Low-power EEG monitor based on Compressed Sensing with Compressed Domain Noise Rejection

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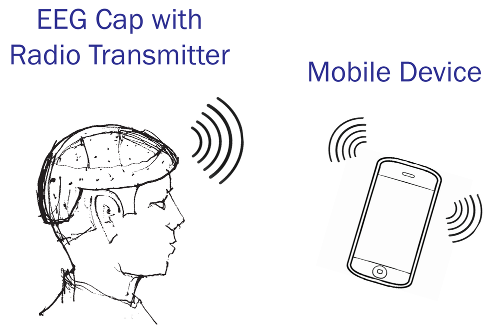
Introduction

<|> Real-time monitoring of biological signals such as heartbeat and brain waves by means of wearable or implantable devices is of great concern for e-health future developments.

<||> The advantage of a **portable system** is that the subject can be monitored during normal life activities without being forced to stay inside clinical facilities. Such a system must be tiny enough that it does not represent an obstacle for the patient's movements. Unfortunately, since portable devices are battery powered, a trade-off exists between device size/cost and minimum desired operational lifetime.

<|||> The key idea of this work is to move towards development of ad hoc wireless sensor nodes for biosignals introducing **low-power, real-time compression** of the raw physiological data in the sensor node in order to reduce the total amount of data to be transmitted. In this way the overall required power is reduced as well and device lifetime can be extended when physical size constraints are fixed.



EEG evoked response

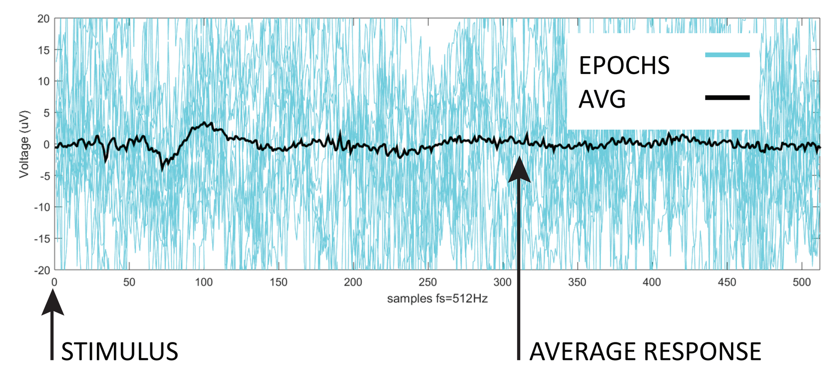
Electoencephalographic (EEG) signals are essential in identifying and studying several **neurological disorders** such as epilepsy and schizophrenia and are usually measured inside a laboratoy using a wired cap featuring a number of electrodes placed on the scalp.

Particularly, **Evoked Potentials** (EP), recordings of brain electrical activity arising when an external stimulus is delivered to the subject, are extremely challenging to acquire for two main reasons:

1) there are several noise sources corrupting the measurements such as environmental noise, sensor noise and physiological noise (unwanted components of biological origin);

2) the spontaneous EEG amplitude (alpha waves, beta waves, etc.) is usually much higher than evoked activity (tens of microvolts).

The commonly adopted solution when the stimulus is periodically triggered is averaging over several signal epochs (time intervals between two subsequent stimuli) so that any contribution that is not time-locked to the stimulus is averaged out while shared (evoked) features are retained and become more evident.



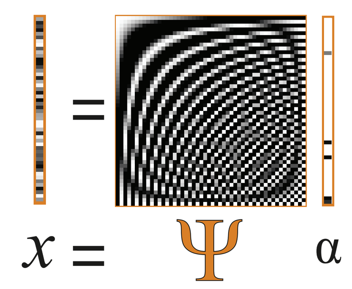
CS in a nutshell

BACKGROUND

Compressive Sensing (CS) is an emerging topic that merges signal acquisition and compression tasks. This means that CS is able to acquire all the signal information content using fewer samples with respect to the standard limit imposed by Shannon-Nyquist theorem. This is possible thanks to the fact that the instances of the n-dimensional signals x to be processed are sparse.

