Compressed Sensing Approach for Physiological Signals: A Review

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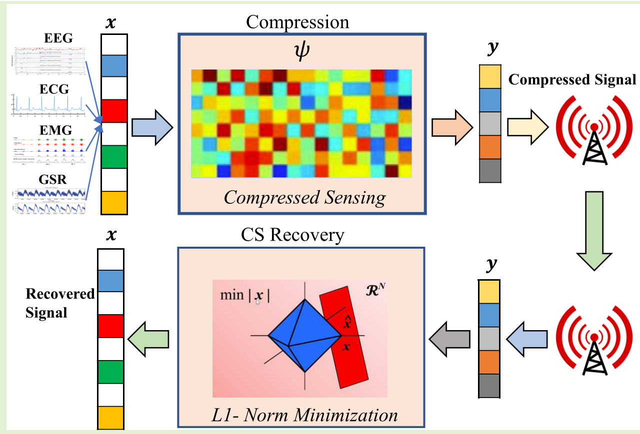
***Abstract*—The immense progress in physiological signal acquisition and processing in health monitoring allowed a better understanding of patient disease detection and diagnosis. With the increase in data volume and power consumption, effective data compression, signal acquisition, transmission, and processing techniques are essential, especially in telemonitoring healthcare applications. An emerging research area focuses on integrating compressed sensing (CS) with physiological signals to deal with a massive amount of physiological data, transmission bandwidth, and power-saving purposes. A review of CS for physiological signals is presented in this article, including electroencephalography (EEG), electrocardiography (ECG), electromyography (EMG), and electrodermal activity (EDA), focusing on the pros and cons of CS in treating such signals and the suitability of CS for hardware implementation. Furthermore, we emphasize performance matrices, such as compression ratio (CR), signal-to-noise ratio (SNR), Percentage Root-mean-square Difference (PRD), and processing time to evaluate the performance of CS. We also investigate the current practices, challenges, and opportunities of using CS in healthcare applications.**



***Index Terms*—Compressed measurements, compressed sensing (CS), electrocardiography (ECG), electrodermal activity (EDA), electroencephalography (EEG), electromyography (EMG), galvanic skin response (GSR), physiological signals.**

I. Introduction

RECENT advances in wireless and sensor technologies enabling the Internet of Things (IoT) and big-data-based services have put new and more stringent requirements on the way signals are acquired and processed. To preserve information, the conventional approach based on Nyquist's theorem requires a sampling frequency of at least twice the bandwidth of the original signal. However, with the ever-growing number of sensing devices involved in modern IoT networks, this paradigm must face two main challenges related to a large amount of data and the high transmission rate, which could come into conflict with the characteristics of current embedded processing platforms in terms of speed performance, on-chip storage capacity, and power budget. To mitigate the effects of the problematics, data reduction techniques at the sensor node can represent an effective solution as long as the time/energy/area overhead due to the additional compression step is lower than the one saved by reducing the transmitted samples. In addition, it must be noted that such a paradigm involves three consecutive stages (i.e., sampling at Nyquist's frequency, compressing to reduce the amount of information to be transmitted, and, eventually, decompressing at the receiving node), which significantly slower the acquisition process.

The compressed sensing (CS), also called compressive sensing theory, proposed by Taghouti [1] and Candès and Tao [2] has emerged as an efficient approach to acquiring and reconstructing signals. It exploits the property that all the physical signals are either sparse in the original or on some well-chosen basis (e.g., Fourier or wavelet transform) to acquire a compressed form of the signal directly, thus performing within a single stage. To this aim, it uses mathematical

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tools, such as the L1 norm at the receiving node to represent or reconstruct the original sparse signal from only a few samples. In recent years, it has gained the attention of researchers for its applicability in several fields, such as compressive imaging [3], [4], [5], [6], biomedical applications [7], [8], [9], communication systems [10], pattern recognition [10], and speech processing [11]. This indicates that a small number of linear projections can better reconstruct the original signal than a large number of linear projections.

