International Journal of Future Generation Communication and Networking
Vol. 13, No. 3, (2020), pp. 742 – 763

Wavelet Data-Driven Extreme Learning Machine Auto-Encoder based Compressive Sensing for Physiological Signal Reconstruction over Wireless Body Area Network

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Abstract

The exponentially rise in the demands of Internet-of-Things (IoTs) enabled Wireless Body Area Network (WBAN) and Personalized e-Health systems for which compressive sensing (CS) technique has played decisive role. CS being potential towards low redundant data communication and resource efficient transmission is of great significance; however, majority of classical CS methods don't address non-linear sparsity problems in physiological signals that confines it to exhibit low reconstruction quality and high compression error. In this paper a novel wavelets data-driven Extreme Learning Machine Auto-Encoder (ELM-AE) based CS model is developed for multiple physiological signal reconstruction. The proposed CS model at first estimates different wavelets containing approximated coefficient and detailed coefficient values, where the first is learnt over the modified ELM-AE to obtain sparse representation of the input physiological-signal. Executing ELM-AE learning over the approximated coefficients, we performed threshold-adaptive optimal sparse feature generation, which was subsequently processed for Inverse-SWT in conjunction with the SWT-detailed coefficient to perform signal-reconstruction. Simulation over ECG and PPG signals revealed that the proposed CS model achieves better performance in terms of Percent Root Mean Square Difference (PRD), Signal to Noise Ratio (SNR), Compression Ratio and compression quality score (QS) for the different physiological signals.

Keywords: *Adaptive Thresholding; Auto-Encoder; Compressive Sensing; Extreme Learning Machine; Machine Learning; Stationary Wavelet Transform*

1. Introduction

The exponential rise technologies and allied applications have revitalized academia-industries to achieve more efficient solutions. Amongst the major applications, healthcare sector has always been the dominant research area motivating academia-industries to explore and identify suitable solution for up-surging or contemporary health issues. Computer Aided Diagnosis (CAD), bio-physiologic parameter's tele-monitoring, tele-medicine etc have gained wide-spread attention globally. The technology's revolution has given rise to a new dimension called e-health technology, which exploits efficacy of software computing, signal processing and communication systems to detect bio-physiological signals, monitor, examine and make early decisions. On the other hand, tele-monitoring and tele-medicine purposes too have gained widespread attention globally. Towards these purposes, technology scaling has enabled ultra-low power and time-efficient Wearable body sensor network (BSN) which

ISSN: 2233-7857 IJFGCN

continuously monitors bio-physiological parameters, compress it and transmits to the body node coordinator (BNC) or base station to make optimal timely decision. This process employs multiple distributed bio-sensors which are often resource constrained and battery-powered. Additionally, these distributed bio-sensors constitute or employ Wireless Body Area Network (WBAN) protocol to enable continuous bio-parameter (tele-) monitoring, rehabilitation, personalized health monitoring, and well-being management. However, being resource constrained network with limited energy and resource it often undergoes exhaustion imposing severe condition of link-vulnerability and disruption making tele-monitoring and allied diagnosis difficult, especially in real-time applications. On the other hand, e-health technologies geared with Internet-of-Things (IoTs) and WBAN performs continuous data communication with varying size and rate, and thus the occurred non-linearity makes signal retrieval complex and sometime ineffective. Thus, to achieve an optimal e-health system it becomes inevitable to design an ultra-powered sensor system with low computational cost, low power exhaustion, delay and enhanced quality of signal. Noticeably, in major wearable healthcare systems, BSNs or WBAN systems the efficient signal reconstruction (say, quality signal retrieval) and resource efficient transmission has always been the challenge for industries. On the other hand, the different personalized medicine processes encompass tele-monitoring the Electro-Myogram, Electro-cardiogram (ECG), Photoplethysmographic (PPG), fetal- analysis ECG (fECG), Magnetic Resonance Imaging (MRI), etc possess different resolutions and spatio-temporal characteristics. Additionally, these tele-monitoring applications with bio-sensors continue transmitting bio-signals to the base station and hence are energy as well as resource exhaustive. On contrary, being resource constrained sensors and channel it demands more resource efficient signal processing mechanism. Addition to energy and time efficiency, maintaining optimal signal quality is of inevitable significance.

Classically, to achieve resource-efficient transmission compression techniques have been proposed; however majority of the classical methods undergo reduced signal quality at the received due to data loss, reconstruction inefficacy etc. As a viable signal reconstruction and communication, Compressed Sensing (CS) technology intends to sample sparse signal below the Nyquist frequency. Data sparsity enables CS technology to provide time-efficient, energy-efficient, quality-centric and resource efficient data transmission for different BSN or WBAN based tele-monitoring purposes. Additionally, CS helps achieving energy-efficient wireless sensors for long-term health monitoring. CS has been applied in numerous low-complexity compression purposes for ECG, fECG and EEG tele-monitoring over WBAN. Though, CS methods have played vital role to achieve energy-efficient signal detection and communication for aforesaid purposes; however classical model-driven approaches are limited due to confined compression ratio, reconstruction quality, etc. Practically, CS techniques have been designed to meet personalized purposes such as data compression, signal sparse representation and reconstruction, secure communication etc. On contrary, the difference in sparsity, non-linear sparsity, standalone feature (traits) such as time or frequency components make majority of the classical CS methods limited to deal with multi-model data compression and optimal reconstruction (at the receiver) for resource-efficient transmission over BSN or WLANs. Undeniably, CS methods reduce the quantity of data to be transmitted over channel and hence make overall process resource as well as time efficient. However, in major classical approaches retaining leveraging higher compression and enhanced reconstruction quality has remained challenge. In past, different CS methods have been proposed including wavelet based compression, rakeness-decoder based CS, where the sparse signal(s) are analyzed in time as well as frequency domain. Majority of the existing CS methods hypothesizes sparsity to be constant over time, on contrary researches reveal that

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signal-sparsity varies over time, especially in ECG, EEG and PPG bio-signals. The variations or the non-linearity of sparsity over operating period makes major existing approaches limited. Additionally, the varying sparsity imposes reconstruction error and instability making it inferior. Exploiting significant feature extraction, wavelet analysis, spatial as well as temporal feature-correlation assessment and learning can enable a better CS scheme for bio-physiological signal detection, analysis, compression, transmission and reconstruction. In other words, multi-model bio-physiological parameter detection, transmission and reconstruction exploiting significant wavelet representation, coefficient learning and its dependencies assessment can be of utmost significance. Observing literatures, It has been found that the use of machine learning methods can be of utmost significance to learn over the sparse information throughout the data, and it can also reduce the less-significant data to be transmitted (as it can be trained over the extracted features and can contain non-zero values for further signal reconstruction). In other words, the use of machine learning can help reducing size as well as allied computational overhead that eventually will help retrieving suitable sparse matrix representation for efficient signal reconstruction. Though, wavelet techniques such as DWT based methods have achieved better performance in existing literatures, however, it often lacks translation invariance. Literatures find that wavelet techniques such as stationary wavelet transform (SWT) can achieve translation invariance by eliminating the down-samplers and up-samples in DWT. In addition, SWT exhibits up-sampling of the wavelet-filter coefficients by certain factors to the n-th level and thus retains significant inherent features of the input signal even after decomposition of N-levels. Being shift invariant in nature, it is more suitable for compressive sensing purposes. Similarly, as feature learning or data learning approach, machine learning can be vital to perform signal compression and reconstruction, though it requires better (sparse) signal adaptive sampling matrix generation ability.

Considering above discussion and allied motives, in this paper a robust data-driven machine learning assisted CS method has been proposed by exploiting efficacy of stationary wavelet transform (SWT) technique followed by a modified ELM Auto-Encoder (ELM-AE) to achieve optimal sparse matrix or sample matrix for signal reconstruction. The proposed SWT and ELM-AE model has been applied over different bio-physiological signals for compression and respective performance has been assessed in terms of CR, PRD, Compression Quality, and Signal to Noise Ratio performance. Functionally, our proposed model at first applies SWT over the input bio-physiological signal(s) and estimates two different coefficients including approximated coefficient and detailed coefficient, which is also called horizontal coefficient. Thus, obtaining the approximated coefficient, it was fed as input to the proposed threshold adaptive weight adjustment based ELM-AE model. Our proposed ELM-AE model obtains the optimal set of the sparse matrix also called optimal sparse matrix (OSM) as the weights of the hidden layer. Obtaining the OSM sampling matrix (obtained from the approximated coefficient of the SWT), it was fed as input to the Inverse-SWT that in conjunction with the detailed coefficient reconstructed the original signal or the compressed signal. The efficiency of the proposed model has been examined in terms of Compression Ratio (CR), Percent Root Mean Square Difference (PRD), Quality Score (QS) and Signal to Noise Ratio (SNR). MATLAB based simulation over different bio-physiological signals including ECG and PPG revealed that the proposed SWT (HAAR) wavelet assisted (threshold adaptive weight adjustment based) ELM-AE CS model achieves high CR and SNR while maintaining low PRD. On the other hand, the moderate value of QS too was found suitable over different input bio-signals (ECG and PPG).

The remaining sections of the presented manuscript are divided as follows. Section 2 discusses the related works pertaining to the at hand CS research domain, while Section 3 presents the research questions. In Section 4 proposed methodology and allied implementation is discussed, which is followed by results and discussion.

