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Technical Note

Robust compressive sensing algorithm for wireless surface electromyography applications

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ABSTRACT

Surface EMG (sEMG) can be processed to detect medical abnormalities, activation level, or recruitment order or to analyze the biomechanics of human or animal movement. Today's sEMG systems suffer of limited processing time, limited storage capacity, and high power consumption. The main motivation of this work is to present a new algorithm based on analog-Compressed Sensing (CS) for the receiver side of an ultra-low-power wearable and wireless sEMG sensor. The novel algorithm based on analog-CS at the sensing step attempts to keep the percentage root-mean-square difference (PRD) and compression ratio (CR) in linear relationship that is very important for sEMG data compression to prevent dramatic information loss in high CR situations. The proposed algorithm allows reducing the power consumption to 63%, the PRD to 0.098%, the root mean square error (RMSE) to 0.7%, and signal difference to noise ratio (SDNR) to 0.015%. In addition, the proposed algorithm achieves a good level of accuracy at 98.85% for the reconstruction process.

1. Introduction

The existing long-term recording sEMG systems are based on wired/fixed sensors. Thus, they suffer from low processing time and speed, limited mobility, cost, and size [1,2]. These limits create the real need for the implementation of new wearable and wireless sEMG sensors that deliver healthcare services to anywhere and at anytime [3]. The sEMG bio-signals can be processed to detect medical abnormalities or to analyse the biomechanics of the human or animal movement [4,5]. After an exhaustive search, we did not find any new study that aims an effective random sampling-rate data acquisition algorithm for wireless sEMG systems. In this paper, we apply analog-CS theory as a random data acquisition procedure to the transmitter side in order to compress analog input signal at the sensing step before Analog-to-Digital converter (ADC). Then, the reconstruction algorithm based on ℓ_1-optimization is applied to the receiver side in order to recover the original sEMG bio-signals. The experimental results show the proposed algorithm obtains a superior performance, particularly in high CR and low PRD situations. The algorithm based on analog-CS attempts to keep the PRD and CR in linear relationship that is very important key for sEMG data compression to prevent dramatic information loss in high CR situations. The proposed algorithm allows reducing the power consumption to 63%, the PRD to 0.098%, the RMSE to 0.7%, and the SDNR to 0.015%. In addition, the proposed algorithm achieves a good level of accuracy at 98.85% for the reconstruction process. The proposed algorithms are created using C, HSPICE, and Matlab/Simulink toolboxes. The proposed algorithm is tested over several records of clinical EMG healthy signals of the following databases: (1) PhysioNet (PhysioBank ATM) [6]; (2) EMG Bank [7]; (3) EMG project lab [8]. The structure of this paper is organized as follows: In Section 2, an overview about CS theory as a random data-acquisition method is presented. In Section 3, the proposed algorithm for the transmitter side of a wireless sEMG sensor is presented. In Section 4, the results on PRD, power consumption, RMSE, and SDNR are illustrated. The conclusion is given in Section 5 and future works in Section 6.

2. Overview of compressed sensing theory

The existing digital sampling techniques rely on the Shannon sampling theorem and have two major drawbacks. First, for bio-signals with large bandwidth, they generate large number of samples which are not tolerated in wireless and wearable applications [9,10]. Second, even for the bio-signals with low bandwidth, they produce a large amount of redundant samples [11] which increase the load of sampling and power consumption [12]. The CS framework enables continuous data acquisition and compression

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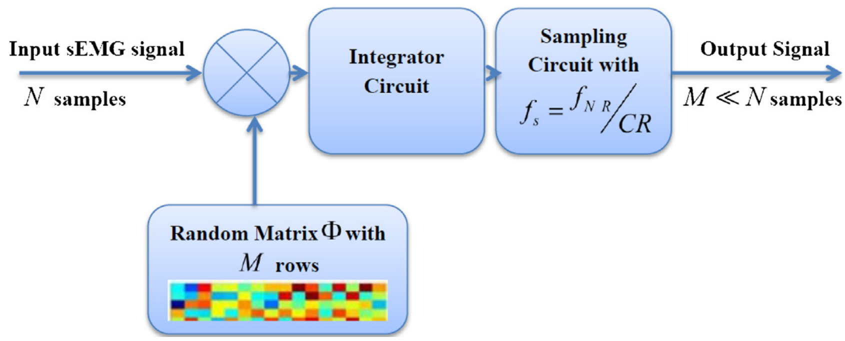

Fig. 1. Analog-CS framework.

that are suitable for wearable and wireless biomedical applications that addresses both the energy and telemetry bandwidth constraints of wireless bio-sensors. CS theory is a mathematical framework in acquiring and recovering for sparse signals with the help of an incoherent projecting basis that provides insight into how a high resolution dataset can be inferred from a relatively small and random number of measurements using simple random linear process [13]. The basic idea of CS theory as a random sampling approach is that when the biomedical signal is sparse or near sparse in terms of the number of non-zero coefficients, relatively few well-chosen observations suffice to reconstruct the original signal. In fact, CS is a new approach for the acquisition and recovery of sparse or compressive biomedical signal D significantly below the classical Nyquist-Rate (NR). Any sEMG signal D can be expressed as:

$$\begin{bmatrix} D_1 \\ D_2 \\ \cdots \\ D_N \end{bmatrix} = \begin{bmatrix} \Psi_{1\times1} & \Psi_{1\times N} \\ \Psi_{2\times1} & \Psi_{N\times2} \\ \cdots & \cdots \\ \Psi_{N\times1} & \Phi_{N\times N} \end{bmatrix} \times \begin{bmatrix} S_1 \\ S_2 \\ \cdots \\ S_N \end{bmatrix} \quad (1)$$

which ψ is sparsity matrix and S is coefficient matrix. In the CS theory, we have a $M \times N$ measurement matrix Φ and sEMG signal D with $N \times 1$ dimension such that $M \ll N$; therefore, the compressed signal C can be expressed as [14,15]:

$$\begin{bmatrix} C_1 \\ C_2 \\ \cdots \\ C_M \end{bmatrix} = \begin{bmatrix} \Phi_{1\times1} & \Phi_{1\times N} \\ \Phi_{2\times1} & \Phi_{N\times2} \\ \cdots & \cdots \\ \Phi_{M\times1} & \Phi_{M\times N} \end{bmatrix} \times \begin{bmatrix} D_1 \\ D_2 \\ \cdots \\ D_N \end{bmatrix} \quad (2)$$

