# Compressed Sensing based on Deep Learning in Wireless Body Networks

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

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

## 1. INTRODUCTION

Compressed sensing (CS) techniques have shown great potential for signal compression to deal with the huge amount of data problem, which allows higher compression rates with lower power consumption at a level of acceptable distortion. First, the sampled signals are compressed by projecting onto a lower dimension with a random matrix. Then, the compressed signals are transmitted through the nearby device and remote terminal. Finally, the original signal can be recovered by the CS recovery techniques for monitoring and analysis. Unfortunately, however, traditional CS focuses on signals with sparse structures [1]. In recent years, due to the increasing number of source data that contain sparse or low-rank structures, considerable work has been done on modeling such source data using the structural characteristics of the signals to improve the performance and speed of CS reconstruction algorithms. Some research has been done into the usability and structure of CS when utilized for signal acquisition in WBAN. Mamaghanian et al. [2] evaluated the efficiency of CS for ECG capture in detail, as previously stated. Lastly, the energy savings were enhanced to 52.04 percent. The CS acquisition of non invasive baby ECG, which is a key branch in healthcare systems and can be employed for the identification of embryonic development and behavior, was also studied by the researchers. The downsides of fetal ECG, such as strong noise and non-sparsity, which are incompatible with standard CS frameworks, have been well remedied by sparse Bayesian learning; raw foetal ECG recordings are recreated with acceptable quality while synchronously maintaining interconnectedness relationships of multi-channel signals. Brunelli and Caione [3] investigated the energy usage issue of both digital and analog CS, conducting a valid assessment utilizing real resource-constrained hardware architecture to investigate the influence of CS variable on signal recovery performance and sensor longevity. Yang et al. [4] studied the signal processing of the electrocardiogram (ECG) on the basis of the CS technique. Simulations are used to evaluate the performance of four typical CS recovery algorithms – the pursuit orthogonal matching algorithm, the basic algorithm, the Bayesian sparse learning algorithm and the compressive MP sampling algorithm. We designed an adaptive ECG signaling system based on CS that delivers satisfactory performance, while adapting the amount of data transmitted in compliance with the channel state that is based on the evaluation results. Sawant et al. [5] presented an orthogonal matching pursuit (OMP) algorithm in ultrasound sensor-based application structural health monitoring (SHM) to recover lost data packets. In order to recovers information from the lost transmission, OMP utilizes the sparse ultrasonic sensor signals shaped through a Hanning window. We emulate data loss fractions of 10% -90% in a data set of 8 ultrasonic transducers, which are used by OMP to retrieve the signals from the loss datasets generated, to illustrate a case study in disbond application in the presence of data loss for SHM honeycomb composite sandwich structures (HCSS). The estimate of damages (DI) by the retrieved signals shows that OMP is a reliable and efficient method of signals retrieval and consistently generates estimated errors < 1.5 percent. The original image is first compressed by BCS and then transformed by a dead-zone quantizer into ternary symbols, as suggested by Zheng et al. [6], which is called JSCC with BCS and SC-LDGM. A ternary SC-LDGM coding is used to encode the quantized sequence, which is modulated by ternary pulse amplitude modulation (3-PAM). The advantages of this scheme are that entropy coding is not used and quantified symbols are compatible with ternary coded modulations. The suggested approach outperforms the traditional unequal error protection (UEP) scheme by around 6 dB in terms of energy-to-noise ratio(ENR), according to simulation data. The Deep Encoder-Decoding Architecture of Leinonen et al. [7] was proposed, consisting of a quantizer , DNN decoder and deep neural network encoder(DNN), which performs vector quantization's with low-complexity intended to minimize mean square reconstruction errors at a certain quantized cost. To train the system blocks, we devised a supervised learning method based on stochastic gradient descent and backpropagation. Approaches are presented to resolve the problem of disappearing gradients. The suggested non-iterative DNN-based QCS technique has superior rate-distortion performance with lower algorithm complexity than typical QCS methods, making it suitable for delay-sensitive applications with large-scale signals, according to simulation results.

## 2. METHODOLOGY

Biomedical signals, such as ECG, necessitate long recording times, resulting in large amounts of data, which necessitates a lot of processing and transmission bandwidth in wireless body sensor networks. Furthermore, Wireless body sensor nodes that are powered by batteries utilize more energy. As a result, a low-energy ECG transmitting and restoration system is needed. Leading up to transmitting, CS (Compressed Sensing) can be used to decrease data rate and thus power usage, but a CS requirement is that the signal be sparse in the domain where it is compressed. Furthermore, neither the time nor the frequency domains of the ECG signal are sparse. Sampled signals bases are extensively employed, but their characteristics are not well understood. The goal of this research is to find a suitable sampled signal dictionary by analyzing incoherence and vanishing moment in order to improve the accuracy of ECG signal reconstruction.