2. Related Work

To enable CS based fetal-ECG (fECG) detection, Poian et al [1] focused on sparse-representation over the components obtained from independent component analysis (ICA). Similarly, Patel et al [2] exploited sparse binary matrix exploitation based sparse representation of the ECG waveforms to perform fetal arrhythmias monitoring. Unlike, [1], authors [3] recommended using pre-processing technique such as notch filtering to remove noise components like impulsive artifacts from fetal ECG detection [4]. Similar to [1], Kuo et al [5] proposed CS-ECG monitoring system for atrial fibrillation (AF) detection. Authors recommended applying discrete wavelet transform (DWT) based AF signal compression to achieve better sensitivity and specificity. Exploiting the ICA components and projecting it for sparse representation, Gurve et al [6] performed fetal ECG detection with multichannel abdominal ECG signal. Authors applied ICA to distinguish fetal-ECG from mother on the compressed signal. To achieve better reconstruction quality, they applied ℓ-p regularized least-squares (ℓ p-RLS) algorithm. Polanía et al [3] designed CS concept for energy-efficient WBAN applications to be used for ECG tele-monitoring. Authors exploited the structure of the wavelet representation of ECG signal to enhance reconstruction quality and compression efficiency. Additionally, the use of prior information signifying wavelet dependencies across scales enabled better reconstruction. Pareschi et al [7] proposed rakeness based CS for ECG signal detection and communication. Authors designed rakeness based CS-decoder for low-redundant ECG sensing. Marchioni et al [8] developed disturbance rejection with rakeness-based CS for ECG signal detection. Rakeness based decoder at the receiver enabled better signal reconstruction while rejecting the disturbance dynamically. Similarly, Mangia et al [9] inherited rakeness based CS concept which exploited the uneven energy-distribution over the sensed ECG signal to enable better performance with low computational cost and resource consumption. Bortolotti et al [10] found rakeness based CS more energy-efficient and with better reconstruction quality. Mangia et al [11] proposed rakeness based CS, where second order statistical features were used for signal reconstruction. Applying weighted ℓ1-minimization Zhang et al [12] designed an energy-efficient CS-ECG model for wireless biosensors. For reconstruction, authors applied minimal mutual coherence pursuit, which helped to achieve sparse binary measurement matrices for ECG signal encoding. The weighted $\ell - 1$ minimization exploited the multisource prior knowledge in wavelet domain to perform signal reconstruction.

Chou et al [13] used subspace-based dictionary for both encrypting and decoding the CS measurements online. Authors prepared subspace based dictionary by dividing signal space into discriminative and complementary subspace offline. However, its computational complexity can’t be ignored. Similarly, Tsai et al [14] considered pre-trained subspace-based dictionary to project interfered and compressed data onto the subspace with high learn-ability and low complexity to achieve better ECG signal tele-monitoring. Zhang et al [15] designed CS-ECG signal reconstruction model by performing ECG signal (random) sub-sampling and subsequent mapping into onto a 2D-space using Cut and Align (CAB) technique. It enabled better signal sparsity to achieve

ISSN: 2233-7857 IJFGCN

better reconstruction. Authors used a nonlinear optimization scheme for 2D signal construction. To perform signal compression, authors mapped ECG signal into frequency domain, followed by a sequence of multiplication and addition between the original ECG and a Gaussian random matrix. For signal reconstruction, authors used matching pursuits (MP) algorithm with two blocks sparse Bayesian learning (BSBL). Wang et al [16] proposed a data data-driven sampling matrix Boolean optimization concept for CS-based biomedical signal detection and tele-monitoring. To enable reliable and low-redundant transmission Lalos et al [17] developed random linear network condign (RLNC) for cooperative-CS for energy-efficient biomedical signal tele-monitoring. Authors found their approach more efficient under link-vulnerability. Singh et al [18] proposed block-sparsity based joint-CS for multi-channel ECG signal reconstruction over WBAN. Recalling the fact that in multi-channel ECG contains spatio-temporal correlations, authors processed with Bayesian learning method to perform signal reconstruction. Authors [10] proposed DWT domain block sparsity analysis to perform simultaneous signal reconstruction. Zhang et al [19] designed a weighted $\ell_{1,2}$ minimization method for multichannel ECG signal reconstruction. Authors applied both multi-source prior in wavelet domain and inter-channel correlation to perform signal reconstruction. Yu et al [20] developed an adaptive compressive engine for real-time ECG monitoring under varying (signal) sparsity. Authors proposed sparsity variation accumulation method based on adaptive feedback architecture for CS-ECG tele-monitoring. Zhang et al [21] designed different CS-ECG signal reconstruction schemes, encompassing compressed sampling matching pursuit (CoSaMP), orthogonal matching pursuit (OMP), expectation-maximum-based block sparse Bayesian learning (BSBLEM) and bound-optimization-based block sparse Bayesian learning (BSBL BO). Authors found BSBL_BO and BSBL_EM methods performing better. To recover non-sparse physiological signals Akil et al [22] applied Block Sparse Bayesian Learning (BSBL) algorithm over fECG signals. Kanhe et al [23] designed 2D DWT features and Hermite coefficients assisted ECG signal compression. Authors spread ECG signal over the discrete Hermite functions basis, which was processed for 2D wavelet based compression. To enhance performance of CS-ECG signal detection and reconstruction, Craven et al [24] designed an adaptive dictionary reconstruction model. This approach encompassed multiple dictionary learning based dictionaries for CS signal reconstruction. Authors found their model more efficient that wavelet based lossy compression techniques.

Liu et al [25] applied Quantized-CS (QCS) model for energy-efficient data compression in wireless tele-monitoring. To reconstruct signal from the quantized compressed signal, authors applied Bayesian de quantization (BDQ) algorithm, which exploited quantization errors and correlated structure. Yang et al [26] focused on reducing aliasing components generated during signal reconstruction in CS-MRI. Authors used split Bregman method by minimizing a joint optimization term containing the total variation term, fitting data term and a median filter term to achieve better signal reconstruction. To reduce scan-time in MRI, Datta et al [27] proposed interpolated compressed signal reconstruction for 3D-MRI applications. Authors used weighted wavelet forest sparsity, and joint total variation regularization norms on different interpolated/non-interpolated slices to achieve signal reconstruction. However, computationally complexity can't be ignored. Tashan et al [28] designed a multilevel CS-MRI where authors split image into equi-sized multiple frames and projected pixels into sparse domain to be subsequently processed for CS compression over each frame

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with different compression's level. To retain better tradeoff between signal reconstruction quality and compression ratio, Liu et al [29] applied adaptive compression ratio for ECG signal. Employing relationship between compression ratio and sparsity authors performed signal reconstruction. Rahimi et al [30] designed an efficient serialized Walsh-Hadamard transform based feature-extraction for information-aware CS for bio-physiological signal(s) reconstruction in wearable applications. Authors executed feature learning using quadratic Support Vector Machine (SVM) to detect signal. As data driven approach Pant et al [31] applied machine learning for CS-ECG signal detection and reconstruction for arrhythmia detection. Obtaining the QRS complex information, authors applied two distinct features; sum of absolute differences (SAD) and maximum of absolute differences (MAD) for each ECG segment, which were learnt for better-quality signal reconstruction. Pei et al [32] designed block sparse Bayesian learning (BSBL) for CS-ECG signal reconstruction. Marchioni et al [33] developed a sparse sensing matrix based CS-ECG signal detection and reconstruction. Xu et al [34] designed a data-driven CS model suitable for energy-efficient wearable sensing. Though, numerous CS methods are proposed for ECG signal(s); however very fewer efforts have been made towards PPG signal, which has been gaining widespread attention due to its increasing biomedical CAD significances. PPG signals demand CS with high-resolution process capacity. Designing a robust CS model with the ability to process different bio-physiological signals comprising ECG, EEG and PPG can be of great significance. Natarajan et al [35] developed an end-to-end CS model for continuous bio-signal(s) compression for wearable body sensor network (BSN). Authors used Binary Permuted Block Diagonal (P-BPBD) matrix encoder and input-signal (symmetric) padding to achieve high CR performance for ECG and PPG signals. Muduli et al [36] proposed a deep learning based CS model for fECG signal reconstruction. Authors proposed a non-linear mapping model with a stacked de-noising auto-encoder (SDAE) in which initially the non-sparse fECG signal was compressed at the transmitter using deep learning method. Authors enhanced pre-training and tuning by mini-batch gradient descent back-propagation algorithm. The reduced matrix vector multiplication enabled SDAE model more time-efficient at the receiver. Yang et al [37] proposed a refinement learning to alleviate aliasing issue in CS-MRI for optimal signal reconstruction. As refinement learning authors performed U-Net stabilization to achieve aliasing-free signal reconstruction. Additionally, authors used texture and edge information in frequency-domain to achieve better reconstruction quality. Sun et al [38] applied deep learning model named a binarized auto-encoder based CS for wireless neural recording. Their model optimizes binary sensing matrix and a non-iterative recovery solver concurrently to retain better performance. Gogna et al [39] proposed a semi-supervised stacked label consistent auto-encoder for ECG reconstruction.

3. Research Questions

Considering the overall research motives and allied (identified) methods, a few research questions have been identified. These research questions intends to assess whether the proposed methodology in can achieve the intended goals.

RQ1: Can the use of Stationary Wavelet Transform (SWT) be efficient to yield more significant features or patterns to enable optimal sparse representation for bio-physiological signal compression, detection and (signal) reconstruction?

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RQ2: Can the implementation of ELM-AE be an efficient solution to perform data-driven sparse representation and optimal sample matrix generation?

RQ3: Can the use of adaptive thresholding concept enhance ELM-AE to achieve better sparse representation for bio-physiological signal compression and reconstruction?

RQ4: Can the strategic and efficient implementation of above stated SWT ELM-AE model enable an optimal compressive sensing solution for bio-physiological signals (ECG and PPG) detection, compression and reconstruction?