main Hp:

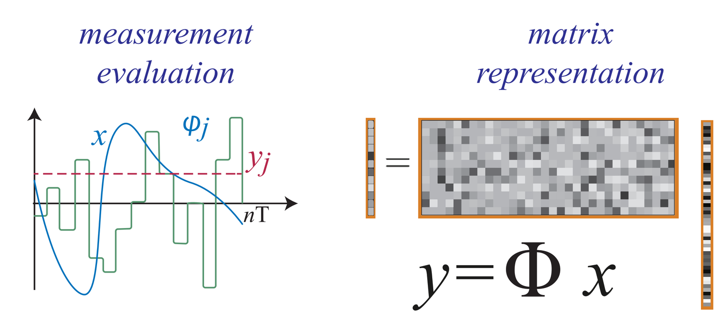
The **sparse assumption.** Slices in time of the input signal x, expressed in a proper basis Ψ (an nxn matrix), are associated to vectors with at most k non-null coefficients with $k << n$. These classes of signal are called k-sparse.



EEGs are sparse over the orthogonal Daubechies 8 wavelet basis

signal acquisition:

The **Encoder.** Over each time window, the signal is acquired by projections on proper set of m different sampling sequences φ_j collected row by row in the sensing matrix Φ (note that $m < n$). As guideline for the sampling sequences generation, the CS theory suggests to use **i.i.d. random vectors**.

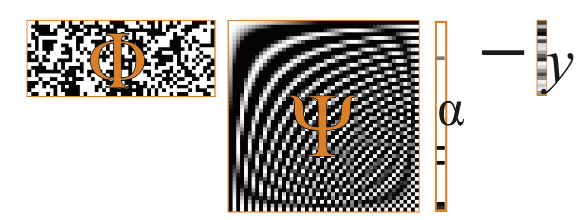


Make it easy!
Antipodal Random Vectors to optimize the phisical realzation of the ecoder stage

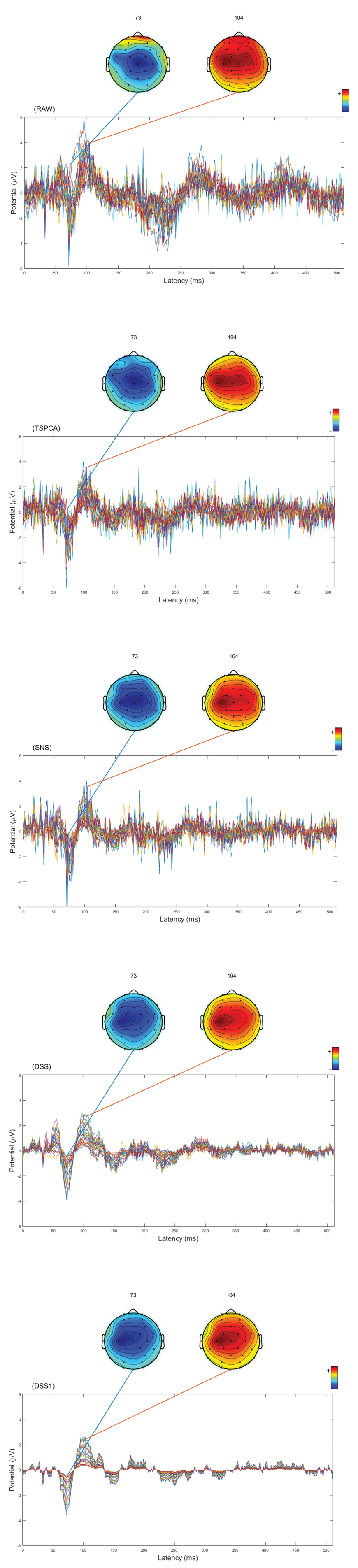
signal reconstruction:

The **Decoder.** The reconstruction of x can be achieved by solving the following optimization problem which looks at the sparset vector mapped in the collected measurements. Its convergence to x is guaranteed by the so-called restricted isometry property of the matrix $\Phi\Psi$ which roughly ensures that its application must be able to preserve the input signal $l2$ norm.
In this case classical CS theory guarantees reconstruction for $m > m_{\min} = 4k \log(n/k)$.

$$\min_{\alpha} \|\alpha\|_{l1}$$
$$\text{s.t. } \|\Phi\Psi\alpha - y\|_{l2} < \varepsilon$$



standard EEG offline filters



Experimental Setup

Actual EEG recordings taken from a normal hearing subject who performed a simple auditory task, consisting of listening to one second spaced speech syllables.

