea, in the case of many wireless sensor network applications, the cost of each wireless sensor, composed by the sensing, the data acquisition system, the processing unit and the radio communication devices, has to be lower than some euros [1]-[4]. To this aim low cost measurement platforms as those based on microcontroller, FPGA and so on are frequently considered. These devices integrate all the above mentioned parts in a single chip thus allowing cost-effective sensor realizations. In addition, they are generally characterized by limited hardware resources in terms of internal memory and ADCs (they use a multiplexer the share different channels over the same ADC), and good processing capability thanks to floating point processor and even increasing clock frequencies. It is worth noting that the reduced quantity of internal memory, and the use of multiplexer devices to share the same ADC over different physical channels strongly influences the overall measurement process. The former limitation influences the maximum observation time these devices are able to collect with a single shot acquisition, the latter imposes unwanted phase displacement on the acquired signals.
In this context, in the last years modern acquisition and processing techniques have been proposed in the literature with the aim of reducing hardware requirements of ADC devices and allowing reliable signal measurements. One of the most promising technique is that named Compressive Sampling (CS) [26-28]. CS is an the innovative paradigm of acquisition capable of assuring reliable signal reconstruction from a reduced, apparently insufficient number of samples [29]-[30]. The innovative idea underlying the CS is the simultaneous execution both of acquisition and compression stages, thanks to the in-line acquisition of a reduced number of samples that is deeper lower than those required by applying the Nyquist-Shannon rule. Thanks to its some attractive features, CS overcomes the limitation of the sampling theorem, without requiring no information about the signal of interest but its sparsity in a suitable orthonormal basis [26]-[30]. Moreover, CS turns out to be non-adaptive, differently from traditional sampling protocols, that require the knowledge of the signals bandwidth.
In this paper the authors, starting from their previous experience on data acquisition devices [20],[22], cost

effective measurement systems [3],[10],[11], microcontroller based measurement systems [2],[4],[5] and CS [29]-[32], propose the implementation of a CS-based data acquisition technique on a low cost microcontroller-based ADC. The study will investigate some important features as: (i) the accuracy in the reconstructed signal and the influence of real ADC resolution and (ii) the capability to recover the phase displacement in order to achieve synchronized measurement. The experimental study has been carried out on microcontrollers belonging to the Microchip PIC18TM family characterized by several input channels (up to 16 independent channels).
In the following after some theoretical background about the CS, the proposed implementation and the obtained experimental results are presented and discussed.

II. Theoretical Background

In the following details about the fundamental of sampling and compression theory together with notes about the CS are given.

A. Fundamental of sampling and compression theory

The traditional sampling paradigm is based on the Nyquist–Shannon theorem to reliably recover a signal, an image or a video. In particular, to reconstruct a signal from a sequence of acquired samples, it must be characterized by a finite bandwidth and it must be sampled with a frequency at least twice its bandwidth:

$$f_s = 2 * B \qquad (1)$$

where$B$ is the low-pass bandwidth of signal of interest.
From a mathematical point of view, time–domain sampling of discrete signals can be expressed as:

$$\mathrm{y} = \varphi \cdot \mathrm{x} \qquad (2)$$

where $y \in R^n$ is the vector of measurements, $x \in R^n$ is the unknown input signal, $\varphi \in R^{n\,x\,n}$ is a sampling matrix.
There is a wide set of signals that have a sparse representation if the signals are expressed in a proper orthonormal basis ψ:

$$\mathrm{x} = \psi \cdot \mathrm{f} \qquad (3)$$

where$f \in R^n$ is a sparse representation of the signal x in the orthonormal basis ψ [26].
In other words, in the considered basis ψ there are only few coefficients of *x* whose value is significantly different from zero. It is worth noting that these coefficients account for almost the whole information needed to reconstruct the original signal. As an example, a sinusoidal signal is characterized by an endless evolution versus time, while its Fourier transform contain the same information in only two coefficients different from zero.
If condition (3) holds, the signal *x* proves to be compressible and the sparsity of the signal is a characteristic that can be used to compress its information [27]. This is, indeed, the typical operating technique of most compression algorithms; the signal of interest is firstly sampled according the Nyquist–Shannon theorem, and, successively, only the few coefficients of the transformed signal containing most of useful information are retained, dropping those coefficients characterized by null or negligible value.