4. System Model

This section primarily discusses the proposed CS model and its implementation. Before discussing the proposed ELM-AE based sparse CS, a snippet of sparse signal reconstruction problem in bio-physiological signal is given as follows:

A. Sparse Reconstruction for Continuous Bio-Physiological Signals : Problem Formulation and Conceptualization

Consider x be the bio-physiological signal representing continuous system with instant value of $x \in \mathbb{R}^N$. For the aforesaid value let the corresponding sparse representation be $\tilde{x} \in \mathbb{R}^P$, where $P \ll N$. Then, with above stated case, the sparse (signal) reconstruction problem signifies the problem to extract or reconstruct x with the available $\tilde{x}$ comprising the bio-sensor(s) position in the form of a sample or the measurement matrix C, as defined in (1). Noticeably, here the matrix C signifies the sparse representation of the input (or sensed) bio-signal $\tilde{x}$ obtained from the sensed data x. The other variables P states the total number of the sparse measurements, while N refers the high resolution field's dimension. Mathematically, the sparse representation of the input x can be presented as (1).

$$\tilde{x} = Cx \tag{1}$$

In the proposed CS model, we primarily emphasize on the sparse vector x possessing sparse representation in certain basis space given as $\Phi \in \mathbb{R}^{N \times K}$. Noticeably, $\Phi \in \mathbb{R}^{N \times K}$ is acceptable only when $K \ll N$, so as to ensure eventual result as $x = \Phi a$. Typically, due to information loss in a system, the signal reconstruction turns out to be non-absolute and gives rise to the reconstruction error. In this case, merely performing inverse of C can't give or reconstruct the signal x as depicted in (2). This is because it is infeasible since the inverse would turn-out to be the same as obtaining or solving an under-determined system.

$$C^{+}\tilde{x} = x \tag{2}$$

Undeniably, sparse representation and reconstruction concept has played vital role towards inverse problems and hence so far has the irreplaceable significance in different research and applications including geophysics [40, 41], image processing, signal reconstruction [42, 43]. Broadly speaking, aforesaid applications signify the inverse problems [44], where sparse reconstruction theory has played inevitable role [45-50]. However, its implementation strategy or approaches have been different for the different applications, data environment or expected signal nature. Since, the current study focuses on CS of the bio-physiological signals the further discussion emphasizes on sparse reconstruction problem in bio-signal(s) reconstruction in WNS or WBAN for personalized e-health applications. In general, majority of the bio-signals used to be "compressible", signifying their sparsity in K-sparse basis Φ. Mathematically,

$$x = \sum_{i=1}^{N_b} \phi_i a_i \text{ or } x = \Phi a \quad (3)$$

In (3), $\phi \in \mathbb{R}^{N \times N_b}$ and $a \in \mathbb{R}^{N_b}$. Noticeably, in (3) K presents the non-zero elements. For bio-physiological signals to achieve sparse reconstruction the more favourable condition can be $\phi \in \mathbb{R}^{N \times N_b}$ as compared to $\Phi \in \mathbb{R}^{N \times K}$. This condition is more suitable when the sparsity of the system K is not known a priori. This as a result requires a more sophisticated basis set with dimension $N_b \approx P > K$. Practically, the feaisble basis count is not inevitably needs to be equal to N and can be $N_b \ll N$. This is because to represent the sensed signal up to certain expected quality merely K (basis counts) are required. This condition states a situation where the K-sparse basis Φ embodies the most suitable or optimal data-driven basis vectors. Thus, the (bio-) signal reconstruction problem functions towards the identification of those K coefficients. There are numerous real-time bio-signal analysis or reconstruction scenario or even application environment where Φ and K are not known as a priori, and consider N_b, N as user-defined input. The transform coding approaches, especially in compression purposes at first perform gathering the high resolution sample, which is then processed using Fourier or wavelet basis space where the data used to be in sparse and obtains the optimal K-sparse structure while alleviating and dropping remaining information. This approach not only reduces redundant data processing or transmission but also enhances computational efficiency, thus making bio-signal communication more energy and resource efficient. Considering this motive, in this paper we applied wavelet basis space over the input bio-signal(s) which were later processed using (data-driven) machine learning method to retain optimal sample matrix for signal reconstruction. However, practically the samples and compression technique needs high resolution signal or sample acquisition, before performing dimensional reduction. Unfortunately, it is a highly complex and tedious task because of continuous large scale data, which demands significantly large processing power, memory, and time. As alternative solution, CS enables direct sparse sensing by assessing K-sparse coefficients, as depicted in (4).

$$\tilde{x} = C\Phi a = \Theta a \quad (4)$$

In (4), $\Theta \in \mathbb{R}^{P \times N_b}$ signifies a map derived in between the basis coefficient(s) a and the sparse measurements $\tilde{x}$. To be noted, in (4), a states the data in feature space, while $\tilde{x}$ used to be in physical space. Thus, the key problem in solving reconstruction problem (for x) using (1), especially in bio-signals is that the measurement matrix C can be ill-posed or ill-conditioned, and even x can be non-sparse in nature. On contrary, with x as sparse within Φ, the signal reconstruction with the help of Θ in (4) becomes feasible. It becomes possible by solving for the basis coefficients a which is nothing else but the K −sparse. In this manner, with P constraints one can solve reconstruction problem by estimating a sparse solution a using (7) by means of certain s-norm minimization. x can be reconstructed as per the model derived in (3). Here, towards the original bio-signal (x) reconstruction, the value of s selected is 2, signifying l_2-norm reconstruction which achieves a with better computational efficiency and minimum energy. Here, we formulate l_2-norm minimization as (5).

$$\min \|\tilde{x} - \Theta a\|_2^2 \tag{5}$$

Applying pseudo-inverse of Θ, above derived l_2-norm minimization problem (5) can be converted as (6).

$$a = (\Theta)^{+}\tilde{x} \tag{6}$$

In (6), Θ^{+} can be easily be approximated as a solution to the following formulation (7).

$$(\Theta^{+}\Theta)^{-1}\Theta^{T} = \tilde{x} \tag{7}$$

With l_2-norm minimization to estimate optimal K-sparse solution and to optimise sparsity of a we can maximize the counts of the non-zero elements and minimize $\|a'\|_0$ in such manner that it fulfils the condition (8).

$$\Theta a' = \tilde{x} \tag{8}$$

With the considered bio-signals such as ECG or PPG with $P = K + 1$ (typically, $P > K$) self-regulating assessment, the sparse coefficients can be obtained with high-probability by means of l_0 reconstruction. Such condition infers that for each assessment or measurement we need to excite a distinct basis vector ϕ_i so as to identify the corresponding a_i optimally. In case multiple measurements excite the same ϕ_j, then there can be the need of supplementary measurements so as to generate or reconstruct the signal of the expected quality. On contrary, for $P \leq K$ sovereign measurements, the likelihood of reconstructing the sparse solution gets too compromised, which results into significantly large reconstruction-error. Moreover, l_0-norm minimization is highly complex task and possesses ill-conditioned process, NP-hard and even can't guarantee stability of the signal reconstruction, which is must for continuous tele-monitoring or the bio-physiological signals over e-health infrastructures of systems.

$$a = \arg\min \|a'\|_0 \quad \text{such that } \Theta a' = \tilde{x} \tag{9}$$

The robustness of CS methods [45–48] ensures optimal or at least near-optimal (signal) reconstruction of the uncompressed information by means of $K-$sparsest coefficients estimation. To achieve it l_2-norm minimization based reconstruction can be a potential solution. Additionally, it provides convex optimization of the at hand problem where it exploits linear programming techniques to obtain the optimal coefficients and the basis pursuit [45, 48, 51]. Even classical brutal search can also be applied to obtain or localize the largest K coefficients of the basis a , however it increases the computational cost with increase of the dimension. To alleviate it, different greedy approaches [52-54] can be applied to solve l_1- minimization of (7) with computational complexity of $\mathcal{O}(N^3)$ for $N_b \approx N$. However, with such models to get K-sparse vectors for reconstruction the cost optimization needs $P > \mathcal{O}(K\log(N = K))$ measurements [45, 48, 55]. Summarily, in bio-signal (sparse) reconstruction there can be three different parameters $N_b; K; P$ which can have significant influence on the reconstruction quality. Here, N_b signifies the potential (candidate) basis space dimension applied for signal reconstruction. Noticeably with $N_b \approx N$ it can adversely affect the reconstruction quality. Similarly, K refers the expected sparsity, bound to the level of signal reconstruction quality. Therefore, it is significant to select K in such manner that with optimally selected or predicted features it achieves satisfactory reconstruction quality. To achieve it, in this research a threshold sensitive approach is applied which maintains smaller K to retain high sparsity and hence eventual reconstruction quality. Here, the variable P signifies the bio-sensor(s). Typically, the relationship in amongst the aforesaid variables N_b; K and P decides whether to use l_1 or $l_2 -$ norm minimization to achieve expected level of reconstruction quality. In practical real-time scenario of ECG/PPG CS, K remains unknown or (not) a priori, however highly associated with the expected level of reconstruction quality. Here, N and N_b can be selected on the basis of the feature space for which the reconstruction has to be done. Here, N signifies the expected dimension of the reconstructed (signal) state, while N_b presents the dimension of the candidate basis space where the reconstruction problem is defined. In case of $K = N_b$ the optimal signal reconstruction can be accomplished by predicting K weights precisely (with help of l_2 norm-minimization). On contrary for $P < K$, l_2 norm-minimization can be applied. With $K < N_b$ and $N_b > P > K$, it can show worst performance for K-estimation causing reduced reconstruction quality. On the other hand, with $K < N_b$ and $N_b > K > P$, the best signal reconstruction can be achieved as the P weights by applying l_1 or l_2 norm-minimization. Similarly, for $P \geq N_b > K$, the optimal reconstruction would give rise to N_b weights in comparison to the K for the worst scenario.

I. Discrete Stationary Wavelet Transform Feature Space Projection

In this research, at first the input or sensed (original) bio-physiological signal was processed for wavelet sparse analysis, where unlike classical continuous wavelet transform (CWT) or the discrete wavelet transform (DWT), we applied discrete stationary wavelet transform (SWT) algorithm so as to get low-dimensional feature space as input to the proposed data-driven ELM-AE model. Theoretically, SWT has taken different shapes based on enhancement and independent formulation by the different researchers. For example, SWT has also been named as undecimated wavelet transform (UWT), invariant wavelet transform etc. Unlike classical DWT methods, SWT provides better approximation results, which is usually attributed due to its linear, redundant and shift-invariant characteristics. Considering such robustness to yield a robust CS model which could deal with linear as well as non-linear bio-signal detection, compression and communication we have applied SWT as initial process. In the proposed model, the input sensed bio-physiological signal x(k) is fed as input to the SWT, which as a result generates two distinct coefficients, named detailed coefficient $w_{i,k}$and approximated coefficient $v_{i,k}$. As depicted in Figure 2 to generate these two distinct coefficient values SWT applies two different filters, standard low-pass filters (LPF) H_i and high-pass wavelet filters (HPF) G_i. Here, in our proposed system, the filters H_1 and G_1 were obtained by performing up-sampling of the filters by applying previous step (say, H_{j-1} and G_{j-1}) [6]. Typically, the value of detailed coefficient $w_{i,k}$ used to be same as the HPF output and similarly the $v_{i,k}$ output too is equal to the LPF output.