From (1) and (2) we have:

$$\begin{bmatrix} C_1 \\ C_2 \\ \cdots \\ C_M \end{bmatrix} = \begin{bmatrix} \Phi_{1\times1} & \Phi_{1\times N} \\ \Phi_{2\times1} & \Phi_{N\times2} \\ \cdots & \cdots \\ \Phi_{M\times1} & \Phi_{M\times N} \end{bmatrix} \times \begin{bmatrix} \Psi_{1\times1} & \Psi_{1\times N} \\ \Psi_{2\times1} & \Psi_{N\times2} \\ \cdots & \cdots \\ \Psi_{N\times1} & \Phi_{N\times N} \end{bmatrix} \times \begin{bmatrix} S_1 \\ S_2 \\ \cdots \\ S_N \end{bmatrix} \quad (3)$$

which Θ can be expressed as:

$$\begin{bmatrix} \Theta_{1\times1} & \Theta_{1\times N} \\ \Theta_{2\times1} & \Theta_{N\times2} \\ \cdots & \cdots \\ \Theta_{M\times1} & \Theta_{M\times N} \end{bmatrix} = \begin{bmatrix} \Phi_{1\times1} & \Phi_{1\times N} \\ \Phi_{2\times1} & \Phi_{N\times2} \\ \cdots & \cdots \\ \Phi_{M\times1} & \Phi_{M\times N} \end{bmatrix} \times \begin{bmatrix} \Psi_{1\times1} & \Psi_{1\times N} \\ \Psi_{2\times1} & \Psi_{N\times2} \\ \cdots & \cdots \\ \Psi_{N\times1} & \Phi_{N\times N} \end{bmatrix} \quad (4)$$

The original signals can be exactly reconstructed, with a high level of accuracy and probability via ℓ_1 norm by solving the following convex optimization problem [16]:

$$\min \|D\|_1 \ s.t\ C = \Phi D, \quad (5)$$

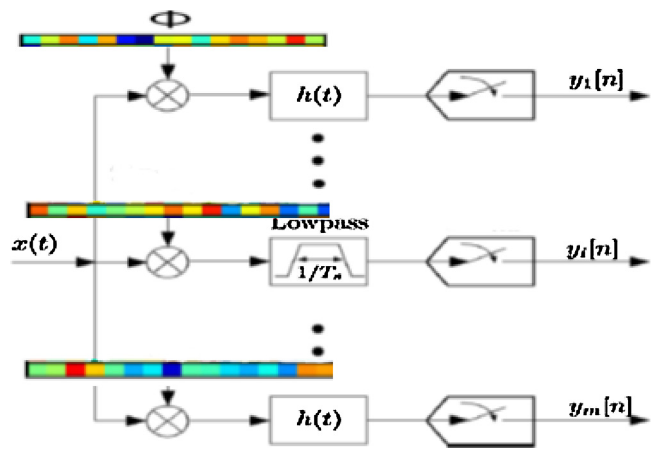

Fig. 2. Analog-CS for the proposed algorithm.

where $\|D\|_1$ is defined as $\|D\|_1 = \sum_n \|D_n\|$ with $D \in \Re^N$. However, certain conditions must be met to guarantee accuracy of the reconstruction process [17,18]. To grantee the success of the reconstruction process, random sensing matrix ϕ must obey the following conditions: (1) Matrix ϕ has Restricted Isometry Property (RIP) condition; (2) Matrix ϕ exhibits high degree of incoherence with the sparsity matrix ψ, where coherence measures the largest correlation between any row of ϕ and column of ψ. The less coherence between ϕ and ψ, the fewer the measurements M needed to recover the signal; (3) Matrix ϕ consists of independent and identically distributed (iid) random measurements [18].

2.1. Analog-CS scenarios

Fig. 1 shows the block diagram of analog-CS framework.

Fig. 2 shows our procedure for applying the analog-CS to the proposed algorithm. Fig. 1, the analog sEMG signal is mixed with matrix ϕ and then, integrated and sampled with the lower sampling frequency at $f_s = f_{(NR)}/CR$.

Based on Fig. 2, The analog-CS consists of the following steps: (1) The analog sEMG bio-signal multiplies with each row of the random sensing matrix ϕ based on Gilbert approach [19]; (2) The output signal of multiplier goes to an active integrator; (3) The $M \times 1$ dimension compressed version of the input sEMG healthy bio-signal generates at the transmitter side. Therefore, in the analog-CS scenario at the transmitter side, the input analog sEMG healthy bio-signal $[D]_{N\times1}$ is compressed to output analog bio-signal $[C]_{M\times1}$ such that $M \ll N$ and then, the ADC needs to digitize a smaller amount of data [20,21]. Therefore, the main motivation of analog-CS can be classified as: (1) To replace the conventional sampling and reconstruction operation with a general random linear measurement process and an optimization scheme in order to recover the original