A typical WBAN situation is initially explored in this work. We suppose there are n time-varying signals (or n sensors collecting data in synchrony), which are represented by- $\mathcal{F} = [\mathscr{f}_1, \mathscr{f}_2, \ldots \ldots, \mathscr{f}_n]^T \in \mathcal{R}^{m\times n}$, where $\mathscr{f}_i \in \mathcal{R}^{m\times 1}$, and $i \in [1,2,3 \ldots\ldots, n]$. The ith signal gathered from the ith sensor is denoted by $\mathscr{f}_i$ and comprises of m samples. ECG information is routinely made up of 12 time-varying signals, such as 12 $m \times 12$ vectors, which can also be written as $\mathcal{F} = [\mathscr{f}_1, \mathscr{f}_2, \ldots \ldots, \mathscr{f}_{12}]^T \in \mathcal{R}^{m\times 12}$. Furthermore, we consider that the signal $\mathcal{F}$ in the DWT domain, indicated by $\mathcal{S} \in \mathcal{R}^{m\times n}$, $\mathcal{S}$ is an sparse matrix. It can be expressed as $\mathcal{F} = \psi\mathcal{S}$, where Rmm is the DWT matrix. To reconstruct the actual signals, we employ a specific method. As a result, we have

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

where $\mathcal{S}$ must be retrieved and $\varphi = \Theta\psi$ is a dictionary matrix. Using the DWT matrix $\psi$, we may acquire the ECG signals $\mathcal{F}$.

The suggested deep compressed estimate (DCE) algorithm relies on CS, which is represented in Fig.4.2, is explained in this section. In the suggested technique, the sensor initially detects the $d \times 1$ vector $\overline{x_k}(i)$ at every node, and then estimates$\omega_0$ in the compressed region with the support of the $d \times M$ measurement matrix Γ.

To put it another way, the suggested technique predicts $d \times 1$ vector $\overline{\omega_0}$ Rather than $M \times 1$ vector, use $\omega_0$ Where $d \times M$ and d–dimensional values are denoted by an over bar. A decompression mechanism at every node uses a $d \times M$ measurement matrix $\Gamma_k$ and a reconstructing technique to calculate an approximation of at every node $\omega_0$ . The deep compressed estimator technique has the advantage of requiring fewer variables to be communicated between nodes in the network. The scalar assessment $D_k(i)$ supplied by begins the explanation of the suggested deep compressed estimator technique.

$$D_k(i) = \overline{\omega_0^h}\,\overline{x_k}(i) + n_k(i) \text{ where i = 1, 2 , and I}$$

The $d \times 1$ input signal vector is $\omega_0$ equals $\Gamma_k\omega_0$ *and* $\overline{x_k}(i)$. Figure 1 shows how to perform this process by the compressing component.

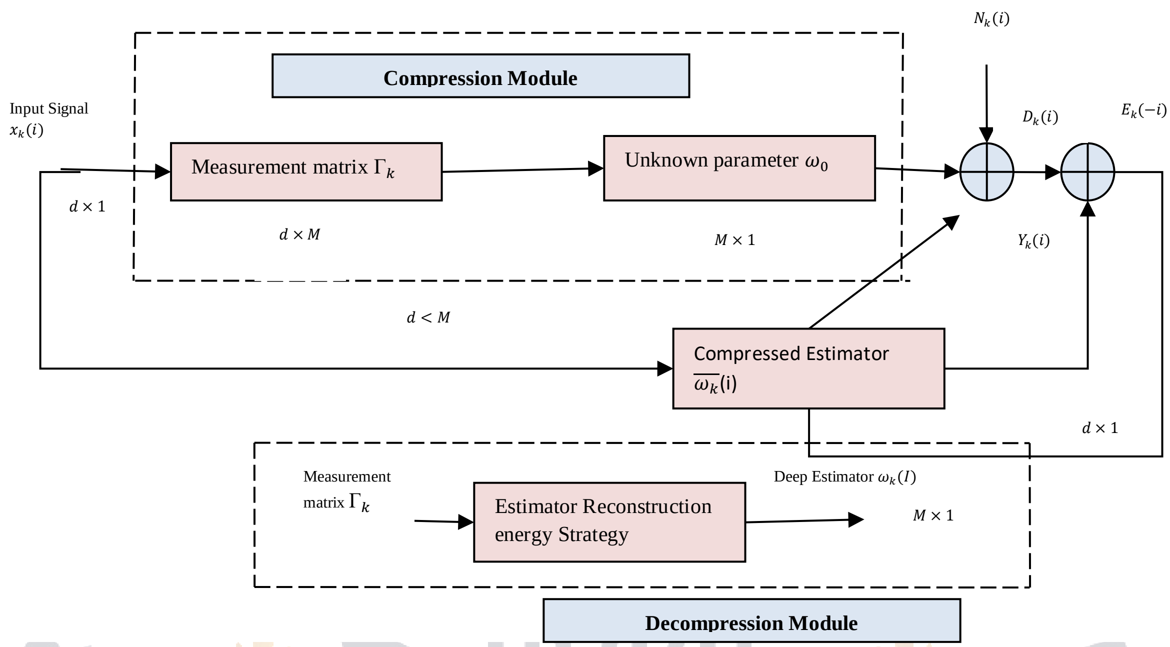


**Figure 1: Proposed Compressive Sensing Modules**

## 3. CONCLUSION

Wireless Body Networks (WBANs) are expected to become increasingly important in 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 huge advance. in information and communication technologies (ICT). Compressed Sense (CS) has recently proven to be an excellent data compression approach for wireless remote monitoring of multi-channel ECG signals in the body network. Most current multichannel EEG-CS algorithms ignore noise. In first scenario, the simulation was performed with variable number of nodes and with variable compression ratios. It was observed that the MSE was evaluated between -30 to -40 db. In second scenario, the simulation was performed with variable SNR for WBAN nodes as well as with different CR. From the result it is analyzed that the MSE was evaluated between -30 to -40 db and it seems to be increasing.

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