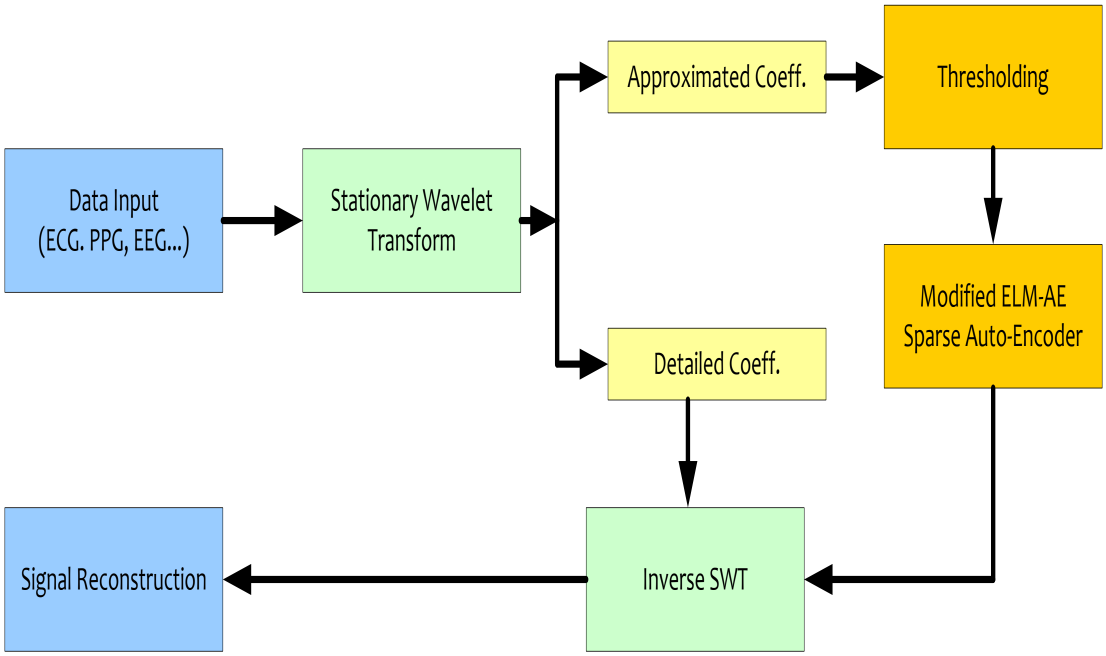

Figure 1. Stationary Wavelets Assisted Data-Driven Modified Extreme Learning Machine based Compressive Sensing

As depicted in Figure 2 SWT estimates two distinct coefficients, approximated coefficient and detailed coefficient using LPF and HPF, respectively. Considering level of significance and feature depth, in our proposed CS method, we considered mainly Level-2 approximated coefficient values (v_{2k}) for further computation in ELM-AE.

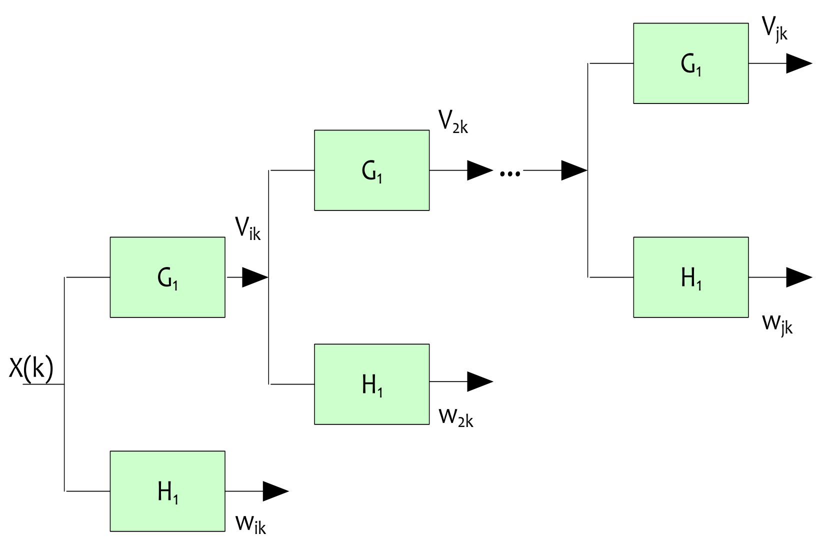

Figure 2. Discrete SWT based feature space projection

ISSN: 2233-7857 IJFGCN

This selection was made based on the hypothesis to leverage the computational cost and level of significance of the feature space or vector. In our proposed method we applied a threshold (Th) based feature projection for the approximated coefficient. We selected Th value as the percentage of the R peak. Though, the results were tested over different threshold values, we found $\mathrm{Th} = 0.98$ as the most suitable condition. Obtaining the Level-2 coefficients we applied threshold ($\mathrm{Th} = 0.98$) and the approximated coefficients with R-values lower than the threshold $\mathrm{Th} = 0.98$ were removed. The remaining approximated coefficients having R-value more than 0.98, here onwards we state as the input x, we executed the ELM-AE model for further sparse feature vector estimation or the optimal sampling matrix estimation (as the weight vector of ELM-AE as depicted in Figure 3). Noticeably, since ELM-AE processes over the approximate coefficients derived using SWT algorithm, we refer the at hand learning model as data-driven learning approach. Additionally, the detailed coefficients $w_{i,k}$obtained from the same bio-physiological signal (from SWT) is employed by Inverse-SWT (ISWT) in conjunction with the ELM-AE model (optimal sparse matrix of the input bio-physiological signal) to reconstruct the signal. The detailed discussion of the proposed (data-driven) ELM-AE based sparse sampling matrix estimation is given in the subsequent section.

II. Modified ELM-AE assisted Data-driven Sparse Basis Computation

To reconstruct data, especially under real-time systems with no (significant) prior knowledge, different approaches have been proposed such as Fourier functions [45, 46], radial basis function (RBFs) or Gaussian function regression. RBF and Gaussian function regression based representations used to be more robust, especially for the dynamic systems and continuous evolving flow conditions [56]. Considering this fact, in this research we intended to use a highly robust data driven sparse basis estimation model using ELM auto-encoder [57, 58]. In our proposed data-driven CS model, ELM-AE functions as a regressor by employing a Gaussian prior. Recalling the fact that the higher input data, which is common in continuous tele-monitoring of the bio-physiological signals, and input layers confines classical machine learning methods due to unavoidable local minima and convergence issues. Moreover, in major classical neural-computing models, the problem of convergence and error increases with increase in the number of hidden layers that eventually can affect the overall reconstruction quality in at hand CS problem. Additionally, increased hidden layers will introduce more number of weights to be computed which can result into huge computational burden and complexity. Due to such computational issues, the conventional neuro-computing models can't be suitable for CS functions [57, 58]. On contrary, ELM as advance neuro-computing model alleviates or avoids aforesaid problems due to its single-layered multi feed forward neural network (SL-MFNN) characteristics which make it suitable for at hand data-driven CS problem. Its ability to perform swift learning by performing random hidden node selection and respective weight estimation makes potential towards our proposed sparse-representation or coefficient estimation for optimal (bio-) signal reconstruction in CS task. In our proposed CS method we have applied ELM-AE as learning scheme which embodies a SL-MFNN with arbitrarily generated weights for associated hidden layers or connected hidden nodes) and bias components. In addition it encompasses an activation function over hidden layer before estimating the output weights by confining to the output data. With the number of hidden nodes lower than the dimension of the input bio-signal the compressed sparse feature representations of the original bio-signal can be obtained as the output weight of ELM-AE. This overall process is depicted in Figure 2.

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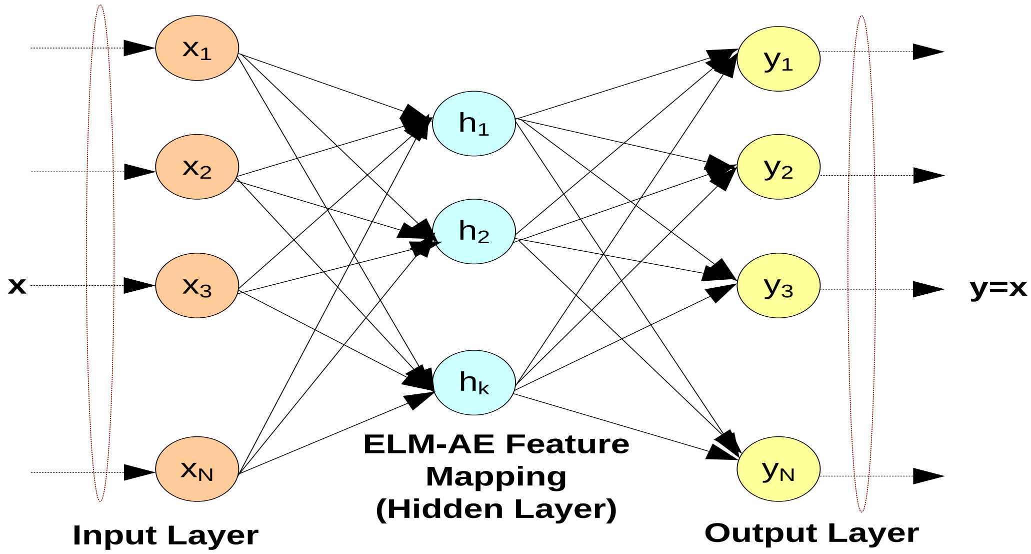

Figure 3. ELM-AE model with output expected same as the input signal x

Consider that the input approximated coefficients of the original bio-physiological signal be a set of data representing $\Phi \in \mathbb{R}^{N \times M}$ with N as the dimension and M be the total snapshots. In other words, let the input signal be in a vector form $x_j \in \mathbb{R}^N$ for $j = 1, \ldots, M$. Then, this input signal can be mapped to the K-dimensional hidden layer signifying the feature space, then the ELM-AE output can be presented as (10).

$$x_j = \sum_{i=1}^{K} \phi_i a_i^j = \sum_{i=1}^{K} \phi_i h_i^j(x_j) = \sum_{i=1}^{K} \phi_i g\left(w_i^T x_j + b_j\right) \tag{10}$$