There has been increased interest in monitoring and extracting physiological signals over the past few years, i.e., electroencephalography (EEG), electrocardiography (ECG), electromyography (EMG), and galvanic skin response (GSR) in telemonitoring health care applications. Monitoring such signals offers excellent benefits, such as constant patient observation, reducing health care risk, increasing patient mobility, and reducing healthcare costs. At the same time, many challenges arise, including wearable device cost, power consumption (PC), and data transmission bandwidth. In the wireless health monitoring device, physiological signals generate a large amount of data, which must be handled efficiently to deal with the low power and data transmission requirements. Many lossy compression techniques are efficiently used to reduce PC and bandwidth, while some quality of signals is degraded at the receiving end. From such a perspective, CS is an attractive technique widely used in wireless healthcare applications to compress the data at the acquisition time. By using CS, it is possible to reduce the PC from the transmission side, as well as the amount of data stored and the resources required for analog to digital converters, which is the main objective of data compression. Concerning the receiver side, because the computational cost for quality signal reconstruction is relatively large compared to other compression strategies, this step can be executed offline where time and power constraints do not represent a big concern. Moreover, recent studies suggested that signal features can be extracted directly from compressed measurements, thus enabling the so-called reconstruction-free CS. Researchers have investigated various reconstruction-free CS applications, such as compressive cameras [12] and text data classification [13]. Furthermore, Lohit et al. [14], [15] and Braun et al. [16] prove that the reconstruction step in CS can be ignored, and machine learning can be used to extract features directly from compressed measurements.

A. Objective of This Review Work

The CS framework has been broadly used for physiological signal acquisitions, reconstruction, feature extractions, and classifications to deal with many challenges, specifically faster signal acquisition, quality reconstruction, and energy efficiency. This review article aims to identify the CS techniques for ECG, EEG, EMG, and GSR signals' studies by reviewing published articles in the past 12 years from January 2010 to October 2022. The review has been conducted based on CS techniques for physiological signals and their applications, covering different aspects, such as acquisition strategies, reconstruction algorithms, measurement matrix, sparse bases, and evaluation matrices, with a particular focus on reconstruction-free CS techniques and possible hardware implementations. It also discusses the challenges in current state-of-the-art CS techniques that lead to developing an effective system and answers the following research questions.

RQ1: What kind of sensing matrix/strategies are being used to acquire physiological signals for low PC in wireless devices, and how efficient are they in terms of restricted isometry property (RIP)?

RQ2: What types of reconstruction algorithms are used to reconstruct the original signals from compressed measurements, and how efficient are they in terms of complexity?

RQ3: What are the performance evaluation parameters for CS acquisition and reconstruction strategies?

RQ4: How to deal with the sparsity constraint of physiological signals?

RQ5: Which features can be extracted from physiological signals using CS?

RQ6: Which physiological signal best suits the CS technique?

Indeed, there are good, related review papers available, as shown in Table I. Most reviews highlight acquisition and reconstruction strategies along with sparse bases but miss the challenges and performance evaluation matrices, and few articles evaluate parameters for only single applications. Since the CS systematic review for physiological signals is missing in the literature, this review will be helpful for scholars in the mobile-health and wearable computing fields in terms of CS acquisition and reconstruction strategies, sparse bases, evaluation parameters, feature extraction from physiological signals, and hardware approach.

B. Search Strategy

The articles were searched from the following digital libraries: ScienceDirect, IEEE Xplore, Scopus, and Web of Science. The search focused on CS strategies, sparse bases, reconstruction algorithms, hardware approach, and feature extraction from CS for physiological signals. Considering the search strategy, the following keywords were identified: (*"Compressed Sensing" OR "Compressive Sensing" OR "Reconstruction free compressed sensing "AND "EEG" OR "ECG" OR "EMG" OR "GSR" OR "EDA" OR "Sensing matrix" OR "Sparse Base" OR "Reconstruction" OR "Features extraction" OR "Compressed Sensing Processing"*).

C. Eligibility Criteria

The selection criteria applied to the articles found in the search strategy are given as follows.

1) Research work uses CS as the primary solution for signal compression.
2) The work uses at least one physiological signal, i.e., EEG, ECG, EMG, GSR, electrodermal activity (EDA), and so on.
3) One or more CS-based signal acquisitions and reconstruction strategies have been used.
4) CS is used to deal with data storage and PC constraint.
5) A specific hardware approach is used for circuit realizations.
6) At least one parameter (evaluation parameter section) has been evaluated.

