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A Brief Review: Compressed Sensing of ECG Signal For Wireless System

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ABSTRACT

CS, as a new compression paradigm, relies on three main requirements: sparsity representation, incoherence measurement, and nonlinear reconstruction, which pertain to the signals of interest, the encoding modality, and the decoding method, respectively. The main goal of the CS is to accurately reconstruct a high dimensional sparse vector using a small number of linear measurements. As in wireless sensor networks they have used battery back-up for transmission of data to base stations and considerable energy has been lost during transmission of data packets. As in intra-hospital environment there is need of automated data collection system from different ECG acquisition nodes wirelessly handled by nurses/doctors, they send data to a single hub for further processing and by this they provide easiness of handling of ECG equipment's as there are no wires in this communications process. They send the acquired ECG signal by Zigbee etc. to nearest point. As ECG signals have repetitive pattern, they can be compressed and transmitted at the transmitter end and hence can save energy of the battery back-up of transmitters, there is need to explore compressed sensing for ECG signals. In this work we have studied the existed methods especially the better from all called DWT based compressed sensing techniques for ECG signals. Our aim is to propose further enhancements in the existed system. We have taken as objective for DWT and DCT combination which can be applied for getting better performance. In this work, we have reviewed some existed methods along with explanation of compressed sensing based on sparse matrices.

Keywords: Wireless sensor Networks, compressed sensing, Health monitoring, ECG signals, DWT AND DCT.

1. INTRODUCTION

Wireless body area networks (WBANs) and cellular network provides support for telemedicine. To facilitate early diagnosis and treatment the WBANs collect and transmit the crucial biomedical data to provide a continuous health monitoring by using various biomedical wireless sensors used for the human body. And then, collected signals are sent to a remote data center via cellular network. One of the features of WBAN is that its power consumption and sampling rate should be minimum. Compressed sensing (CS) is an signal acquisition/compression methodology which gives an alternative to traditional signal acquisition. Medical monitoring system helps doctors to remotely monitor the patient's medical condition and feedback in time. The whole system of hybrid wireless sensor network model contains the WBAN and cellular network is shown in Figure 1.

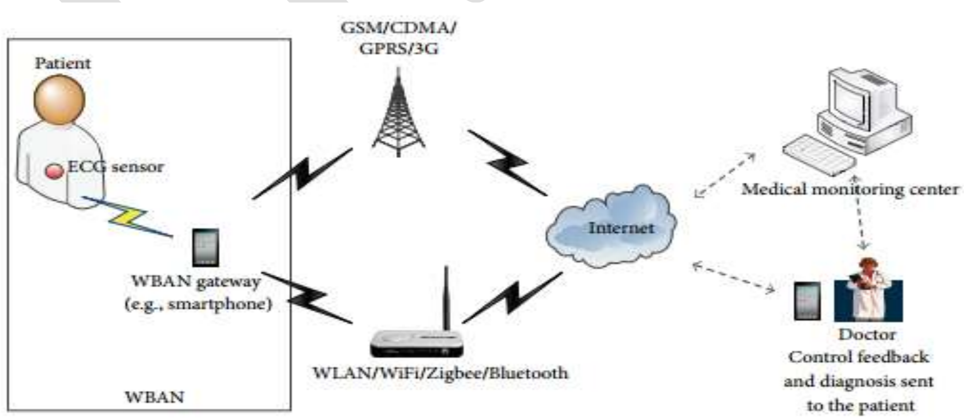

Figure 1: The whole system of hybrid wireless sensor network model.

