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An Algorithm for Recovering Data for e-Health Applications using Compressed Sensing

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Abstract: A deep signal recovery algorithm is proposed in this paper to retrieve ECG data in the context of spatial and temporal data. Wireless body networks (WBANs) are becoming increasingly important for future communication systems, particularly in the field of e-health monitoring systems, such as electromagnetic cardiogram (ECG) data acquisition systems via WBAN in online healthcare applications. Compression sensing (CS), on the other hand, clearly consumes less power than traditional approaches based on transformation coding.

Keywords: *WBAN, ECG, Compressed Sensing, Deep Learning, MSE.*

I. Introduction

Compression Sensing recovery techniques can be used to retrieve the original signal for monitoring and evaluation. Traditional Compression Sensing, on the other hand, focuses on signals with fragmented structures [1]. Because the number of source data with fragmented or low-rank structures has increased in recent years, much effort has gone into modelling such data using the structural properties of the signals to improve the effectiveness and speed of Compression Sensing reconstruction methods. Compression Sensing's usability and structure when used for signal acquisition in WBAN have been investigated. As previously stated, Mamaghanian et al. [2] thoroughly evaluated the efficacy of Compression Sensing for ECG acquisition. Finally, the energy savings reached 52.04 percent. The researchers also looked at the acquisition of non-invasive infant ECG using Compression Sensing, which is an important branch in health services and can be used to identify embryonic development and behaviour. Sparse Bayesian learning has successfully addressed the drawbacks of foetal ECG, such as strong noise and non-sparsity, which are incompatible with standard Compression Sensing structures; raw foetal ECG recordings are recreated with acceptable quality while synchronously maintaining multi-channel signal interconnectedness relationships.

Brunelli and Caione [3] investigated the energy consumption of digital and analogue Compression Sensing, performing a valid assessment using genuine resource-constrained hardware architecture to investigate the impact of Compression Sensing variables on signal recovery performance and sensor longevity. Yang et al. [4] investigated electrocardiogram signal processing using the Compression Sensing approach (ECG). Simulations are used to assess the performance of four common Compression Sensing recovery techniques: the pursuit orthogonal matching strategy, the fundamental algorithm, the Bayesian sparse training algorithm, and the compressed MP sampled algorithm.

Based on the evaluation results, we developed an adaptive ECG signalling system based on Compression Sensing that provides satisfactory performance while changing the amount of data conveyed based on channel status. Sawant et al. [5] proposed an orthogonal matching pursuit (OMP) technique for recovering lost data packets in structural health monitoring, an ultrasonic sensor-based application (SHM). To recover information from a lost transfer, OMP employs sparse ultrasonic sensor signals shaped through a Hanning window.

To present a case study in disbond application in the presence of data loss for SHM honeycomb composite sandwich constructions, we simulate data loss fractions ranging from 10% to 90% in a data set of 8 ultrasonic transducers, which OMP uses to retrieve signals from loss datasets created (HCSS). The estimated damages (DI) caused by the retrieved signals show that OMP is a dependable and efficient signal retrieval method that produces estimated errors of less than 1.5 percent on a regular basis. The original image is compressed with BCS and then converted into ternary symbols using a dead-zone quantizer, as recommended by Zheng et al. [6], resulting in JSCC with BCS and SC-LDGM.

The quantization sequence is encoded with ternary SC-LDGM coding and modulated with ternary pulse amplitude modulation (3-PAM). The absence of entropy coding and the compatibility of quantized symbols with ternary coded modulations are two advantages of this method. According to simulation results, the proposed approach outperforms the traditional uneven error protection (UEP) system in terms of energy-to-noise ratio by about 6 dB. (ENR). Encoder-Decoding Architecture [7] by Leinonen et al.

A quantizer, DNN decoder, and deep neural network encoder (DNN) system was proposed, which performs low-complexity vector quantization with the goal of minimising mean square reconstruction errors at a quantized cost. To train the system blocks, we proposed a supervised learning method based on stochastic gradient descent and back propagation. Fading gradients are discussed, and solutions are provided. As according simulation results, the proposed non-iterative DNN-based QCS technology outperforms conventional QCS methods in terms of rate-distortion performance and algorithm complexity, making it ideal for lag time implementations with large-scale signals.

II. METHODOLOGY

Brief recording intervals for biomedical signals, such as ECG, generate lots of data, necessitating a significant amount of processing and transmission bandwidth in wireless body sensor networks. Furthermore, wireless body sensor nodes powered by batteries consume more energy. As a result, a method for transmitting and retrieving low-energy ECGs is required. Compressed sensing (CS) can be used prior to transmission to reduce data rate and thus power consumption, but the signal should be infrequent in the domain in which it is compressed. Further to that, the temporal and frequency domains of the ECG signal are both infrequent.

Despite the fact that sampled signal bases are widespread used, their characteristics are poorly understood. The goal of this research is to create a suitable sampled signal dictionary by analysing incoherence and disappearing moment in order to improve the accuracy of ECG infrastructure needs.