TABLE I
SUMMARY OF PREVIOUS RELATED SURVEYS

Ref.	Sensing Strategy	Sparse Base	Reconstruction Algorithms	Hardware Approach	EEG	ECG	EMG	GSR	Performance Evaluation	Challenges
[113] 2015	•	•	•	•	•	•			•	
[125] 2021	•	•	•	•						
[126] 2013	•	•	•							
[17] 2018	•	•	•	•					•	•
[18] 2019	•	•	•			•				
[127] 2019			•	•						•
[128] 2020	•		•	•						•
[75] 2017	•		•			•				
[129] 2020	•	•	•							
[130] 2016	•	•	•						•	
[131] 2011	•	•	•			•			•	
[24] 2020	•	•	•						•	
[132] 2020	•	•	•	•	•				•	•
[133] 2022	•	•	•	•		•			•	
[134] 2020	•	•	•	•	•				•	•
[84] 2020	•	•	•	•		•			•	
[30] 2020	•		•						•	
[135] 2018	•	•	•	•	•	•			•	•

7) The work highlights the limitation, challenges, and future scope of the proposed method.

As per identified keywords, there were about 2000 articles found in the above libraries; after setting the eligibility criteria, we found 105 valuable articles for this review paper, and all of them are included.

The remainder of this review article is organized as follows. Section II provides theoretical concepts of CS, the mathematical model, the acquisition and reconstruction model, CS conditions, and performance evaluation matrices. Section III provides a detailed review of previous work on CS framework for physiological signals (EEG, ECG, EMG, and GSR) in terms of measurements matrices, sparse basis, reconstruction algorithms, reconstruction-free CS, state-of-the-art hardware implementation, and performance evaluation matrices along with its merits, demerits, and applications. Section III focuses on the possible challenges, limitations, and future recommendations. Finally, Section IV outlines the conclusion remarks.

II. CS Framework for Physiological Signals

In CS, the measurements are compressed directly from the signal of interest instead of: 1) sampling the signal at the Nyquist rate; 2) then compressing it by computing the transform coefficients to retrain the larger coefficients; and 3) discarding the smaller ones for transmission or storage. With growing progress in electronics for healthcare, physiological signals are the most promising approach for advanced diagnosis of many diseases and treatment accordingly. For ambulatory health monitoring of the patient, wireless devices are used, in which batteries are the primary energy source for devices; practically, acquiring, processing, and transmitting significant data for a long time consume a substantial amount of power and storage space. CS techniques for physiological signals sensing and compression can save battery consumption

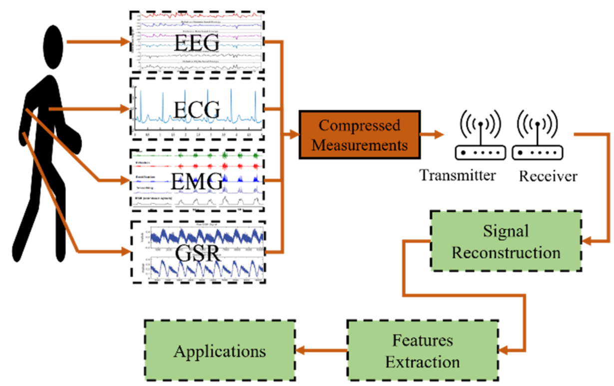

Fig. 1. Block diagram of CS approaches for physiological signals.

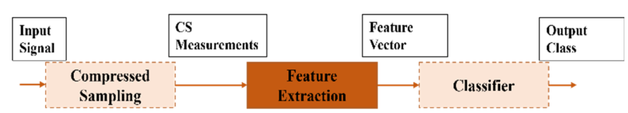

Fig. 2. Reconstruction-free CS.

and less storage space, as well as the transmission of data. Generally, the CS approach applied to physiological signals is divided into four steps: signal acquisition, signal transmission and reception, signal reconstructions, and feature extractions, as shown in Fig. 1. Many research works have been proposed to improve these steps that we discussed applicationwise.

A. CS Acquisition Model

Let x be the signal of concern (physiological signal) and K be sparse in domain ψ. It is possible to gather only small random measurements or compress measurements instead of directly measuring x (n measurements) and compressing them.

Mathematically, CS measurements y are given by the following equation:

$$y = Cx \tag{1}$$

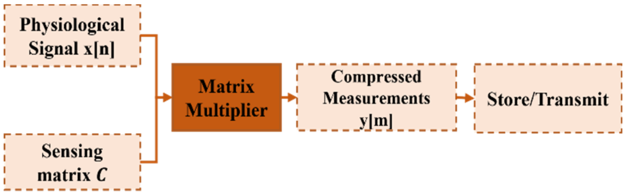

Fig. 3. CS acquisition model.

where $x \in \mathbb{R}^n$ is the signal of interest (input signal), $y \in \mathbb{R}^p$ are the compressed measurements, including $K < p \ll n$, and $C \in \mathbb{R}^{p\times n}$ is the measurement matrix that shows p linear measurement on the signal x; choosing the measurement matrix is critically essential, further discussed in measurement matrix sections for each physiological signal. A random projection is made from the original signal of interest, and its entries may be Gaussian or Bernoulli-distributed random variables. A further signal acquisition model is shown in Fig. 3.

