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Orthogonal matching pursuit algorithm for roll bearings on eeg signals using stationary wavelet transformation

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Abstract

Signal processing requires the efficient representation and processing of data. In an emerging trend the compressed signals gives the collection of linear projections of a sparse signal and information for reconstruction. In this paper, we propose that an application of compressed sensing in the field of signal processing, particularly electroencephalogram (EEG) collection and storage. The proposed framework is based on the EEG signals are sparse in a Gabor frame. Gabor frames are commonly used in science and engineering to synthesize signals from, or to decompose signals into, building blocks which are localized in time and frequency. The sparsity of EEG signals in a Gabor frame is utilized for compressing the signals. The matching pursuit algorithm is shown to be effective in the recovery of the original EEG signals from a small number of projections. The OMP algorithm improves the efficiency of finding the frequency-time atoms and rapid noise rectification. The experiments results are investigated up to 100 iterations and reduction of noise in weak signals.

Index Terms - Signal processing, Electroencephalography, Signal Reconstruction, Sampling, Orthogonal matching pursuit algorithm

I. INTRODUCTION

Electroencephalogram (EEG) is a commonly used brain imaging method with high temporal resolution with applications in neurology and psychology .The proposed research deals with weak signals background of noisy structure, which highly reduces the theories and algorithms. The collection of EEG signals over the multiple channels with multiple trials. EEG activity collected from a single subject can correspond to 2-4 hours of data. The compressed sensing of EEG data would allow for the stationary wavelet transformation.

Existing methods detects the weak signal under Signal to Noise Ratio (SNR) and computes the lower value. Its not able recover weak signal truly form computational analysis. The wavelet transform is fixed, flexibility of wavelets, decomposition processes is significantly limited. Mallat and Zhang investigated the decomposed signal over the dictionary[1].This paper deals with framework of compressed signal for EEG signal compression and reconstruction. The reconstruction of the original EEG signal from these projections is attained using matching pursuit algorithm [2].

The sparsity of individual EEG signals are established, we extend the CS framework to joint recovery of multiple signals using recent results in distributed compressed sensing [3]. The sparsity of multiple EEG signals is shown and a simultaneous matching pursuit algorithm is used to reconstruct the signals.

The paper is organized as follows, In section 2, material and method, it covers the algorithm and experimental analysis of results. In section 3, conclusion summary. The orthogonal matching pursuit algorithm offers the optimal signal from noisy structure. The comparative analysis is discussed.

II. MATERIALS AND METHOD

Orthogonal matching pursuit Algorithm

The orthogonal matching pursuit algorithm is used. The OMP algorithm selects k_n in the n-th iteration by finding the vector best residuals formed by projecting b_p onto the dictionary D , it is defined as

$$k_n = \arg\max \left|\langle a_l, b_p \rangle\right|$$

The selected vector component a_{kn} is orthogonalised by the Gram-Schmidt algorithm as

$$u_p = a_{k_p} - \sum_{l=0}^{p-1} \frac{\langle a_{k_p}, u_l \rangle}{\|u_l\|^2} u_l.$$

The residual b_p is updated as

$$b_{p+1} = b_p - \frac{\langle b_p, u_p \rangle}{\|u_p\|^2} u_p$$

The orthogonal matching pursuit algorithm is faster convergence with comparable computational complexity.

III. The Experimental Results And Analysis

A.Exprimental platform:

We use MATLAB 13 a as the development of environment

B. **Exprimental targets:**

The original wave signal is used as the original signal. The Gaussian white noise of different SNR are added to the signal for analysis.Wavelet algorithm and orthogonal matching pursuit algorithm are programmed respectively.

C. Process of experiments:

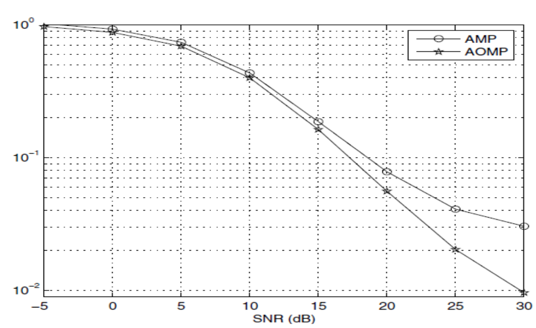
Given a dictionary D in which all of the basic functions $g_i(t)$ are known as atoms. The functions are dependent and demand value of $\|g_i(t)\|_2 = 1$ are not required.The algorithm is used to decompose the signal to linear wave forms, which are selected from the dictionary D of $g_i(t)(i=1.2\ldots N)$. After n-iterations we get,

$$f(t) = \sum_{n-1}^{N} \langle R_{n-1} f(t), h_n(t) \rangle h_n(t) + R_n f(t)$$

The correlation of residues and dictionary elements are based on the decay of the function $\|R_n f(t)\|_2$. Now we define the correlation ratio with respect to dictionary D is

$$\mu(n) = \frac{\langle R_{n-1} f(t), h_n(t) \rangle}{\|R_n f(t)\|_2}$$

So we get $\mu(n)$ will decreased with increased value of n. It will stop iterations until it reaches the scheduled threshold. In this process of algorithm , the selection of time-frequency atom in the dictionary D is very useful.



IV. CONCLUSION

The algorithm has proposed to reconstruct the EEG signals of noisy structure. This algorithm offers the at each iteration optimization technique is performed over all vectors in the dictionay.This OMP algorithm provides the enhanced the quality of signals and comparing the different dictionary atoms . Experimental analysis show that the OMP is a better algorithm for recovered signals.

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