32 brain channels (International 10-20 system) + 2 differential ocular channels used as noise references to reject eye blinks artefacts

All channels are 1-200Hz band pass filtered and organized into 700 epochs, each of one-second duration.

The entire dataset is divided into two halves: a TRAINING SET (TS) and a DATA SET (DS).

Standard EEG Offline Filters

TS and DS are resampled at 512Hz and filtered using 3 OFFLINE DENOISING ALGORITHMS which actually represent the state-of-the-art in EP analysis but are much too power demanding to be directly implemented in a portable device.

1 Time-Shift PCA (TSPCA):

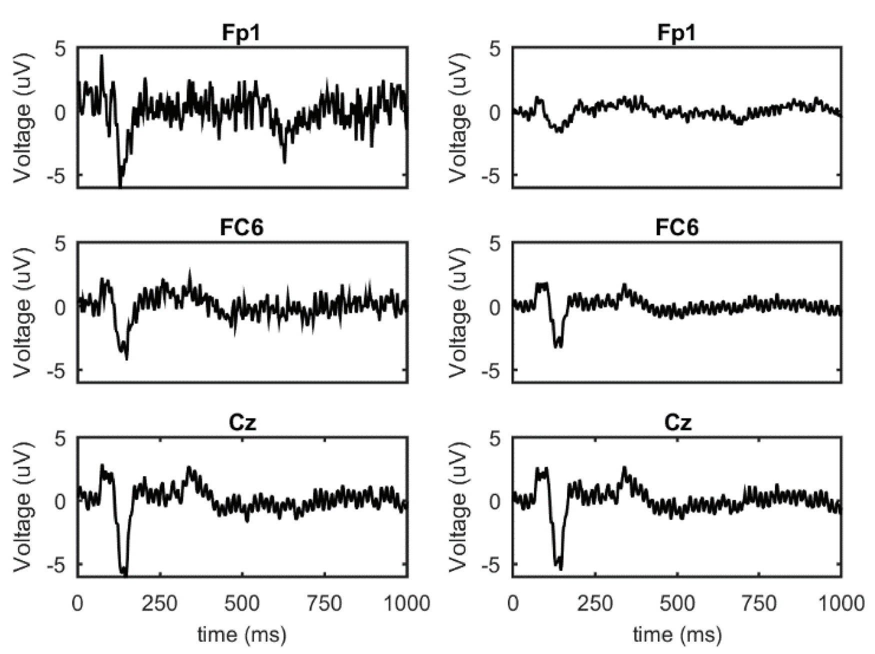
Environmental noise removal (external noise due to electromagnetic interference and 50-60Hz power line hum) obtained by delaying signals collected by sensors used as noise reference channels, orthogonalizing them, projecting the brain sensors onto the noise derived basis, and finally remove projections to obtain clean data. [ref5]

2 Sensor Noise Suppression (SNS):

This method is based on the assumption that every source of interest is picked up by more than one sensor while wide-band noise and glitches arising from problems like momentary variation of skin contact are not shared by neighbors. In the denoising process each signal is projected on the subspace spanned by its neighbors and then replaced by its projection. [ref6]

3 Denoising Source Sepatration (DSS):

Physiological noise removal is addressed by partitioning the recorder activity into stimulus-related and stimulus-unrelated components by means of a spatial filtering based on a criterion of stimulus-evoked reproducibility. [ref7]



adapted CS (Rakeness) and filters

The Rakeness approach relaxes the restricted isometry property when the class of signals to acquire is also localized,i.e., the information content is not only sparse, but also non-uniformly distributed in the whole signal domain. In this setting, antipodal random sensing sequences are also designed to maximize the average energy which one is able to collect (i.e. rake) when the input signal is projected into them. Exploiting such an approach one is able to reduce $M_{\min}$.