There is a great degree of sparsity and high compressibility in several physiological signals, such as EEG, ECG, and EMG. By compressing the signal, only a few modes are active when written on an appropriate basis, thus reducing the number of values needed for precise representation. Alternatively, a compressible signal $x \in \mathbb{R}^n$ can be written as a sparse matrix $s \in \mathbb{R}^n$ (mainly composed of zeros) in some transform basis, such as Fourier or wavelet basis $\psi \in \mathbb{R}^{nxn}$, if K nonzero elements are present in the vector s; then, it is called K-Sparse in ψ

$$x = \psi s = \sum_{i=1}^{N} \psi_i s_i. \tag{2}$$

Equation (1) can be written as

$$y = C\psi s. \tag{3}$$

However,

$$\theta = C\psi \tag{4}$$

where θ is the $m \times n$ reconstruction matrix, compresses, and transforms the signal x into the $m \times 1$ measurement y, and it depends on the input signals' sparsity, how large the measurement matrix will be, or how many measurements will be taken. Ideally, acquiring fewer measurements and measurement matrices should be incoherent with the basis to reconstruct the signal.

Therefore, (1) can be written as

$$y = \theta s. \tag{5}$$

B. CS Reconstruction Model

The reconstruction matrix θ and the compressive measurement vector y are the input to the reconstruction algorithm, as shown in Fig. 4. The original signal can be retrieved from compressive measurements by solving (1), an underdetermined linear equation system.

The sparse vector s is consistent with the measurement vector y. Thus, CS has the primary objective of finding the sparsest vector $\hat{s}$ that satisfies the following conditions:

$$\hat{s} = \min \|s\|_0 \quad \text{subject to } y = C\psi s \tag{6}$$

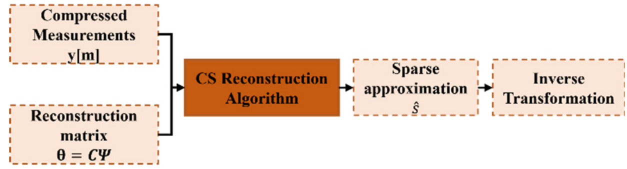

Fig. 4. CS reconstruction model.

where $\|\cdot\|_0$ is the l_0-pseudonorm that gives the number of entries that are not zero [17] and $\hat{s}$ is the estimate of s. Searching for the solution or optimization in (6) is the nonconvex and trying for all possible solutions, which is computationally cost even for the standard sized problem; hence, it is declared as an NP-hard problem. However, other approaches have been suggested in the literature, under some conditions on C measurement matrix, relaxing the optimization in (6) to the convex l_1-minimization approach, as shown in (7). Solving l_1-minimization problems in near polynomial time can be achieved using linear programming solvers, and the l_1-norm approach is sparse, while the l_2-norm minimum approach is not [18]

$$\hat{s} = \min ||s||_1 \quad \text{subject to } y = C\psi s \tag{7}$$

where $\|\cdot\|_1$ is the l_1-norm, and the generalized norm expression is given as follows:

$$l_P = ||x||_P = \sqrt[p]{\sum_i |x_i|^P}. \tag{8}$$

The CS reconstruction algorithm returns the sparse representation of the signal of interest x, such as $\hat{s}$, and the restored signal $\hat{x}$ can be achieved from $\hat{s}$ by getting its inverse transform.

In some well-known basis or dictionaries, the CS reconstruction algorithm is used to determine the sparse estimation of the original input signal from the compressed measurements. Researchers have been studying this aspect of CS to develop a better algorithm to achieve a sparse solution. Several state-of-the-art CS algorithms are presented, such as OMP [19], IHT [20], GP [21], and BCS [22]. There are several factors driving research in this area. These include the ability to reconstruct from a minimal number of measurements and the robustness of the system against noise, speed, complexity, and performance requirements [23], [24], [25]. The reconstruction algorithms can be categorized into six types, as shown in Fig. 5. A significant aspect of the CS framework is effectively recovering the original signal from compressed measurements. Convex class algorithms solve convex optimization problems through linear programming. Exact reconstruction requires a small number of measurements, but the methods are computationally complex. Nonconvex problems are commonly encountered in practical situations, and most nonconvex problems are difficult to solve within a reasonable time. In recent years, iterative greedy algorithms have been widely used in compression sensing because of their fast reconstruction and low complexity. A combinatorial or sublinear algorithm recovers sparse signals by group testing. Compared to convex relaxation and greedy algorithms, these algorithms are extremely fast and efficient, but they require a specific pattern in the measurements, which should be sparse.