In (12), $x_j \in \mathbb{R}^N$ signifies the original sensed input bio-physiological data, while the other parameters j and N signifies the index of snapshot and the dimension of input data. The other parameter, $w_i \in \mathbb{R}^N$ states the random input weights which help mapping the input nodes to the hidden nodes, and b_i presents the random bias component. $g(.)$ presents the non-linear activation function functional on a scalar, while $\phi_i \in \mathbb{R}^N$ presents the resulting output weights which map the estimated hidden features to the output nodes of ELM-AE. In our proposed ELM-AE model we applied different kernel functions including RBF, Sigmoid, Sine, Hard Limit, and Triangular Basis Function (TBF) as activation function to output (11). Though, for performance analysis we applied ELM-AE with different kernel functions, considering space constraints in this manuscript only RBF based ELM-AE model and associated performance are discussed.

$$g(z) = e^{-(z^2)} \tag{11}$$

The above derived linear model (12) can also be derived as matrix form, given in (12).

$$X = \Phi a \tag{12}$$

In (12), a signifies the output's matrix possessing a_i^j elements (retrieved) from the hidden layer of the ELM-AE (13).

$$a = \begin{bmatrix} a_1^1 & \cdots & a_k^1 \\ \vdots & \ddots & \vdots \\ a_1^M & \cdots & a_k^M \end{bmatrix}^T = \begin{bmatrix} h(x_1) \\ \vdots \\ h(x_M) \end{bmatrix}^T = \begin{bmatrix} h_1(x_1) & \cdots & h_k(x_1) \\ \vdots & \ddots & \vdots \\ h_1(x_1) & \cdots & h_k(x_M) \end{bmatrix}^T \quad (13)$$

In (13), $h(x_j) = [h_1(x_j), \ldots, h_k(x_j)] = [a_1^j, \ldots, a_k^j,]$ signifies the results generated or the output obtained from the K hidden nodes. Usually it used to be the row vector for the $j-th$ input snapshot x_j. Noticeably, $h(x_j)$ is also referred as the feature transformation which often maps the input data x_j from the N dimensional input space to the K dimensional hidden layer feature space a (13). Now, the ELM-AE output weights can be presented as a matrix (14), with Y as (15).

$$\Phi = \begin{bmatrix} \phi_1^1 & \cdots & \phi_1^N \\ \vdots & \ddots & \vdots \\ \phi_k^1 & \cdots & \phi_k^N \end{bmatrix}^T \quad (14)$$

$$X = \begin{bmatrix} x_1^1 & \cdots & x_N^1 \\ \vdots & \ddots & \vdots \\ x_1^M & \cdots & x_N^M \end{bmatrix}^T \quad (15)$$

In ELM-AE model Moore-Penrose Pseudo-inverse method (16) to solve (12) and obtain the values of Φ.

$$\Phi_{train} = \Phi = Xa^+ = Xa_{train}^+ \quad (16)$$

Unlike major conventional ELM encoders, in this research we designed a novel dynamic weight adjustment based ELM-AE where the final weight vectors or the sparse vectors were obtained in reference to an expected threshold level. Here, we applied a $Th_w = 0.98$. Once solving $l_2 - norm$ minimization and obtaining the pseudo inverse solution the final weight vector was estimated, which was subsequently processed for weight adjustment using following model. Consider the final ELM-AE weight vector be $x(t)$, then scale values for the obtained output was obtained using (17).

$$x_{scale} = X - \min(X) \quad (17)$$

Now, setting $Th_w = 0.98$ as a minimum value component, output data was obtained using (18).

$$X_{output} = (x_{scale}/\text{range}x_{scale}(:)) * (1 - Th_w) \quad (18)$$

In the subsequent phase, the weights W are updated as (19).

$$W = X_{output} + Th_w \quad (19)$$

The final weight vector at the hidden layer of the ELM-AE is obtained as(20).

$$X_1 = X * \text{mean}(W') \quad (20)$$

Now, with updated weight vector X_1, we obtain the eventual sparse matrix output by solving Moore-Penrose Pseudo-Inverse method. Once obtaining the final sparse matrix it was processed for signal reconstruction using ISWT, which takes both detailed coefficient information of the input signal and the final ELM-AE sparse matrix output.

5. Results and Discussion

Taking into consideration of the significance of a robust compressive sensing approach, in this paper the predominant emphasis was made on exploiting the efficacy of advanced wavelet basis and computationally efficient neuro-computing model such as extreme learning machine. Here, as wavelet basis estimation we applied stationary wavelet transform (SWT) with level-2 coefficient estimation. Noticeably, SWT estimates two distinct coefficient data, approximated coefficient and the detailed coefficient also called as horizontal coefficient. Realizing the feature significance of approximated coefficient we considered a threshold adaptive coefficient selection, where the threshold Th was selected as 0.98. With reference to the threshold values only those coefficients higher than 0.98 were considered for further computation. Now, once obtaining the eventually selected approximated coefficient, we fed that as input to the ELM-AE. In our proposed threshold adaptive weight adjustment based ELM-AE model $l_2 - \text{norm}$ minimization was performed to achieve the final sparse matrix using Moore-Penrose Pseudo-Inverse. To be noted, unlike conventional ELM-AE methods, we introduced a dynamic weight adjustment model to ensure optimal weights with an expected threshold level of 0.98. With the obtained weight vector or the sparse solution, we performed ISWT to reconstruct the original signal (Figure 1). For signal reconstruction we applied both detailed coefficient as well as ELM-AE generated sparse solution. Noticeably, to assess efficacy of the proposed modified ELM-AE model with reference to the different kernel function or activation functions, we applied five different types of kernel functions, RBF, TBF, Sine, Sigmoid and Hard Limit. Similarly, we tested performance over different SWT wavelets such as db4, db8 and HAAR. In order to examine the efficacy of the proposed model, we applied different bio-physiological signals including ECG and PPG signals obtained from the benchmark datasets such as MIT-BIH Database. Additionally, the PPG data were considered from IEEE Signal Processing Cup 2015 [59]. The overall proposed system was developed and simulated over MATLAB2019b tool, with Microsoft Window 2010 operating systems and Intel-i3 processor. For performance evaluation we examined each bio-physiological signal with different wavelet selection and ELM-AE kernel or the activation functions. To assess statistically, we obtained three key performance parameters, Compression Ratio (CR), Percentage Root Mean Square Difference (PRD), Quality Square (QS) and Signal to Noise Ratio (SNR). Before discussing the statistical outputs for these above stated parameters, a snippet of their mathematical equation is given as follows.

1. Compression Ratio (CR)

CR signifies the ratio of the original bio-signal bits(S_0) bits and the reconstructed signal- bits (S_R). Mathematically, it is obtained as (21).

$$CR = \frac{S_0}{S_R} \tag{21}$$

2. Percentage Root Mean Square Difference (PRD)

PRD represents the percentage of root mean square between the original signal S_0 and the reconstructed signal S_R.

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$$\text{PRD}(\%) = \sqrt{\frac{\sum_{n=1}^{N}(S_0(n) - S_r)^2}{\sum_{n-1}^{N}(S_0(n))^2}} \tag{22}$$

3. Quality Score (QS)
QS represents the ratio of CR and PRD. Mathematically,

$$\text{QS} = \frac{\text{CR}}{\text{PRD}} \tag{23}$$

4. Signal to Noise Ratio (SNR)
SNR in CS model is defined as (24).

$$\text{SNR} = 10 \times \log \frac{\sum_{n=1}^{N}(S_0(n) - \bar{S})^2}{\sum_{n=1}^{N}\left(S_0(n) - S_R(n)\right)^2} \tag{24}$$

In terms of PRD, SNR can be obtained using (25).

$$\text{SNR} = -20\log 10(0.01\text{PRD}) \tag{25}$$

Noticeably, in this research four different types of ELM-AE kernels were applied; however amongst the employed kernels (sigmoid, RBF, TBF, Sine and Hard-Limit) RBF kernel function was found performing the best. Considering this fact, in the subsequent analysis we have discussed the RBF based ELM-AE learning model and its allied simulation results. We simulated our proposed CS model with both ECG and PPG datasets. To assess performance with different benchmark data, we considered five datasets distinctly from each signal categories (i.e., five datasets from ECG and PPG distinctly). The statistical results obtained for the different datasets in terms of CR, PRD, QS and SNR for ECG and PPG datasets are given in Table 1 and Table 2 respectively.

Table 1. Performance results for ECG bio-physiological signals

MIT-BIH Single Channel ECG	Mother wavelet											
	db4				db8				HAAR			
	CR	PRD	QS	SNR	CR	PRD	QS	SNR	CR	PRD	QS	SNR
100m	74.47	1.220	61.04	38.26	74.72	0.881	84.81	41.09	75.85	0.178	416.12	54.96
215m	74.76	0.820	91.17	41.68	75.12	0.343	219.00	49.28	73.97	1.956	37.81	44.17
124m	74.52	1.156	64.46	74.52	75.37	0.007	10767.0	82.17	75.19	0.254	296.02	51.88
200m	74.63	1.017	73.38	39.84	74.40	1.313	56.66	37.63	75.37	0.007	10767.0	82.17
234m	75.09	0.548	137.02	45.21	74.46	1.229	60.58	38.20	74.55	0.841	88.64	60.31

