A Systematic Overview on Wireless Body Area Network for Healthcare E-monitoring System

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Abstract: *The recent improvement and advancement of information and communication technologies has aided people in several aspects of their lives. Most crucially, this has become increasingly connected with information and communication technology-based services in the healthcare industry. One of the most significant services is remote patient monitoring, which allows healthcare professionals to examine, diagnose, and treat patients without having to be physically there. The benefit of miniature is action of sensor technologies is that they can be installed in, on, or off the body of patients, and they can send physiological data wirelessly to remote servers. Wireless Body Area Network is the name given to this type of technology (WBAN). WBAN architecture, communication technologies for WBAN, obstacles, and many features of WBAN are discussed in this study. The structural limitations of existing WBAN communication frameworks are also described in this article. In addition, implementation requirements based on the IEEE 802.15.6 standard are described. Finally, research combining Software Defined Networking (SDN), Energy Harvesting (EH), and Blockchain technology into WBAN is offered as a source of motivation for future growth.*

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

For monitoring and assessment, the original signal can be retrieved using Compression Sensing recovery techniques. Traditional Compression Sensing, on the other hand, concentrates on signals with fragmented structures [1]. Because the number of source data with fragmented or low-rank structures has increased in recent years, a lot of work has gone into modelling such data utilising the structural properties of the signals to boost the effectiveness and speed of Compression Sensing reconstruction methods. The usability and structure of Compression Sensing when used for signal acquisition in WBAN have been investigated. As previously noted, Mamaghanian et al. [2] assessed the efficacy of Compression Sensing for ECG acquisition in depth. Finally, energy savings increased to 52.04 percent. The researchers also looked at the Compression Sensing acquisition of non-invasive infant ECG, which is an important branch in health services and can be used to identify embryonic development and behaviour. Sparse Bayesian learning has effectively 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 interconnectedness relationships of multi-channel signals.

Brunelli and Caione [3] looked at the energy consumption of both digital and analogue Compression Sensing, completing a valid assessment using genuine resource-constrained hardware architecture to look into the impact of Compression Sensing variables on signal recovery performance and sensor longevity. On the basis of the Compression Sensing approach, Yang et al. [4] investigated the signal processing of the electrocardiogram (ECG). The performance of four common Compression Sensing recovery techniques is evaluated using simulations: 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 built an adaptive ECG signalling system based on Compression Sensing that provides satisfactory performance while changing the quantity of data conveyed in accordance with the channel status. Sawant et al. [5] introduced an orthogonal matching pursuit (OMP) technique for recovering lost data packets in an ultrasonic sensor-based application called structural health monitoring (SHM). OMP uses sparse ultrasonic sensor signals shaped through a Hanning window to retrieve the information from a lost transfer.

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 of 10% to 90% in a data set of 8 ultrasonic transducers, which are employed by OMP to retrieve the signals from the loss datasets created (HCSS). The estimated damages (DI) caused by the retrieved signals reveal that OMP is a reliable and efficient signal retrieval method that routinely produces estimated mistakes of less than 1.5 percent. The original image is compressed using BCS and then turned into ternary symbols using a dead-zone quantizer, as recommended by Zheng et al. [6], which is known as JSCC with BCS and SC-LDGM.

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

A system comprising of a quantizer, DNN decoder, and deep neural network encoder (DNN) was proposed, which conducts low-complexity vector quantizations with the goal of minimising mean square reconstruction errors at a quantized cost. We proposed a supervised learning method based on stochastic gradient descent and backpropagation to train the system blocks. The subject of fading gradients is discussed and solutions are offered. According to simulation results, the proposed non-iterative DNN-based QCS technology has superior rate-distortion performance and reduced algorithm complexity than traditional QCS methods, making it ideal for delay-sensitive applications with large-scale signals.

II. Compressive sensing

Compressive sensing (CS) is a method of enabling real-time data transfer in wireless networks by dramatically lowering the amount of local computation and data sets that must be delivered over wireless links to a remote fusion centre. WSAN is enabled by the large data volume of array signals, which is a restriction. When compared to more traditional data compression methods. Compressive sensing (CS) improvements have sparked new ideas and approaches for developing energy-efficient WSNs with low-cost data collection. CS has been regarded as a key paradigm for successful high-dimensional sparse signal collection. Compression, in particular, is a straightforward linear process that is unaffected by signal properties and is carried out with random projection matrices. To reconstruct the original high-dimensional signal from its compressed version, a variety of reconstructing algorithms have been devised, each of which differs in terms of recovery performance and processing complexity. CS is well-motivated for a variety of WSN applications for a variety of reasons. Due to the fundamentally limited energy communication resources in WSNs, data compression during transmission is crucial. On the other hand, sparsity is a typical trait of many signals of interest that can be recognised in a variety of design elements. As a result, data gathering with lower rate samples is a quick use of CS in WSNs, as required by numerous atmosphere infrastructure tracking apps. Data gathering with CS can benefit from temporal and/or geographic sparsity.

III. Literature reviews

The usability and structure of CS when used for signal acquisition in WBAN have been investigated. As previously noted, Mamaghanian et al.[13] assessed the efficacy of CS for ECG collection in depth. Finally, energy savings increased to 52.04 percent. The researchers also looked at the CS acquisition of noninvasive baby ECG, which is a significant branch in healthcare systems and can be used to identify embryonic growth and behaviour. Sparse Bayesian learning has effectively addressed the drawbacks of foetal ECG, such as strong noise and non-sparsity, which are irreconcilable with standard CS structures; raw foetal ECG recordings are recreated with adequate standard while synchronously maintaining multi-channel signal interconnectedness relationships.