M. Mangia, R. Rovatti, and G. Setti, *"Rakeness in the design of analog-to-information conversion of sparse and localized signals,"* IEEE Transactions on Circuits and Systems I: Regular Papers, vol. 59, no. 5, pp. 1001–1014, May 2012.

M. Mangia, J. Haboba, R. Rovatti, and G. Setti, *"Rakeness-based approach to compressed sensing of ecgs,"* Biomedical Circuits and Systems Conference (BioCAS), 2011 IEEE, pp. 424 –427, Nov. 2011.

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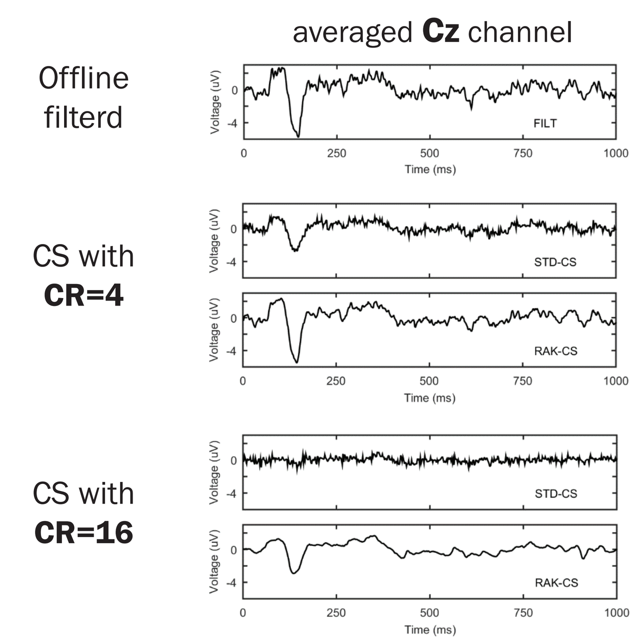
V. Cambareri, M. Mangia, F. Pareschi, R. Rovatti, and G. Setti, *"A rakeness-based design flow for analog to information conversion by compressive sensing,"* Circuits and Systems, IEEE International Symposium on, pp. 1360–1363, 2013.

RESULTS

Rakeness-based CS Improves CS performance in terms of RECONSTRUCTION ACCURACY vs CR (n/m) w.r.t. standard CS

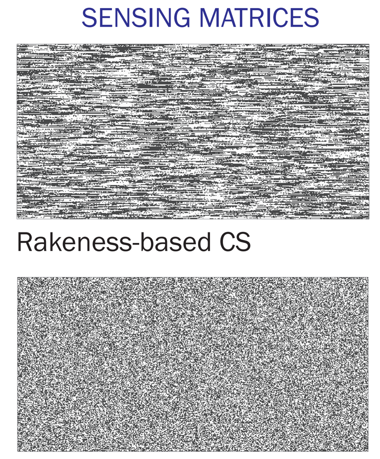


The input signal autocorrelation matrix, required by the rakeness-based CS is estimated using the TS portion of the offline denoised midline centered channel Cz, which tipically gives the strongest auditory response. To increase the robustness of the estimation, each epoch of Cz is replicated 100 times and randomly shifted.

Standard CS (bottom figure) has acceptable performance but the match with the offline filtered signal is greatly improved by introducing rakeness-based CS (top figure)

Standard CS is no able to reconstruct the EP waveform shape while rakeness-based CS still ensures a good match