This paper begins with an examination of a typical WBAN scenario. Suppose there are n time-varying signals (or n sensors gathering data in synchrony) symbolised by F= $[f_1,f_2,......,f_n]$ $T\in\mathcal{R}_{m\times n}$, where $f_i\in\mathcal{R}_{m\times 1}$, and $i\in[1,2,3.....,n]$. and is composed of m samples ECG data is typically made up of 12 time-varying signals, such as 12m x12 vectors (that can also be written as-$\mathcal{F}$= $[f_{1,2},......,f_{12}]$ $T\in\mathcal{R}_m\times 12$.. Furthermore, users assume that the signal F in the DWT domain is a sparse matrix denoted by $\mathcal{S}\in\mathcal{R}m$, One way to put it is $\mathcal{F}=\psi\mathcal{S}$ where R_{mm} is the DWT matrix. To recreate the original signals, we take a unique technique. We now have as a consequence of this

$$\mathcal{X}=\Theta\mathcal{F}+\mathcal{E}=\varphi\mathcal{S}+\mathcal{E}$$

where $\mathcal{S}$ must be discovered and $\varphi=\Theta\psi$ is a dictionary matrix We can use the DWT matrix to obtain the ECG signals F. This section describes how the proposed deep compressed estimate (DCE) algorithm, shown in Fig.4.2, works.

In the proposed technique, the sensor detects the d x 1 vector $x_{k(i)}$ at each node and then estimates ω_0 in the compact region using the d x M measurement matrix Γ.

In other phrases, the proposed method forecasts d x 1 vector ω_0 As the vector, use ω_0 instead of M x 1. An over bar represents the d x M and d–dimensionality values. At each node, a decompression process computes an estimate of node ω_0 using a d x M measurement matrix Γk and a reconstructive technique. Wide compact estimators benefit from having fewer data points to swap across network nodes. Using the scalar assessment $D_{k(i)}$ provided by, the proposed deep compressed estimator technique is described.

$$D_k(i) = \overline{\omega_0^k}\,\overline{x_k}(i) + n_k\ (i)$$

where I = 1, 2 and I = the input signal vector for d x 1 is $\omega_0=\ \Gamma_k\ \omega_0$ and $x_{k(i)}$. Figure 1 shows the compressing component performing this procedure.