Table 2. Performance results for PPG bio-physiological signals

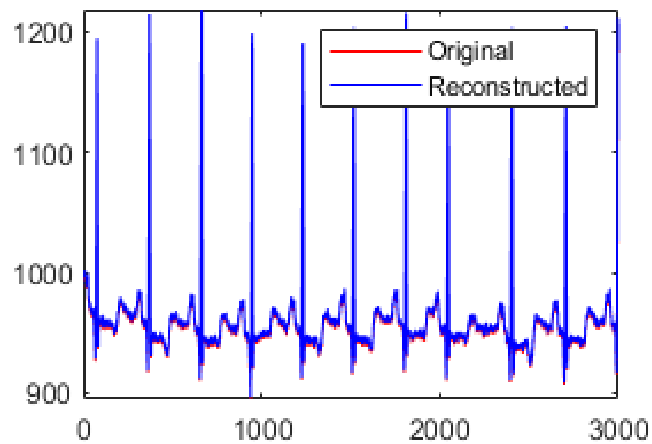
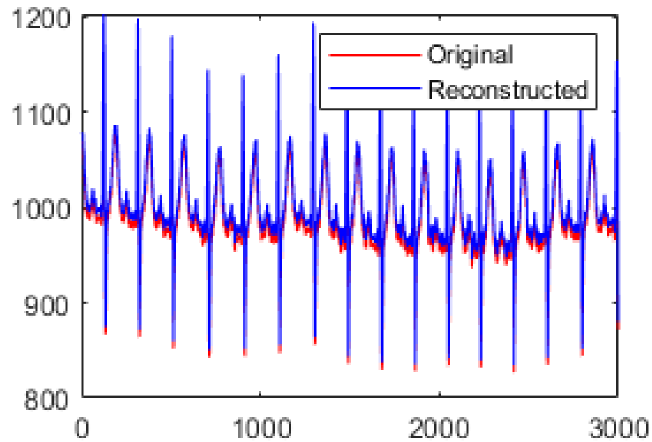
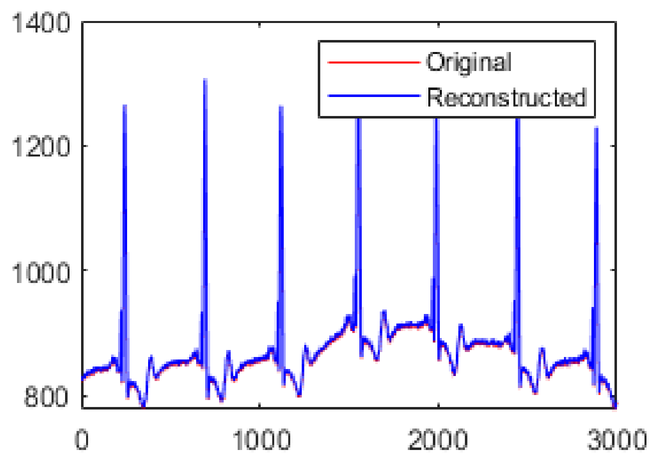
Single Channel PPG	Mother wavelet											
	db4				db8				HAAR			
	CR	PRD	QS	SNR	CR	PRD	QS	SNR	CR	PRD	QS	SNR
3141595m	74.07	0.873	84.84	41.17	74.47	1.217	61.19	36.29	74.81	0.991	74.48	40.02
a44071bm	74.63	1.007	74.11	39.93	74.79	0.869	86.06	41.21	74.85	0.711	105.27	42.91
a45503m	74.66	0.959	77.85	40.35	74.76	0.830	90.07	41.63	74.66	0.933	80.02	40.50
a45543m	74.78	0.799	93.49	41.93	74.70	0.911	81.99	40.80	74.62	1.010	73.88	39.98
a45557bm	74.73	0.869	85.99	41.21	74.50	1.054	70.68	39.60	74.61	0.981	76.05	40.16

Observing the overall results it can be found that for ECG signal with db4 wavelet; our proposed CS model achieves maximum CR of 74.76%, while PRD was obtained as 0.548. Similarly, QS was obtained as 137.02, while the maximum SNR obtained was 74.52%. On the other hand, with db8 mother wavelets, we found that the maximum CR (with db8) with ECG signals 74.72%.The PRD with db8 wavelet was 0.013, while the QS and SNR with db8 wavelets were 10767.0 and 77.23%. The CS simulation with HAAR wavelets over continuous ECG model exhibited that the proposed data-driven CS model achieves CR or 75.85%, minimum PRD of 0.007, while QS was obtained as 423.12 and SNR of 82.17. These simulation results with PPG signal with db4 SWT wavelet exhibited maximum compression ratio of 74.78%, while PRD was obtained as 0.799. Similarly, with db4 wavelets our proposed CS model obtained QS of 93.49, while SNR was 41.93%. With db8 wavelets and allied wavelet sparse basis we obtained maximum CR of 74.79, while the (minimum) PRD, QS and (maximum) SNR were obtained as 0.830, 90.07 and 41.63, respectively. With HAAR wavelets, our proposed CS model exhibited maximum CR of 74.85%, PRD of 0.711, QS of 105.27 and the maximum SNR of 42.91. Observing above stated results (Table 1 and Table 2) it can be found that the proposed SWT wavelet basis with HAAR mother wavelet and proposed modified ELM-AE the optimal CS performance can be accomplished. Thus, observing above stated simulation results, it can be found that the proposed SWT with HAAR wavelets and modified ELM-AE outperforms other combinations. Hence, considering space constraints in this manuscript the original signals and allied reconstructed signal's outputs for all considered ECG and PPG signals are presented in Table 3 and Table 4 respectively.

Observing reconstructed signal, it can be found that the proposed CS model achieves both signal-quality while maintaining low computational complexity. It makes proposed system suitable for any bio-physiological signal communication or transmission while ensuring low redundancy, low resource consumption and energy exhaustion. In this research and allied simulation SWT with different mother-wavelets were applied where it was found that SWT with db8 and HAAR wavelets exhibited significantly better than the classical approaches.

ISSN: 2233-7857 IJFGCN

Table 3. ECG Reconstruction Quality assessment

MIT-BIH Single Channel ECG	Bio-signal Reconstruction Quality assessment (SWT with HAAR wavelet and Modified ELM-AE using RBF kernel function)
100m	
215m	
124m	

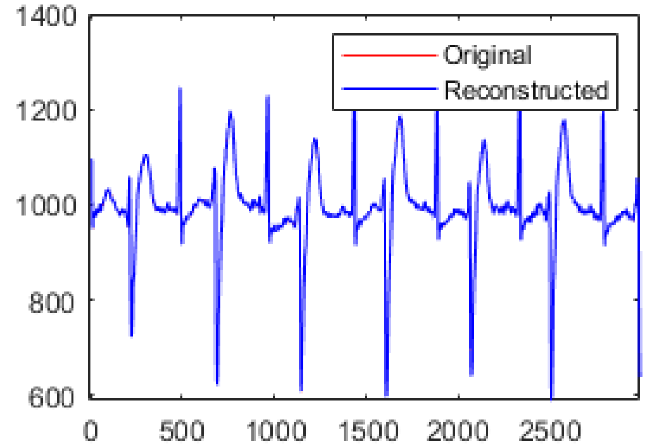
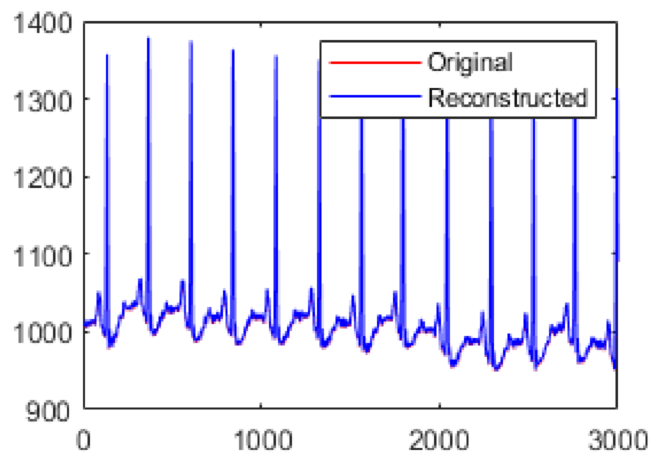
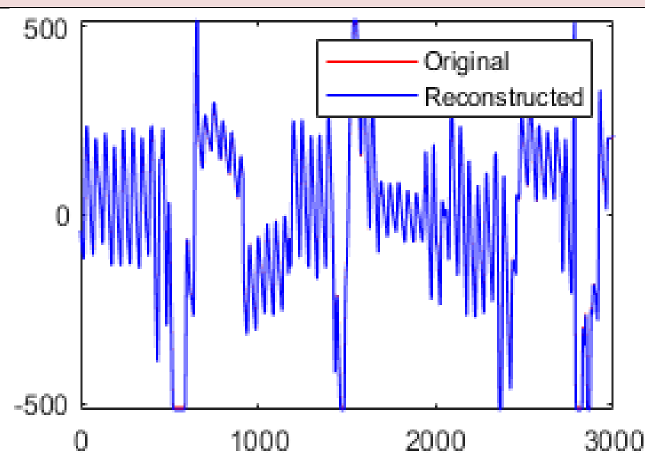
200m	
234m	

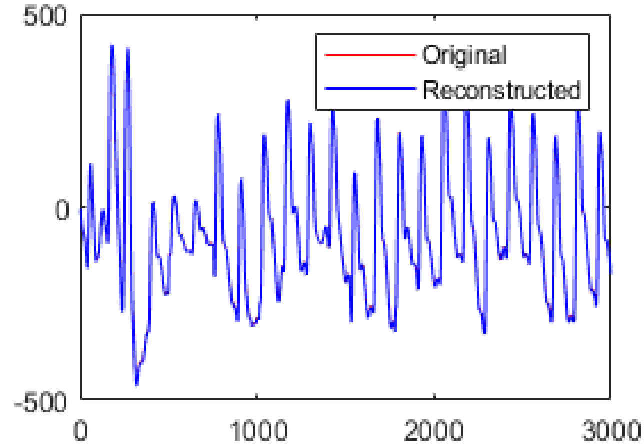
Table 4. Compression Quality assessment for PPG bio-physiological signals

Single Channel PPG	**Bio-signal Reconstruction Quality assessment (SWT with HAAR wavelet and Modified ELM-AE using RBF kernel function)**
3141595m	

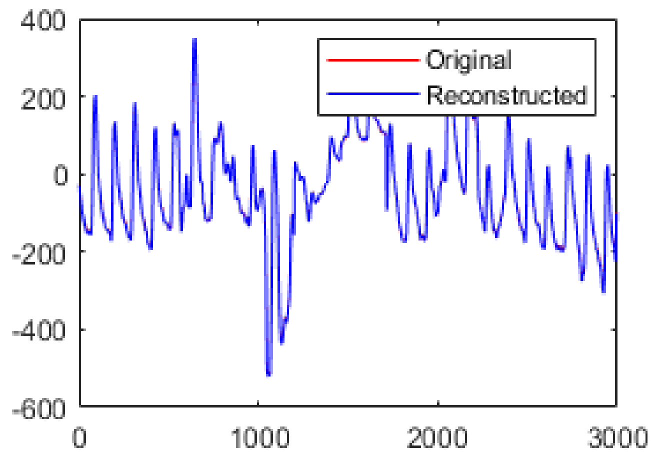
ISSN: 2233-7857 IJFGCN

International Journal of Future Generation Communication and Networking
Vol. 13, No. 3, (2020), pp. 742 – 763