[1] Brunelli D & Caione C. et al. Sparse recovery optimization in wireless sensor networks with a sub-Nyquist sampling rate; studied the impact of digital&analog CS on signal recovery performance&sensor longevity by conducting a valid assessment using real resource-constrained hardware design. A zeroing strategy is used in a rakeness-based CS structure.[14]

[2] **Mangia M, Bortolotti D, Pareschi F, et al.** Zeroing for HW-efficient compressed sensing architectures targeting data compression in wireless sensor networks; investigated the tradeoffs between data compression and signal reconstruction. By building revolutionary cluster-sparse signal reconstruction methods, the potential of CS for signal acquisition in IoT has been intensively examined in terms of sensing, transmitting & reconstructing to relax energy usage & extend network capacity.[15]

[3] Majumdar A &Ward RK et al. Energy efficient EEG sensing&transmission for wireless body area networks; To address the EEG signal restoration issue in WBAN, combine state-of-the-art blind CS & low-rank methods, then build a Split Br egman strategy.[16]

[4] Peng H, Tian Y, Kurths J, et al. considered secure transmission of received signals in WBAN in addition to the expenditure signal sampling technique. Chaos theory was included into the CS network to obtain a secret measurement matrix in order to build a joint signal capture, compression, and encryption system. Such an idea highlights the enormous potential of chaos-based CS for safe CS in WBAN and other IoT applications. In order to make considerable advancements in signal recovery while lowering communication needs, the sliding window treatment method was also abandoned.[17]

[5] Wang A, Lin F, Jin Z, et al. A configurable energy efficient compressed sensing architecture with its application on body sensor networks; They moved on to develop two illuminating customizable uantized CS topologies for body sensor networks after discovering that the quantization module is an underestimated but crucial factor in the entire energy usage of the CS sampling process.Using the sparsity property of bio signals, we developed a weighted group sparse generative model for signal retrieval at the fusion centre. Dixon AM, Allstot EG, Gangopadhyay D, et al. [20] look at how CS is being de veloped and implemented in ECG and electromyography (EMG) sensors.[18]

[6] Yang, Y., Smith, D. B., & Seneviratne, S. Deep Learning Channel Prediction for Transmit Power Control in Wireless Body Area Networks; A long-term channel preview method based on LSTM WBAN was presented. To allow the suggested predictor to perform continually in real-world circumstances, an online approach was developed. When compared to the benchmark Moving Average predictor, the LSTM predictor provided up to 2s of prediction advantage and a 50% NMSE reduction when empirical measurements were used. When compared to other predictive approaches, reliability and power consumption improvements are apparent when sketched to a proper power management technique. The proposed prediction approach is useful for other WBAN resource allocation tasks, such as MAC scheduling and relay transmission.[21]

[7] Liu, B., Yan, Z., & Chen, C. W. et al. CA-MAC: A hybrid context-aware MAC protocol for wireless body area networks; In order to address the issues posed by time and channel circumstances in WBAN, a hybrid context-aware MAC protocol has been designed. The master node dynamically alters the MAC frame's channel status and traffic request structure. This technique can be used by sensor nodes to send data with the appropriate access method, transmission bandwidth, and sampling frequency, while also improving transmission efficiency and reliability. According to simulation studies, CA-MAC minimises packet loss rate in WBAN and achieves an appropriate trade-off between reliability and efficiency.

[8] Wolgast, G., Ehrenborg, C., Israelsson, A., Helander, J., Johansson, E., & Manefjord, H. Wireless Body Area Network for Heart Attack Detection [Education Corner]; A simple antenna design was used to show the propagation of Bluetooth signals in a BAN. Using creeping wave propagation, the signal can be tailored to reach locations on the body that are otherwise inaccessible without scattering off nearby objects. This form of transmission has been proved in this paper to meet the minimum criterion for Bluetooth signals. Any Bluetooth device should be able to communicate with the GG BAN. Because the components used in this prototype aren't meant to measure ECG signals, they're rather cheap. Better hardware and additional electrodes would result in a clearer and more consistent signal. [23]

[9] Sui, D., Hu, F., Zhou, W., Shao, M., & Chen, M. et al. Relay Selection for Radio Frequency Energy-Harvesting Wireless Body Area Network With Buffer; recommended an Optimised RF Energy Conversion Protocol, buffer-aided WBAN, which investigates the efficacy of a breakage probability in both PS&Ts systems. On the one hand, the suggested solution solves the canal malfunction problem and improves uniformity. On the other hand, the performance outperforms the previous approaches. Numerical results demonstrate that the suggested procedure always provides the lowest outage probability when the candidate relay set is approximately eual to N/2 in various conditions.[24]

[10] Rahim, A., & Karmakar, N. C., Sensor cooperation in wireless body area network using network coding for sleep apnoea monitoring system; Proceedings highlighted the BER results of a sensor collaboration technique based on dynamic WBAN channel network coding. The simulation results suggest that WBAN's sensor collaboration communication method outperforms non-cooperative communication strategies. Furthermore, our system's BER performance has been determined to be enhanced when compared to previous work. The suggested system can react to time-varying network circumstances due to patient mobility and changing surrounding environment.[25]

IV. CONCLUSION

Long recording intervals for biomedical signals, such as ECG, result in massive amounts of data, requiring a lot of processing and transmission bandwidth in wireless body sensor networks. Furthermore, battery-operated wireless body sensor nodes consume more energy. As a result, an ECG transmitting and restoration system with minimal energy consumption is required. Prior to transmission, CS (Compressed Sensing) can be used to reduce data rate and consequently power consumption, but the signal must be sparse in the region where it is compressed. Furthermore, the ECG signal's temporal and frequency domains are both sparse. Although sampled signal bases are widely used, their features are little understood. The purpose of this study is to develop a suitable sampled signal dictionary by evaluating incoherence and vanishing moment to improve ECG signal reconstruction accuracy.

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