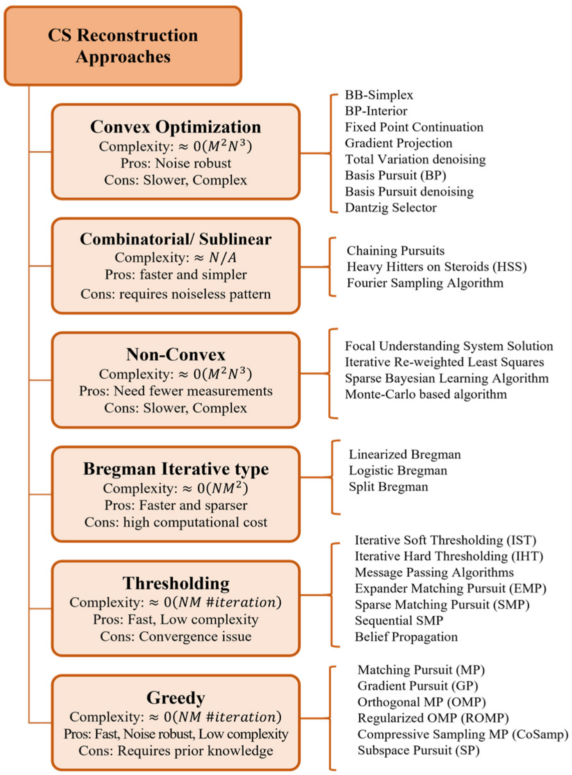

Fig. 5. Reconstruction algorithms.

CS recovery problems can be solved more rapidly by iterative approaches than convex optimization techniques. Soft or hard thresholding is used to recover correct measurements from noisy ones if the signal is sparse. Thresholding depends on the number of iterations and the nature of the problem. For instance, Bregman's method is an effective iterative algorithm for solving convex optimization problems. Using these algorithms, the problem of l_1 minimization can be solved efficiently and straightforwardly.

C. Sufficient Conditions for Perfect Recovery

CS parameters, such as sensing matrix and sparse bases, must satisfy the following conditions to ensure the robustness and accuracy of recovered signals from compressed measurements.

1) Restricted Isometry Property: Let vector s be the k sparse in the transform domain; then, to recover s from compressed measurement y, it is necessary that matrix θ should obey the RIP with order k as follows:

$$1-\delta \leq \frac{\|\theta u\|_2}{\|u\|_2} \leq 1+\delta \tag{9}$$

where vector u has the same entries in s with k-nonzero and $\delta > 0$ remains an RIP constant [26]. As a result of this inequality, matrix θ must keep the distance between two k-sparse vectors. Nevertheless, matrix θ must satisfy the relation given by (9) to yield a robust solution. According to [17], calculating δ is itself challenging. Coherence is another condition that guarantees a stable solution.

2) Incoherence: According to this condition, to make a faithful reconstruction, C measurement matrix and ψ sparse basis should be incoherent with each other. The relationship between the two matrices and coherence can be found in (10). In this case, the largest correlation among any two elements of a selected pair of matrices is taken into consideration, and the range is $\mu(C, \psi) \in [1, \sqrt{n}]$. According to this property, different sensing matrices require different numbers of measurements [17], as shown in Table II, where c represents the positive constant [27]. CS reconstruction requires fewer measurements when the coherence value is lower, which, in turn, requires fewer measurements

$$\mu(c, \Psi) = \sqrt{n} \max_{1 \leq ij \leq n} |\langle c_i, \psi_j \rangle|. \tag{10}$$

TABLE II
NUMBER OF MEASUREMENTS REQUIRED FOR DIFFERENT SENSING MATRICES

Sensing Matrix	Number of measurements
Bernoulli and Gaussian	$m \geq ck \log n \,/\, k$
Random	$m = O(k \log n)$
Partial Fourier	$m \geq c\mu k (\log n)^4$
Deterministic	$m = 0(k^2 \log n)$