B. Compressive sampling

The innovative idea underlying the CS is the simultaneous execution both of acquisition and compression step, thanks to the in-line acquisition of a number m of samples (with $m \ll n$ where n is the dimension of the square sampling matrix) reduced but sufficient for the successive signal reconstruction. In other words, the sampling matrix φ allows selecting *m* measured values from which reconstructing the original signal.

$$y = \varphi \cdot x \qquad (4)$$

where $y \in R^m$ is the vector of acquired samples, $x \in R^n$ is the unknown input signal,$\varphi \in R^{m\,x\,n}$is the so-called sampling matrix.
The traditional approach for gaining *x* from the considered system in (1) would exploit the minimization of the l^2-norm (i.e. the usual least square minimization). Unfortunately, differently from system in (1), the one described in (4) turns out to be an underdetermined system of linear equations; this kind of systems have usually infinitely many solutions, since the associated problem is ill-posed. To assure an efficient and actual solution to the problem, two properties, namely the *sparsity and the incoherent sampling*, have to be required.

C. Sparsity and l1-norm minimization

With the assumption that *x* is characterized by a sparse representation, the sequence of acquired measurements can be expressed in terms of the sparse representation of *x* by combining eq. (3) and (4),

$$y = \varphi \cdot \psi \cdot f \qquad (5)$$

Let us introduce a new matrix, according to

$$A = \varphi \cdot \psi \qquad (6)$$

where $A \in R^{m\,x\,n}$.

To reconstruct the sparse signal *f*, the following equation system has to be solved

$$y = A \cdot f \qquad (7)$$

As state above, the traditional approach adopted to reconstruct *f* would be the minimization the l^2-norm in (7); however, the obtained solution will be characterized by non-sparse features, while we are interested to find a solution vector $\hat{f}$ with the lowest possible of nonzero entries, $\|f\|_{l0}$; in other words

$$\min_{\hat{f} \in R^n} \|\hat{f}\|_{l0} \text{ subject to } y_K = < \varphi_k, \psi\hat{f} > \ \forall\, k \in \{1, \dots, m\} \qquad (8)$$

The considered problem proves to be NP-hard from a computational point of view. Alternatively it has been demonstrated that, in many cases of practical interest, a solutions characterized by the minimum l^1-norm gives the same result as the minumum l^0-norm. As a matter of practice, the reconstruction of signal obtained by means of l^1-norm minimization proves to be exact with overwhelming probability, provided that the sequence *f* is sufficiently sparse [28].

Differently from the l^0 minimization problem, the l^1 minimization problem can be solved more rapidly and efficiently by linear programming or convex programming techniques [26]. To this aim, among all the possible solutions of the considered system, the one characterized by the minimum l1-norm is chosen as useful sparse representation of input signal x, i.e.

$$\min_{\hat{f} \in R^n} \|\hat{f}\|_{l1} \text{ subject to } y_K = < \varphi_k, \psi\hat{f} > \ \forall\, k \in \{1, \dots, m\} \qquad (9)$$

where $\|f\|_{l1} = \sum_{i=1}^{n} |f_i|$.