For real-time health monitoring, devices must integrate into the patient's body which do not interfere with the daily activities of the patient. For continuously sensing, processing, and detection of signal and ECG sensor is used. The real-time ECG data are sent to a personal terminal by Wi-Fi, CDMA, 3G, or other cellular networks used for transmitting the ECG data to a remote data center. In the terminal, the original ECG signals are recovered by computers for diagnosis. By continuous remote heart monitoring, it can enhance ability of prevention and early diagnosis, improve patient condition, mobility, and security. The power in an ECG sensor is mostly consumed when the RF power amplifier transmits the signal to the personal terminal. A large amount of real-time ECG data is collected, stored, and transmitted to the terminal. Therefore it required to decrease the amount of data to be transmitted for reducing the energy consumption

2. COMPRESSIVE SENSING OF ECG SIGNAL

Compressive sensing is signal processing framework where the sparse signal is used and reconstructs it from the incomplete measurements, which contain insufficient amount of information. And can be achieved if the signal is in sparse representation with an orthonormal basis. , CS is given to the to electrocardiogram (ECG) signal for data compression in WBN network. Wavelet compressed signal is used for multi-lead ECG signal. Compressed Sensing based data collection system with wireless bio-sensors is used for bio-signals like ECG and EEG etc. In an ECG signal, essential diagnostic information such as P-wave, QRS-complex and T-wave. These components may carry pathological information. CS based signal processing is not change these information. Sparse representation is an very important compressed sensing of signal. Compression is required for reducing the storage space and transmission times. Thus, ECG data compression is required for efficient storage and transmission of signal for telemedicine applications. CS has some important advantages:

1. It provide simpler hardware implementations for the encoder;
2. The location of the largest not needs to be encoded.
3. It enables to reconstruct sparse or compressible signals from a small number of linear projections

2.1 APPLICATION OF COMPRESSIVE SENSING

CS is used in the linear-systems, sparse coding, multiplexing, sparse sampling,. Because of Its scope it uses in the several innovative CS-enhanced approaches in signal processing. it gives the solution of inverse problems in design of radiating systems, radar and antenna characterization compressive sensing Imaging techniques include coded aperture and computational photography

Photography

Compressed sensing used in the mobile phone camera to give acquire the image efficiently.

Holographysss

Compressed sensing is used in the image reconstruction and image retrieval from sampled signal in many form of holography in the improved form.

Facial recognition

Facial recognition application also uses the compressed sensing.

Magnetic resonance imaging

Magnetic resonance imaging scanning can also used compressed sensing for sessions on conventional hardware

- ISTA
- FISTA

- SISTA.

Network tomography

Compressed sensing gives best result in network tomography to network management.

Shortwave-infrared cameras

Compressed sensing based Commercial shortwave-infrared cameras are avaivalable which contain light sensitivity from 0.9 µm to 1.7 µm those wavelengths invisible to the human eye.

2.2 ALGORITHMS OF COMPRESSIVE SENSING

The algorithms are used reconstruction signal and give better performance.

Matching Pursuit

Matching pursuit is an iterative algorithm that decomposes a signal into a linear expansion of functions to form a dictionary. At each iteration, matching pursuit chooses dictionary elements in a greedy fashion that gives best approximate of the signal

Orthogonal Matching Pursuit

Orthogonal matching pursuit (OMP) is an improvement on matching pursuit. Same principle is used in it. However rather than simply taking the scalar product of the residual and the new dictionary element to get the coefficient weight, we use the original function to all the already selected dictionary elements via least squares, hence it term as orthogonal matching pursuit. Orthogonal matching pursuit has been successfully used for signal recovery, however many problems regarding the performance in compressive sensing

Stage wise Orthogonal Matching Pursuit

Stage wise orthogonal matching pursuit or STOMP, is an improvement on the OMP algorithm. In contrast to OMP it allows multiple coefficients to be added to the model in a single iteration and runs for a fixed number of iteration

Gradient Pursuit

Gradient pursuit (GP) is yet another type of matching pursuit. Instead of taking the update by the scalar-product of the residual and dictionary element, in this the update occurs in a particular direction

CoSaMP

An extension to orthogonal matching pursuit algorithms is the CoSaMP (Compressive Sampling Matching Pursuit) algorithm published in (Need ell and Troop 2008). The basis of this algorithm is OMP but CoSaMP,

3. DWT (DISCRETWAVELET TRANSFORM)

Discrete wavelet transform (DWT) is the wavelet transform in which the wavelets are sampled discretely. A key advantage of DWT over DFT is temporal resolution: it means it captures both frequency and location information