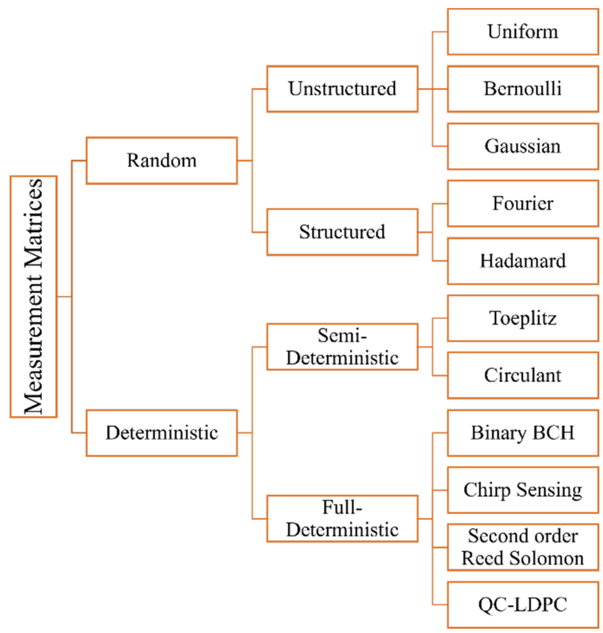

Fig. 6. Measurement matrices.

3) Measurement Matrix and Number of Measurements: The measurement process involves sampling just the elements of the signal, which are most representative of the signal using a measurement matrix. In sparse recovery, the selection of measurement matrix plays an essential role in determining accuracy and processing time because every measurement matrix has a different number of measurements although accuracy and processing time highly depend upon the number of measurements. Therefore, it is of utmost importance to design accurate measurement matrices. There have been numerous measurement matrices proposed in the literature over the past decade [28], as demonstrated in Fig. 6. Measurement matrices in CS are derived from random distributions, such as unstructured (Bernoulli, Gaussian, and uniform) and structured

Fourier and Hadamard matrices. An unstructured random matrix is orthogonal and incoherent to the basis, along with obeying RIP, which guarantees the ideal recovery of original signals in a high probability. The main difficulty through random matrices is that they cannot be stored and regenerated at the receiving end, and they need to be transmitted with signal-compressed measurements, which is impossible for practical application. A structured random matrix is faster to acquire, requires less storage space, is reproducible, and reduces transmission overheads. In addition, random matrices have the disadvantage of requiring more measurements. Thus, the research focused on deterministic and structured matrices. The advantage of a structured sensing matrix is accelerating the recovery procedure, although at the expense of dropping the universality. The deterministic matrices meet the RIP, have little mutual coherence, and are further categorized into semideterministic and full-deterministic matrices. The semideterministic has an advantage like quick decoding and can be applied to several applications; however, another category of the deterministic has the pure deterministic construction based on mutual coherence and RIP. Several articles [29], [30], [31], [32] have been published on the performance analysis of measurement matrices and suggested that deterministic matrices are an excellent option for selection in practical applications, such as physiological signal acquisitions.

Nevertheless, deterministic matrices require a more significant number of measurements to reduce the reconstruction error. As a result, the researcher faces a challenge in designing a specific structure to reduce the sampling rate, recovery error, processing time, and flexibility in matrix size when some preliminary information on the location of nonzero elements of the sparse signal is available. Constructing explicit measurement matrices is still an open challenge for researchers.

4) Sparse Base/Dictionary Matrix: Through CS, it is crucial to choose a dictionary to be used for signal reconstruction to achieve successful signal compression. In wavelet dictionaries, physiological signals, EEG, ECG, and EMG do not have high sparsity. In most cases, authors propose dictionaries specific to a particular signal. According to Maiorescu et al. [33], temporal EEG signal- and channel-specific dictionaries offer significantly better results than standard wavelet dictionaries. The sparsity of physiological signals is often too low to fit into standard dictionaries, such as wavelet, DCT, and DFT [34]. As a result, it is recommended to develop a signal-specific basis or dictionary, which takes into account the analytical characteristics of the signal or the repeated elements of the signal.