D. Incoherent sampling

To assure a reliable reconstruction of the signal, CS theory requires that another condition has to be met. It concerns with the presence of a suitable incoherence level between the sampling matrix φ and the orthonormal basis ψ. The coherence between the matrices φ and ψ is defined as the quantity:

$$\mu(\varphi, \psi) = \sqrt{n} \max_{1 \le k, j \le n} |< \varphi_k, \psi_j >| \qquad (10)$$

where φ_k and ψ_j stands respectively for the k-th row and the*j*-th column of the matrices φ and ψ. As a matter of practice, the coherence measures the maximum correlation between the two matrices [27]. In order to make it a reliable approach, CS requires that the chosen couple of matrices φ and ψ should be characterized by the lowest possible coherence [26],[28]. It can be demonstrated that

$$\mu(\varphi, \psi) \in [1, \sqrt{n}] \qquad (11)$$

As an example, if the sampling matrix consists of a discrete spikes basis

$$\delta_{m,k} = \delta[m-k] = \begin{cases} 1 & m = k \\ 0 & m \ne k \end{cases} \qquad (12)$$

and the transformation matrix ψ is based on the Fourier basis

$$\psi_{n,k} = \frac{1}{\sqrt{N}} e^{j\frac{2\pi}{N}nk} \qquad (13)$$

then the coherence has the minimum allowed value, equal to 1.

The coherence proves to be a fundamental parameter for the compression; the lowest its value, the lowest the number of samples required for a reliable reconstruction of f and, as a consequence, the original signal **x**. In particular, the following condition holds

$$m \ge C * \mu^2(\varphi, \psi) * S * log(n) \qquad (14)$$

where *m* is the number of measurements selected uniformly at random, *C* is a constant and *S* is the sparsity of *f*. It is worth noting that for values of coherence very close to one, only $S * \log n$ of samples are needed to reconstruct the original signal [26].

More generally, it has been demonstrated that, if $\boldsymbol{\varphi}$ is a proper random matrix, then $\boldsymbol{\varphi}$ would be incoherent with respect to a generic basis $\boldsymbol{\psi}$ with high probability; in other words, it is almost always possible to correctly reconstruct a generic signal by means of a limited number of arbitrarily and randomly chosen time samples.

III. The proposed method

Taking advantage of some attractive features of CS theory, the authors propose a new method aiming at realizing low-cost multi-channel synchronous data acquisition systems (DAS) capable of overcoming hardware limitations due to their inherent multiplexed DAS architecture. What is interesting, the proposed method applies whatever the number of considered input channels; for the sake of the clarity, the method will be described in the following with reference to an application example involving a DAS consisting of four independent input channels multiplexed on a single ADC. If this is the case, the acquisition of the same signal on the four channels will result in four digitized waveforms whose phase shifts are mainly due to the interchannel delay; the higher the frequency of the input signal, the worst the associated phase shift among the channels.

A. Sampling instants selection

Let us suppose that each input signal can suitably be reconstructed through $m \ll n$ samples, according to CS approach; this way, four times m samples have to be digitized for all the channels. A traditional random number generator can be adopted in order to set the indices of the sampling instants k_{ij} (with i=1,..,4 that indicates the input channel, and j=1,..,m that indicates the i-th measurement of the selected input channel), i.e. the multiple values of the common sampling period T_s adopted for the signal reconstruction. The corresponding sampling matrix can be arranged to have 4m rows and n columns, as shown in the Fig.1 where $y \in R^{4m}$, $\varphi \in R^{4m\,x\,n}$, and x_1, $x_{2,}$ x_3 and $x_4 \in R^n$, are the input signals for each of four channels.

Without loss of generality, it is possible to operate in such a way as to change the input channel each time a new sample is acquired; this way, the acquisition stage ends with m sample acquired on each channel. As for the entries of the matrix, for each row only one element is different from zero and equal to one; in particular, the considered time index k_{ij} is taken as the entry e_{jk} of the sampling matrix φ to be set equal to one.

This way, the vector y contains the interleaved measures acquired for all input signals. In order to suitably reconstruct all the acquired input signals, the entries of y are reordered and separate in four vector, referred to as y_1, y_2, y_3.and $y_4 \in R^m$. Moreover, starting from the whole sampling matrix $\varphi \in R^{4m\,x\,n}$, four different matrices $\varphi_i \in R^{m\,x\,n}$ (one for each channel) can be attained in a similar way.