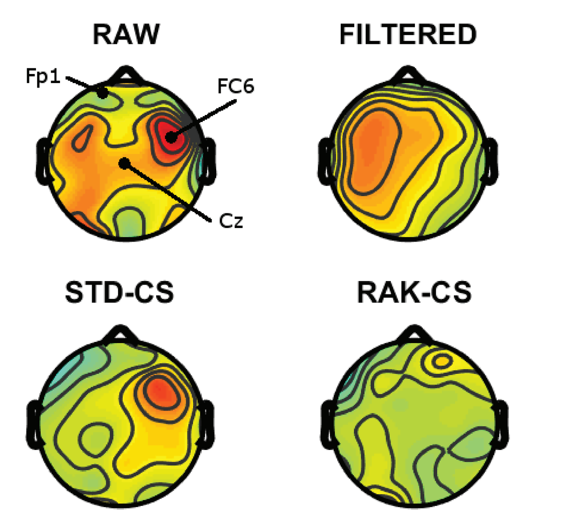
SENSING MATRICES

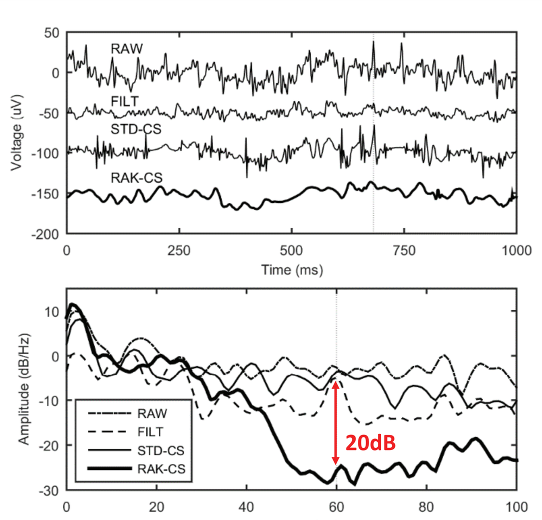


Rakeness-based CS

Standard CS

Implicit DENOISING during acquisition by Rakeness-based CS





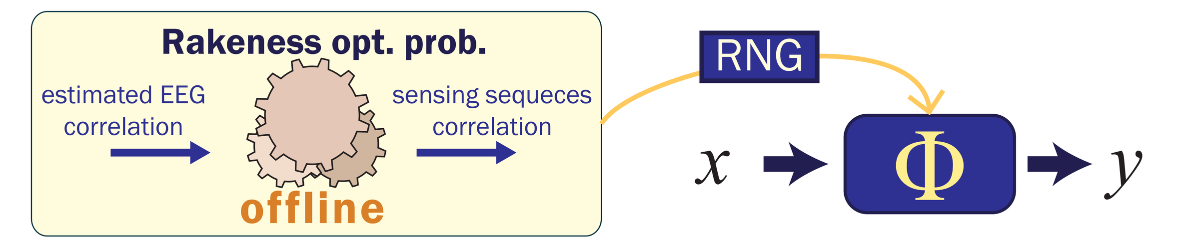
The sharp noise peak localized around the electrode FC6 at 700ms is completely removed by both the offline filtering and the rakeness-based CS.

Additionally, the rakeness-CS acquisition is able to also remove high frequency spectral components such as the 60 Hz power line hum.

This demonstates that some desirable properties of the TS have been implicitly imparted into the acquired signal during the rakeness optimized compression process.

EXPERIMENTAL RESULTS

How it work



conclusion

A novel approach for reducing the power consumption in portable health monitoring systems has been presented along with simulation results on a real dataset of EEG Evoked Potentials.

The proposed method, based on a recent extension of Compressed Sensing theory, called rakeness, outperforms standard CS in terms of quality of reconstruction for a given Compression Ratio, with very good performance up to CR=16.

Some interesting filtering capabilities are introduced, such as suppression of high-frequency noise peaks and 60 Hz power line noise, proving the effectiveness of the proposed methodology also for denoising purposes.

Main references

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[ref5] A. de Cheveigné and J. Z. Simon, "Denoising based on time-shift PCA," Journal of Neuroscience Methods, vol. 165, no. 2, pp. 297 – 305, 2007.
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[ref8] B. Lütkenhöner and J. Mosher, "Source analysis of auditory evoked potentials and fields," in Auditory Evoked Potentials - Basic Principles and Clinical Applications, R. F. Burkard, J. J. Eggermont, and M. Don, Eds. Lippincott Williams & Wilkins, 2007, pp. 546–569.

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