5) Performance Evaluation Matrices: Evaluation metrics are used to investigate the efficiency of each process of CS, such as measurement matrices and recovery algorithms. Many evaluation matrices are proposed in the literature [35], which helps to evaluate CS's performance in physiological signals, such as sparsity, recovery error, coherence, correlation, processing time, recovery time, phase transition diagram, and compression ratio (CR).

a) Coherence: It measures the quality of the measurement matrix and ensures that the recovery process is successful by assessing the coherence parameter. As described in Section II-C.2, low coherence is required, which ensures that fewer samples are required for reconstructing the original signal.

b) NSP and RIP: Matrix null space A can be denoted by

$$\aleph(n) = \{x : Ax = 0\}. \tag{11}$$

For the compressed measurements y, it is necessary to ensure that the original sparse signal is recovered; every set of different vectors $x, x' \in \Sigma_{2k}$ is necessary to fulfill the blow condition $Ax = Ax'$ known as null space property (NSP). This method provides an accurate evaluation of the sampling matrix; however, it is costly and impractical [35]. Therefore, RIP is another way to evaluate the performance of the sampling matrix; when it satisfies the RIP, it is considered that it also satisfies NSP [36].

c) Sparsity level: When physiological signals are projected onto a well-chosen basis, the signal's sparsity indicates that most values are zero or close to zero. The basis (also called the domain) should be carefully selected so that physiological signals are sparse [37]. If the signal x of N samples is the order of k sparse when transformed into a sparse base, then k is the number of nonzero coefficients, and it is much smaller than N; as a consequence, $N - k$ signal coefficients can be removed without affecting the important information within the signal

$$\%\text{Sparsity} = \frac{N-k}{N} \times 100. \tag{12}$$

d) Reconstruction error and mean square error: Reconstruction error is also known as recovery error, as shown in (13). In simple terms, it is the norm of the difference between the original signal of interest and the reconstructed signal divided by the norm of the original signal of interest

$$\text{RE} = \frac{\|x - \hat{x}\|}{\|x\|}. \tag{13}$$

Mean square error (mse) is another way to calculate the change in recovery error over time of algorithms. In this case, the difference between the original x and reconstructed $\hat{x}$ signals is measured by averaging the squared difference between the two signals, wherever N indicates the total measurements. Generally, it refers to how much the retrieved signal differs after the initial signal

$$m_{\text{sE}} = \frac{\Sigma_n \left[x(N) - \hat{x}(N)\right]^2}{N}. \tag{14}$$

e) Sampling time: During sampling time, the sampling matrix acquires and compresses the input signal in a given amount of time. Usually, less sampling time is required for physiological signals acquisition and compression.

f) Compression ratio: CR is determined by dividing the number of measurements M by the number of samples in the original input signals N. CR is calculated as follows:

$$\text{CR} = \frac{M}{N}. \tag{15}$$

g) Recovery time: A sparse recovery algorithm is measured by the time it takes to solve the problem. Usually, this metric measures how fast the recovery algorithm is [35]. In addition, when evaluating the execution time of a compressive sensing technique, we consider all the processes involved in compressive sensing. In other words, recovery time involves the total time required for the reconstruction algorithm to recover the signal back. Eventually, it depends on the complexity level of the reconstruction algorithms.

h) Signal-to-error ratio: Also known as the signal-to-noise ratio (SNR), this metric analyzes a signal's strength over a noise. In terms of CS, it represents the original input signal strength over the reconstructed signal, or it is the ratio of the original input signal over the reconstructed signal. The following mathematical expression can be used to calculate it:

$$\mathrm{SNR} = 10\log_{10}\frac{\Sigma_N\left[x\left(N\right)\right]^2}{\Sigma_N\left[x\left(N\right)-\hat{x}\left(N\right)\right]^2}. \tag{16}$$

i) Recovery success and failure rate: The success rate of recovery indicates how successful an algorithm is at recovering data. It refers to how many original and recovered signals are almost identical (at least 90%) for different values of sparsity level, sample numbers, and measurement numbers [10], [35]. The failure rate is calculated as the reciprocal of the success rate. Over many experiments, the algorithm calculates how often the recovery algorithm does not recover the original signal.

j) Phase transition diagram: Phase transition represents the probability of success recovery against the probability of failure recovery to determine the success of a recovery algorithm [38]. Measuring matrix and recovery processes are evaluated using this metric. A phase space (ρ, δ) can be used to represent the success area and failure area. The CR is denoted by $\delta = {}^{M}/_{N}$, and the number of measurements is expressed by $\rho = {}^{K}/_{M}$. Compressive sensing theory can be understood by analyzing the phase transition diagram; it can clearly represent these conditions based on the signal sparsity level, the signal size, and the number of measurements used in the analysis. The plot can differentiate the success of signal recovery from its failure.

k) Hamming distance: Based on the Hamming distance, it is determined how often the original noisy measurements y and noisy recovered signals $\hat{y}$ differ from each other. It shows how many coefficients of H are nonzero, where $H = y - \hat{y}$.

l) Complexity: Complexity reflects how efficiently an algorithm performs with a large amount of data, and complexity can be measured in computational time or hardware resources. It is important to note that, in CS, the degree of complexity depends upon the sparsity, the number of samples, and the number of measurements.