B. Optimal generation of the transformation matrix and input signals reconstruction

The sequence of acquired measurements for each input signals can be expressed in terms of the sparse representation of x_i by combining eq. (3) and (4)

$$y_i = \varphi_i \cdot \psi \cdot f_i \qquad (15)$$

As for the transformation matrix ψ, it has been generated according to discrete Fourier transform, under the assumption of stationary signals in the observation interval; a new matrix, referred to as A_i, can be determined by applying the following expression

$$A_i = \varphi_i \cdot \psi \qquad (16)$$

This way, in order to reconstruct the sparse signal f, the following equation system has to be solved

$$y_i = A_i \cdot f_i \qquad (17)$$

Thanks to the suitable choice of the measurement matrix φ_i, the matrix A_i turns out to be a submatrix of ψ; this way, the computational burden of the method is reduced since the matrix A_i is not calculated by an actual multiplication, but is evaluated as the rows of the discrete Fourier transform matrix whose index are equal to that of the sampling instants. In other words, each A_i is obtained randomly selecting n row from the n x n discrete Fourier transform ψ. If this is the case, the minimization of l1-norm can now reconstruct S-sparse signal for

$$S \le C \cdot m/(\log n)^6 \qquad (18)$$

According to what stated above, once determined the matrix A_i the spectrum of the input signal can be obtained by finding the sparse sequence $\hat{f}_i$ that is solution of the equation system (15) and characterized by the minimum l1-norm. The estimated input signal $\hat{x}_i$ can thus be evaluated according to (3) and the obtained reconstruction is characterized by a resolution in time domain equal to T_s.

Thanks to the proposed approach, it is possible to reconstruct the input signal on each channel in such a way as all the channels have a common, unique time base. This way, no phase shift related to the interchannel delay is introduced to the detriment of an higher computational burden associated with the algorithm for signals

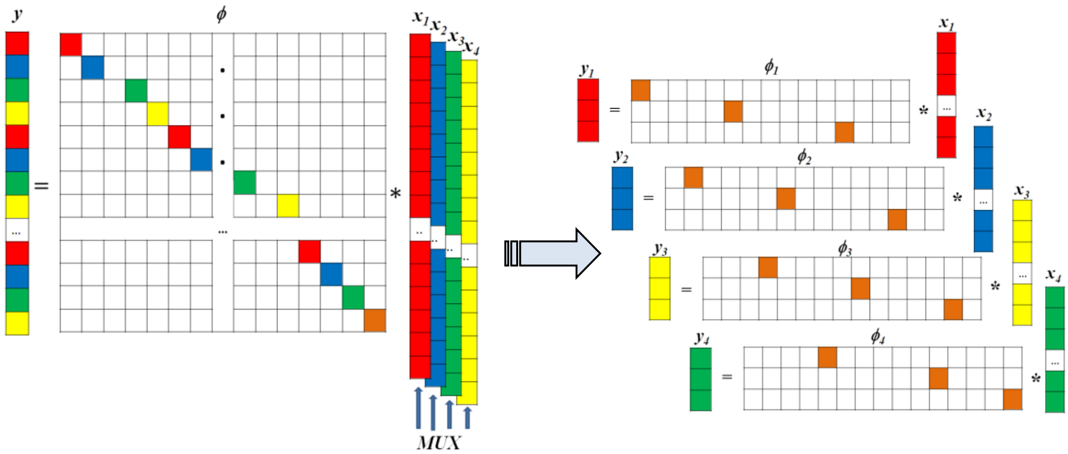

Figure 1. Application of the compressing sensing to the considered problem; the sampling matrix is applied iteratively to the signals acquired on the different channels.

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reconstruction based on the l1-minimization of the equations system (17).