3.1APPLICATION OF DWT

The discrete wavelet transform has a many applications in science, engineering, and mathematics and computer science. Mostly, it is used for signal coding, to represent a discrete signal in a more redundant form, which is further used for data compression. Practical applications of DWT is found in signal processing of accelerations for gait analysis, in digital communications and many others

In this work we will use one form of dwt i.e. daubechies wavelet for better performance. in compressed sensing of ECG signal.
Daubechies wavelets

The most commonly used set of discrete wavelet transforms was explore by the Belgian mathematician Ingrid Daubechies in 1988. This formulation is based on the use of recurrence relations to generate the progressively better discrete samplings of an implicit wavelet function; each resolution is twice than of the previous scale. Daubechies derives a family of wavelets, and many variations of Daubechies' original wavelets were developed

4. DISCRETE COSINE TRANSFORM (DCT)

A **discrete cosine transform** (**DCT**)is the finite sequence of data points in form of cosine function oscillating at different frequencies. DCT used in no of application like science and engineering, in the form of lossy compression of audio (e.g. MP3)and images (e.g. JPEG).spectral method is used for numerical solution of partial differential equation. DCT used to separate the images in segments according to required information. The DCT is same as DFT that it will transforms a signal from the spatial domain to the frequency domain. In this work we will explore IDCT (inverse DCT) on the each segments of the signal .and then find the result difference of the signal compared to previous work.

We will use the combination of the DWT and IDCT. In the inverse form and then evaluation results show that combining the two transforms improved the performance of the compressed sensing algorithms that are based solely on the DWT transform.

5. RELATED WORK

In this section, existed work has been surveyed.

Donoho et al. [1] in (2006) introduce a technique to construct the fast and efficient sensing matrices for practical compressive sensing, called Structurally Random Matrix (SRM). In this, they used the flipping of sensing signal sample sign and done fast-transform the randomized samples and then subsample the obtained transform coefficients to give the final sensing measurements.

Bounoufos et al. [2] (2007) explore the behavior of cross validation to determine the stopping conditions for the optimization algorithms. They demonstrate that by designating the small set of measurements as a validation set to optimize these algorithms and reduce the reconstruction error. Furthermore we use the trade-off between additional measurements for cross validation instead of reconstruction.

Née dell et al. [3] (2009) describe a new iterative recovery algorithm called CoSaMP that delivers the best optimization-based approaches. Moreover, this algorithm tells the bounds on the computational cost and storage.

Cai et al. [4] (2010) consider sparse signal recovery in the presence of noise. A mutual incoherence condition which was previously used for exact recovery in the noiseless case is shown to be sufficient for stable recovery in the noisy case..

lieu et al. [5] (2011). Take a generalized sparse signal model, which simultaneously considers the sampling and representation matrix uncertainties. Based on the new signal model, a new optimization model for robust sparse signal reconstruction is proposed. This optimization model can be deduced with stochastic robust approximation analysis

Polania et al. [6] (2014) explore the structure of the wavelet of the ECG signal to boost the performance of CS-based methods for compression and reconstruction of ECG signals. They use the information about the wavelet dependencies across scales into the reconstruction algorithms and give the high fraction of common support of the wavelet coefficients of consecutive ECG segments

Gu et al. [7] (2015) present an energy-efficient compressed sensing (CS)-based approach for on-node ECG compression. At first, an algorithm called minimal mutual coherence pursuit is proposed to construct sparse binary measurement matrices, which can be used to encode the ECG signals with superior performance and extremely low complexity. Second, in order to minimize the data rate required for faithful reconstruction, a weighted minimization model is derived by exploring the multisource prior knowledge in wavelet domain

6. CONCLUSIONS

In previous works, a new fast greedy pursuit technique named Least Support Orthogonal Matching Pursuit (LS-OMP) and Least Support De-noising OMP (LSD-OMP) has been suggested in which a new method has been proposed for segmentation the signal too many parts. Methods uses discrete wavelet transform for this purposes in which noisy signal is also considered for reconstruction. Our goal is to first implement the provided algorithm and explore the comparison of results using different types of wavelets as base paper has not provide any about the used wavelet type.

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