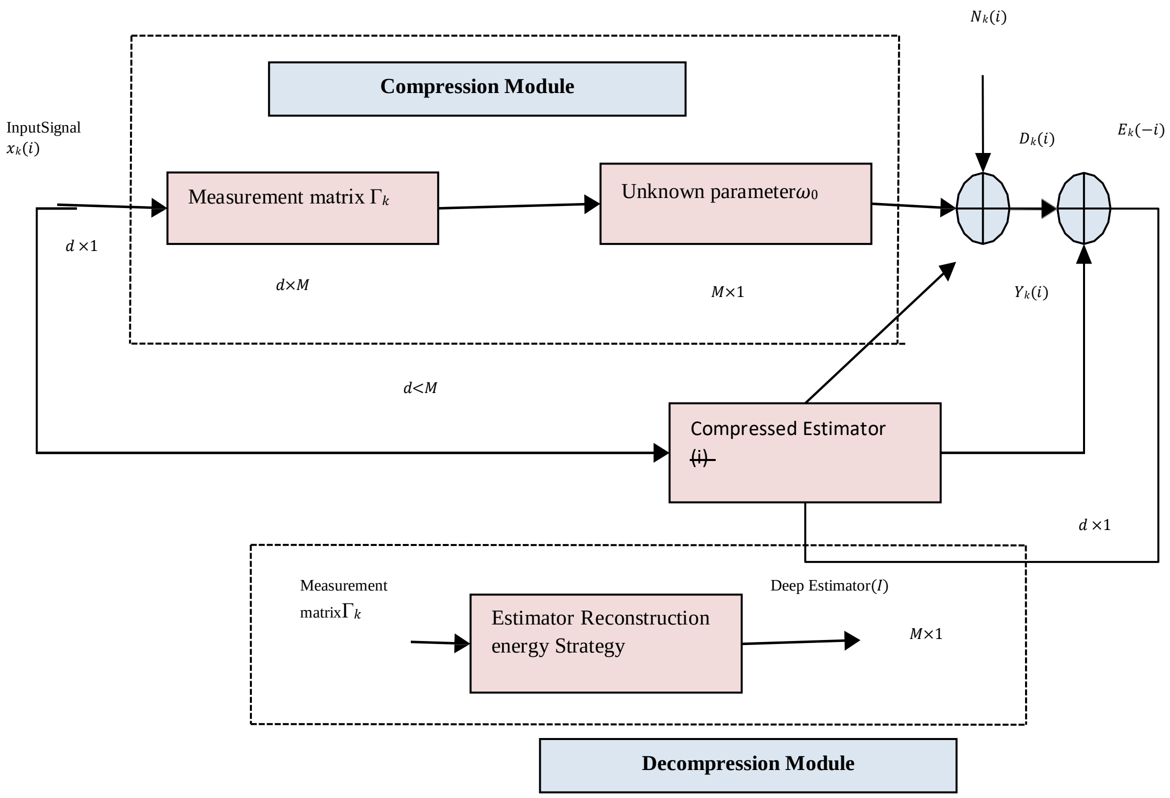

Figure 1: Proposed Compressive Sensing Modules

III. RESULT ANALYSIS

The WBAN scenario is done and the results are analysed using the MATLAB platform. Three factors are examined and investigated in greater depth: In terminology of variable nodes, a variable SNR and a variable compression ratio. The ECG samples used during our tests were obtained from the MIT-BIH Arrhythmia Database (which can be found at http://www.physionet.org/physiobank/database/mitdb/).The research makes use of a total of 100 ECG recordings, that are made up of 10 original recordings, each one provides 1024 distinct recordings.

Analysis with respect to variable number of Nodes

In this section, the simulation is run with a variable number of WBAN nodes and distinct CR. MSE is used to analyze the simulation results. The MSE was defined as a measurement of -30 to -40 decibels.

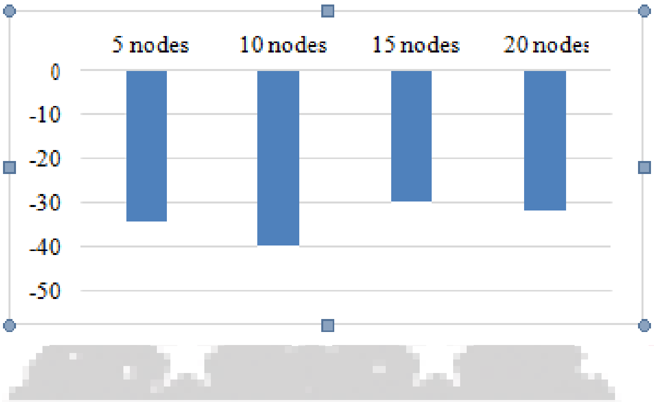

Figure 2 : MSE analysis with variable nodes

Analysis with respect to SNR

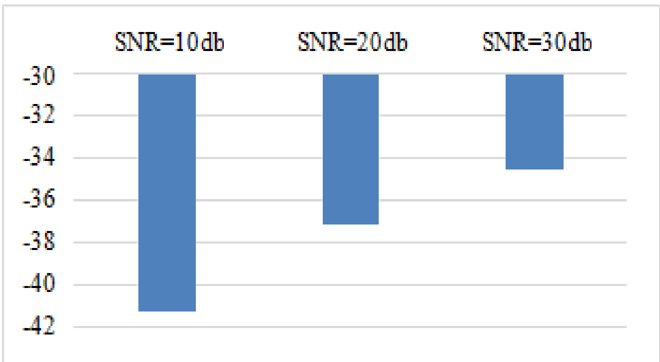

Figure 3: MSE analysis with variable SNR

In this section, the proposed deep Compressed Sensing is compared with existing academic research published by Zhang et al. [1]. The author introduced a sparse signal recovery technique for recovering ECG data in the context of Compressed Sensing. In the method presented in this paper, the MSE ranges from -7 to -18. For suggested work, the MSE score ranges from -30 to -40.

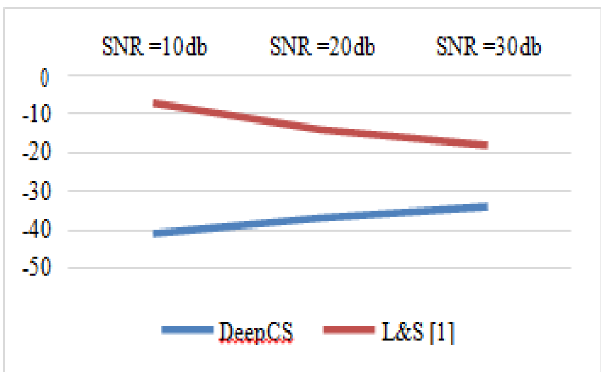

Figure 4: MSE Comparative Analysis with Existing Work

IV.CONCLUSION

Wireless Body Networks (WBANs) are regarded as extremely important for future communication systems, particularly in the field of portable health monitoring systems, with the emergence of the next generation of wireless communication networks, which represents a significant advance in information and communication technologies (ICT). Recently, it was demonstrated that Compressed Sense (CS) is an effective data compression method for wireless monitoring systems of multi-channel ECG signals in the body network. Today, the majority of multichannel EEG-CS algorithms ignore noise. In the first scenario, the simulation was run with a variable number of nodes and compression ratios. The MSE measured between -30 and -40 decibels. In the second case, the simulation was run for WBAN nodes with varying CR and variable SNR. The MSE was measured between -30 and -40 db, and the results show that it is increasing.

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