IV. Experimental results

To preliminarily assess the performance of the proposed method, a number of tests have been carried out on a traditional low-cost microcontroller; to this aim, a suitable measurement station has been setup. The station consisted of (i) an arbitrary waveform generator (AWG) (33220A by Agilent), (ii) a 8-bit microcontroller (PIC18F4620 by Microchip mounted on a PICDEM2 Plus board) and (iii) a personal computer. The sinusoidal signal generated by the AWG was connected to four analog inputs of the microntroller, while the data between the personal computer and microcontroller were exchanged on a traditional RS232 serial port. The first step of measurement is the generation on the personal computer of the random sequence of sampling instants; the sequence is then transferred into the memory of the microcontroller via serial link. The microcontroller acquires the samples of the input signal according to the strategy presented in Section III and send them back to the personal computer for the input signals reconstruction.

As an example, Fig.2 shows the results obtained when a common effective sampling period of 1 ms has been adopted to randomly digitize 20 samples of a for each channel; to make it easier in distinguishing the channel associated with the acquired samples, different markers have been used. Signals have been reconstructed over a record of 1000 samples; time delay never greater than 1.5 μs has been obtained, one magnitude order lower than the inherent minimum interchannel delay (about 25 μs). To better appreciate the method's capability, the sample-by-sample differences between the reconstructed signal on each input channel and that reconstructed on the first channel, taken as reference, are shown in Fig.3.

Similar results have been achieved also in the presence of signals characterized by higher frequency and digitized at higher sampling rate; in such condition the inherent interchannel delay would, in fact, give rise to an unacceptable phase shift among the acquired waveforms. On the contrary, the proposed method has allowed to hardly mitigate the problem, assuring simultaneous acquisitions on all the digitized waveforms.

V. Conclusions

A new method based on compressive sampling for synchronous and simultaneous acquisition of analog signals has been presented. In particular, the method has exploited attractive features of CS to overcome inherent limitations of sequential, multiplexed multi-channels data acquisition systems to make them operate as simultaneous DASs. To this aim, the same time base has been adopted to randomly acquire a reduced number of samples on each channel and the application of CS approach has allowed to reconstruct the original signals as they were simultaneously acquired.

Several tests have been carried out on an actual low-cost microcontroller to preliminarily assess the performance of method; in particular, a suitable measurement station has been setup to (i) generate the random sequence of sampling instants, (ii) transfer the sequence to the microcontroller, (iii) acquire the corresponding samples on the channels of interest, (iv) send back the signals samples and (v) reconstruct the original signals through the CS strategy. The method has shown notable performance in correctly reconstruct the digitized signals thus allowing to assure time delay lower than 3 μs when the inherent interchannel delay were at least 25 μs.

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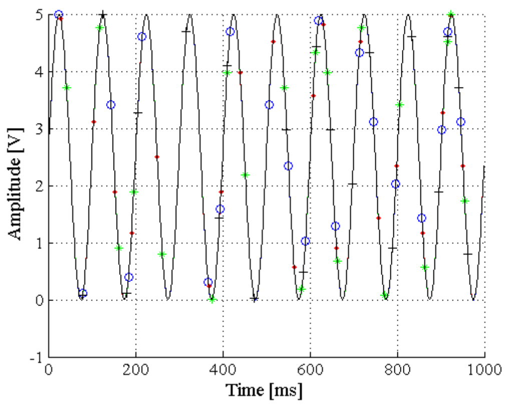

Figure 2. Reconstructed signals obtained through the acquisition of 20 random samples per channel.

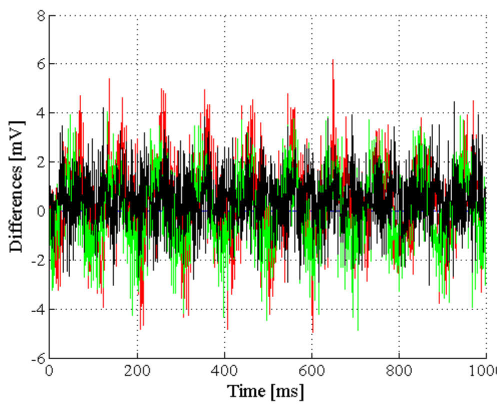

Figure 3. Differences between reconstructed signals on each channel and that of the first channel.

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