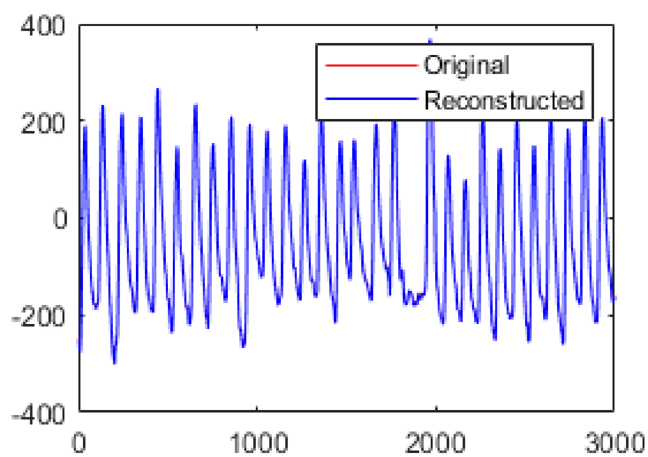
a44071bm



a45503m

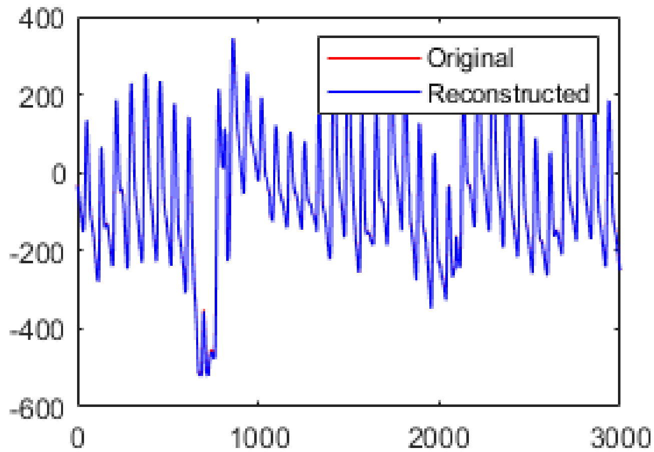


a45543m



ISSN: 2233-7857 IJFGCN

a45557bm



It reveals or infers the robustness of SWT to provide significant bio-signal feature space for further compression. The compression and associated reconstruction performance as discussed above too affirms suitability of SWT. It justifies the affirmative answer for RQ1. In other words SWT can be vital for CS. Though, SWT coefficients provides significant feature space for further compression; however learning over the high dimensional features and identifying optimal sample matrix also called sparse matrix is a challenging task. With this motive, the proposed modified ELM-AE achieved optimal set of matrix as weights at the hidden layer, which enabled higher efficient compression and reconstruction without impacting quality of the bio-signals. Therefore, the research question RQ2 as defined in Section III gets positively satisfied. Noticeably, in this proposed method different thresholding concept was applied which ensured that the R-value of the coefficient having (value) higher than a threshold only would be considered for further computation. It enabled dimensional reduction without influencing the signal quality. On the other hand, our proposed ELM-AE model to applied a thresholding adaptive weight estimation which is directly related to the compression quality or allied sampling matrix. This mechanism accomplished optimal performance towards the targeted CS function. Thus, RQ3 too gets positively justified. Summarily, considering overall proposed model, associated components and contributions made, it can be stated that the strategic implementation of the proposed system can yield optimal CS performance for any type of bio-physiological signal compression and reconstruction without influencing CS quality. It affirms acceptance of the RQ4. The detailed inferences of this research are given in the subsequent section.

6. Conclusion

Considering the significance of low-power, energy and resource efficient bio-physiological parameter's sensing and tele-monitoring systems for wearable body area network or personalized e-Health purposes, this research identified CS as a potential and viable solution. However, observing the fact that the majority of classical CS models hypothesize sparsity as uniform over bio-signals, it contradicts with the real-time scenario where bio-signals such as ECG and PPG might have significant variation or non-linearity in sparse representation. Such non-linearity might greatly affect compression and signal reconstruction error, limiting their respective performance in real-time applications. Moreover, majority of existing approaches are focused either for ECG or MRI signal compression and/or reconstruction, and there exist no significant (CS) solution, which could be applied for major bio-physiological signals, such as ECG, fECG, EEG and PPG. Considering it as motive, this research paper designed a robust Stationary Wavelets and Data-Driven Extreme Learning Machine based

Compressive Sensing System for Bio-Signal Compression and Reconstruction. Noticeably, unlike classical DWT wavelet information this research applied SWT which enabled retaining translation invariant features and allied coefficients to perform learning based signal re-sampling followed by reconstruction. Initially different bio-physiological signals were processed for SWT, which gave rise to the two different features or data, approximated data and detailed (or horizontal) data, where the first was applied as input for machine learning based training. Unlike conventional pattern learning methods, the proposed system applied ELM-AE, which helped retaining the optimal sampling matrix of the approximated data by reducing redundant information and making data more quality-centric. To achieve optimal sample matrix, an adaptive threshold mechanism for $l_2 - \text{norm}$ minimization was applied, which retained optimal sample –sets. This approach strengthened the wavelet information to carry significant information without carrying huge redundant data or imposing computational overheads. Noticeably, the use of ELM-AE over approximated coefficient retained significant information with low-pass filtered low-dimensional traits which carried ahead significant information to make learning. Additionally, learning over the low-pass filtered approximated values, ELM-AE retrieved optimal sampling matrix, which was later used for signal-reconstruction. With the eventual retrieved weight matrix or sparse matrix or sample ISWT performed signal reconstruction. Here, ISWT employed both sparse sample as well as detailed coefficient of the original signal, which enables efficient bio-physiological signal reconstruction. The robustness of the proposed system can be understood by means of its performance in terms of CR and PRD over ECG and PPG signals revealed that the proposed CS model achieves the PRD up to 0.711 for PPG signal and 0.007 for ECG signals. Similarly, simulation over different bio-signals exhibited maximum possible compression ratio of 75.37%, and SNR of 82.17% which reveals its robustness to be used for real-time bio-signal's tele-monitoring, compression and reconstruction purposes. Though, ELM is considered as one of the most advanced machine learning and neural computing model, the recent development recommends deep learning concepts such as sparse-AE to perform sparse data analysis. In future SWT coefficients can be learnt and explored with certain enhanced sparse-AE to achieve more efficient sparse matrix generation for optimal CS over WBAN.

Reference

[1] G. Da Poian, R. Bernardini and R. Rinaldo, "Separation and Analysis of Fetal-ECG Signals From Compressed Sensed Abdominal ECG Recordings," in IEEE Transactions on Biomedical Engineering, vol. 63, no. 6, pp. 1269-1279, June 2016.

[2] P. Patel and P. Mahajani, "Fetal ECG Separation from Abdominal ECG Recordings Using Compressive Sensing Approach," 2018 International Conference on Inventive Research in Computing Applications (ICIRCA), Coimbatore, 2018, pp. 831-834.

[3] L. F. Polanía, R. E. Carrillo, M. Blanco-Velasco and K. E. Barner, "Exploiting Prior Knowledge in Compressed Sensing Wireless ECG Systems," in IEEE Journal of Biomedical and Health Informatics, vol. 19, no. 2, pp. 508-519, March 2015.

[4] S. M. Khorasani, G. A. Hodtani and M. M. Kakhki, "Effects of Pre-Processing on the ECG Signal Sparsity and Compression Quality," 2018 8th International Conference on Computer and Knowledge Engineering (ICCKE), Mashhad, 2018, pp. 268-273.

[5] H. Kuo, Y. Lin and A. Wu, "Compressive sensing based ECG monitoring with effective AF detection," 2017 IEEE International Conf. on Acoustics, Speech and Signal Proc., New Orleans, LA, 2017, pp. 1008-1012.

[6] D. Gurve, J. K. Pant and S. Krishnan, "Real-time fetal ECG extraction from multichannel abdominal ECG using compressive sensing and ICA," 2017 39th Annual International Conference of the IEEE Engineering in Medicine and Biology Society (EMBC), Seogwipo, 2017, pp. 2794-2797.

ISSN: 2233-7857 IJFGCN

[7] F. Pareschi et al., "Energy Analysis of Decoders for Rakeness-Based Compressed Sensing of ECG Signals," in IEEE Transactions on Biomedical Circuits and Systems, vol. 11, no. 6, pp. 1278-1289, Dec. 2017.

[8] A. Marchioni, M. Mangia, F. Pareschi, R. Rovatti and G. Setti, "Disturbance Rejection With Rakeness-based Compressed Sensing: Method and Application to Baseline/Powerline Mitigation in ECGs," 2018 IEEE International Symposium on Circuits and Systems, Florence, 2018, pp. 1-5.

[9] M. Mangia et al., "Application of compressed sensing to ECG signals: Decoder-side benefits of the rakeness approach," 2016 IEEE Biomedical Circuits and Systems Conference (BioCAS), Shanghai, 2016, pp. 352-355.

[10] D. Bortolotti, M. Mangia, A. Bartolini, R. Rovatti, G. Setti and L. Benini, "Energy-Aware Bio-Signal Compressed Sensing Reconstruction on the WBSN-Gateway," in IEEE Transactions on Emerging Topics in Computing, vol. 6, no. 3, pp. 370-381, 1 July-Sept. 2018.

[11] M. Mangia, F. Pareschi, R. Rovatti and G. Setti, "Rakeness and beyond in zero-complexity digital compressed sensing: A down-to-bits case study," 2016 IEEE Biomedical Circuits and Systems Conference (BioCAS), Shanghai, 2016, pp. 356-359.

[12] J. Zhang, Z. Gu, Z. L. Yu and Y. Li, "Energy-Efficient ECG Compression on Wireless Biosensors via Minimal Coherence Sensing and Weightedℓ_1Minimization Reconstruction," in IEEE Journal of Biomedical and Health Informatics, vol. 19, no. 2, pp. 520-528, 2015.

[13] C. Chou, E. Chang, H. Li and A. Wu, "Low-Complexity Privacy-Preserving Compressive Analysis Using Subspace-Based Dictionary for ECG Telemonitoring System," in IEEE Transactions on Biomedical Circuits and Systems, vol. 12, no. 4, pp. 801-811, Aug. 2018.

[14] M. Tsai, C. Chou and A. A. Wu, "Robust compressed analysis using subspace-based dictionary for ECG telemonitoring systems," 2017 IEEE Intl. Workshop on Signal Processing Systems, Lorient, 2017, pp. 1-5.

[15] Z. Zhang et al., "Electrocardiogram Reconstruction Based on Compressed Sensing," in IEEE Access, vol. 7, pp. 37228-37237, 2019.

[16] Y. Wang, X. Li, K. Xu, F. Ren and H. Yu, "Data-Driven Sampling Matrix Boolean Optimization for Energy-Efficient Biomedical Signal Acquisition by Compressive Sensing," in IEEE Transactions on Biomedical Circuits and Systems, vol. 11, no. 2, pp. 255-266, April 2017.

[17] A. S. Lalos et al., "RLNC-Aided Cooperative Compressed Sensing for Energy Efficient Vital Signal Telemonitoring," in IEEE Transactions on Wireless Communications, vol. 14, no. 7, pp. 3685-3699, July 2015.

[18] A. Singh and S. Dandapat, "Block sparsity-based joint compressed sensing recovery of multi-channel ECG signals," in Healthcare Technology Letters, vol. 4, no. 2, pp. 50-56, 4 2017.

[19] J. Zhang, Z. L. Yu, Z. Gu, Y. Li and Z. Lin, "Multichannel Electrocardiogram Reconstruction in Wireless Body Sensor Networks Through Weighted $\ell_{1,2}$ Minimization," in IEEE Trans. on Instrumentation and Measurement, vol. 67, no. 9, pp. 2024-2034. 2018.

[20] W. Yu, C. Chen, T. He, B. Yang and X. Guan, "Adaptive compressive engine for real-time electrocardiogram monitoring under unreliable wireless channels," in IET Communications, vol. 10, no. 6, pp. 607-615, 14 4 2016.

[21] Z. Zhang, S. Wei, D. Wei, L. Li, F. Liu and C. Liu, "Comparison of four recovery algorithms used in compressed sensing for ECG signal processing," 2016 Computing in Cardiology Conference (CinC), Vancouver, BC, 2016, pp. 401-404.

[22] D. A. Akil and R. M. Shubair, "On the efficient application of compressive sensing of physiological signals in medical diagnostics," 2016 5th International Conference on Electronic Devices, Systems and Applications (ICEDSA), Ras Al Khaimah, 2016, pp. 1-4.

[23] R. K. Kanhe and S. T. Hamde, "ECG signal compression using 2-D DWT Hermite coefficients," 2016 International Conference on Signal and Information Processing (IConSIP), Vishnupuri, 2016, pp. 1-6.

[24] D. Craven, B. McGinley, L. Kilmartin, M. Glavin and E. Jones, "Adaptive Dictionary Reconstruction for Compressed Sensing of ECG Signals," in IEEE Journal of Biomedical and Health Informatics, vol. 21, no. 3, pp. 645-654, May 2017.

[25] B. Liu and Z. Zhang, "Quantized Compressive Sensing for Low-Power Data Compression and Wireless Telemonitoring," in IEEE Sensors Journal, vol. 16, no. 23, pp. 8206-8213, Dec.1, 2016.

[26] Y. Yang, X. Qin and B. Wu, "Fast and accurate compressed sensing model in magnetic resonance imaging with median filter and split Bregman method," in IET Image Processing, vol. 13, no. 1, pp. 1-8, 10 1 2019.

[27] S. Datta and B. Deka, "Efficient interpolated compressed sensing reconstruction scheme for 3D MRI," in IET Image Processing, vol. 12, no. 11, pp. 2119-2127, 11 2018.

[28] T. Tashan and M. Al-Azawi, "Multilevel magnetic resonance imaging compression using compressive sensing," in IET Image Processing, vol. 12, no. 12, pp. 2186-2191, 12 2018.

[29] Z. Liu, W. Yu, C. Chen, B. Yang and X. Guan, "Adaptive compression ratio estimation for categorified sparsity in real-time ECG monitoring system," 2016 35th Chinese Control Conference (CCC), Chengdu, 2016, pp. 9439-9444.

[30] A. A. Rahimi, H. Hu, K. Sivakumar and S. Gupta, "Energy-Efficient Serialized Walsh-Hadamard Transform Based Feature-Extraction for Information-Aware Compressive Sensing," 2018 IEEE International Symposium on Circuits and Systems (ISCAS), Florence, 2018, pp. 1-5.

[31] J. K. Pant and S. Krishnan, "Efficient compressive sensing of ECG segments based on machine learning for QRS-based arrhythmia detection," 2016 38th Annual International Conference of the IEEE Engineering in Medicine and Biology Society (EMBC), Orlando, FL, 2016, pp. 4731-4734.

[32] Z. Pei and Y. Wang, "Energy Efficient Compressed Sensing of Bio-Signals with Sparse Binary Matrix," 2017 4th International Conference on Info. Science and Control Engineering, Changsha, 2017, pp. 1492-1496.

[33] A. Marchioni, M. Mangia, F. Pareschi, R. Rovatti and G. Setti, "Sparse sensing matrix based compressed sensing in low-power ECG sensor nodes," 2017 IEEE Biomedical Circuits and Systems Conference, Turin, 2017, pp. 1-4.

[34] K. Xu, Y. Li and F. Ren, "A data-driven compressive sensing framework tailored for energy-efficient wearable sensing," 2017 IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP), New Orleans, LA, 2017, pp. 861-865.

[35] V. Natarajan and A. Vyas, "Power efficient compressive sensing for continuous monitoring of ECG and PPG in a wearable system," 2016 IEEE 3rd World Forum on Internet of Things, Reston, VA, 2016, pp. 336-341.

[36] P. R. Muduli, R. R. Gunukula and A. Mukherjee, "A deep learning approach to fetal-ECG signal reconstruction," 2016 Twenty Second National Conference on Communication (NCC), Guwahati, 2016, pp. 1-6.

[37] G. Yang et al., "DAGAN: Deep De-Aliasing Generative Adversarial Networks for Fast Compressed Sensing MRI Reconstruction," in IEEE Transactions on Medical Imaging, vol. 37, no. 6, pp. 1310-1321, June 2018.

[38] B. Sun and H. Feng, "Efficient Compressed Sensing for Wireless Neural Recording: A Deep Learning Approach," in IEEE Signal Processing Letters, vol. 24, no. 6, pp. 863-867, June 2017.

[39] A. Gogna, A. Majumdar and R. Ward, "Semi-supervised Stacked Label Consistent Autoencoder for Reconstruction and Analysis of Biomedical Signals," in IEEE Transactions on Biomedical Engineering, vol. 64, no. 9, pp. 2196-2205, Sept. 2017.

[40] Simon R Arridge and John C Schotland. Optical tomography: forward and inverse problems. Inverse Problems, 25(12):123010, 2009.

[41] Albert Tarantola and Bernard Valette. Generalized nonlinear inverse problems solved using the least squares criterion. Reviews of Geophysics, 20(2):219–232, 1982.

[42] Ramesh Neelamani. Inverse problems in image processing. PhD thesis, Rice University, 2004.

[43] Animesh Khemka. Inverse problems in image processing. PhD thesis, Purdue University, 2009.

[44] Albert Tarantola. Inverse problem theory and methods for model parameter estimation, volume 89. siam, 2005.

[45] 10. Emmanuel J Candès et al. Compressive sampling. In Proceedings of the international congress of mathematicians, volume 3, pages 1433–1452. Madrid, Spain, 2006.

[46] Emmanuel J Candès and Michael BWakin. An introduction to compressive sampling. IEEE signal processing magazine, 25(2):21–30, 2008.

[47] Kunihiko Taira, Steven L Brunton, Scott Dawson, Clarence W Rowley, Tim Colonius, Beverley J McKeon, Oliver T Schmidt, Stanislav Gordeyev, Vassilios Theofilis, and Lawrence S Ukeiley. Modal analysis of fluid flows: An overview. 55(12):4013–4041, 2017.

ISSN: 2233-7857 IJFGCN

[48] David L Donoho. Compressed sensing. IEEE Transactions on information theory, 52(4):1289–1306, 2006.

[49] Richard G Baraniuk. Compressive sensing [lecture notes]. IEEE signal processing magazine, 24(4):118–121, 2007.

[50] Richard G Baraniuk, Volkan Cevher, Marco F Duarte, and Chinmay Hegde. Model-based compressive sensing. IEEE Transactions on Information Theory, 56(4):1982–2001, 2010.

[51] Scott Shaobing Chen, David L Donoho, and Michael A Saunders. Atomic decomposition by basis pursuit. SIAM review, 43(1):129–159, 2001.

[52] Joel A Tropp and Anna C Gilbert. Signal recovery from random measurements via orthogonal matching pursuit. IEEE Transactions on information theory, 53(12):4655–4666, 2007.

[53] Deanna Needell and Joel A Tropp. Cosamp: Iterative signal recovery from incomplete and inaccurate samples. Applied and Computational Harmonic Analysis, 26(3):301–321, 2009.

[54] Emmanuel J Candes, Michael B Wakin, and Stephen P Boyd. Enhancing sparsity by reweighted S-1 minimization. Journal of Fourier analysis and applications, 14(5-6):877–905, 2008.

[55] Emmanuel J Candès, Justin Romberg, and Terence Tao. Robust uncertainty principles: Exact signal reconstruction from highly incomplete frequency information. IEEE Trans. on information theory, 52(2):489–509, 2006.

[56] Balaji Jayaraman, Chen Lu, Joshua Whitman, and Girish Chowdhary. Sparse convolution-based markov models for nonlinear fluid flows. arXiv preprint arXiv:1803.08222, 2018.

[57] Guang-Bin Huang, Qin-Yu Zhu, and Chee-Kheong Siew. Extreme learning machine: theory and applications. Neurocomputing, 70(1-3):489–501, 2006.

[58] Guang-Bin Huang, Dian Hui Wang, and Yuan Lan. Extreme learning machines: a survey. International journal of machine learning and cybernetics, 2(2):107–122, 2011.

[59] Z. Zhang et al, TROIKA: A general framework for heart rate monitoring using wrist-type photoplethysmographic signals during intensive physical exercise, IEEE Trans. Biomed. Eng., IEEE Trans. Biomed. Eng, 522-531, Feb 2015.

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ISSN: 2233-7857 IJFGCN

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