III. CS FOR PHYSIOLOGICAL SIGNALS

Measurement and analysis of physiological signals are essential for medical monitoring. Wireless sensors help us to monitor the patient remotely, but the low energy consumption is crucial to enable continuous patient monitoring in mobility effectively. CS is a promising framework for addressing this issue due to its energy-efficient data compression method. Recently, ambulatory monitoring of physiological signals has gained popularity. Increasing patient mobility, observing patients constantly, and reducing healthcare costs are all advantages of such monitoring. Ambulatory monitoring of physiological signals is also challenging due to the size of wearable devices, the consumption of power, and the cost of such devices. The biggest challenge is reducing PC. As physiological data are generated in real time in an ambulatory environment, managing the large amounts of data generated effectively is essential. There is an increasing use of lossy compression techniques to manage these data. Using such methods, a greater rate of compression can be achieved that minimizes the consumption of power, although at the cost of slightly degrading the reconstructed signal. Compression aims to minimize data while simultaneously keeping the signal quality. Besides compressing data for mobile devices, wearables, and low-power systems, CS reduces data storage requirements, analog-to-digital conversion (ADC), and microcontroller resources. There are three primary power consumers in a system that uses compression: 1) acquisition of signals; 2) wireless communication; and 3) digital signal processing. In all three components, the use of CS results in a reduction in PC.

CS emerges as a promising technique for low-cost signal acquisition and compression, and reduces the computational complexity of the encoder with a decrease in sampling frequency. Consequently, the computational burden is shifted to the receiver, which is required to use an optimization method to reconstruct the signal. Researchers have employed a variety of CS acquisition methods in order to reduce PC in wireless healthcare applications. In this regard, Mamaghanian et al. [39] presented the CS-based sampling node for ECG signals and extended the battery life by 37.1% compared to its Nyquist counterpart. Similarly, CS has been successfully used for acquiring physiological signals, such as EEG [40], [41], ECG [42], [43], and EMG [44]. Many CS acquisition techniques have already been implemented on hardware [45], [46].

Transmission efficiency and network security are the big challenges in WBSNs. However, CS also satisfies the need for network efficiency and security simultaneously.

Generally, physiological singles are not sparse in the original domain, significantly when they are contaminated by noise; the nonsparsity characteristic of such signals makes most CS algorithms incapable of recovering data. There are two popular ways to reconstruct these nonsparse signals: thresholding [38] and reconstructing signals in the transformed domain [17]. In the thresholding approach, the small-scale magnitude is set to zero and cannot be used for physiological signals because the magnitude is minimal and invisible, and almost impossible to choose a threshold value. Moreover, thresholding can destroy the interdependencies between multichannel recordings, such as independent component analysis (ICA) combining structures. Second, the success of this strategy depends heavily on the sparsity level of the coefficients of representation θ. Unluckily, for most raw biosignals, there are still too many coefficients of small amplitudes concerning the number of coefficients of larger amplitudes [47]. The reconstruction of small amplitude coefficients is essential when signal reconstruction is designed to be mixed with more signal processing/machine learning techniques. Instead of resorting to the above two strategies, the BSBL-BO algorithm reconstructs nonsparse signals directly [48]. The high quality of the reconstruction permits additional signal processing or pattern recognition to be performed for medical diagnosis. The use of block structure and interlock correlation is vital to reconstructing signals.

The purpose of this section is to review the current literature regarding the application of CS to physiological signals. EEG, ECG, EMG, and GSR signals are discussed although other physiological signals are also briefly discussed.

A. Compressed Sensing for EEG Signals

Electrical activity in the brain is recorded by EEG. In clinical practice, it is used to diagnose neurological diseases and disorders, such as sleep disorders, comas, and epilepsy. Research and commercial interests have recently focused on developing mobile EEG technology that can capture events in ambulatory environments, such as seizures. In addition to recording signals on multiple channels, EEG signals may be recorded during multiple sessions, which requires a large amount of storage. With the growing progress in neural engineering, researchers have gained a comprehensive understanding of patients' brain disorders and their neurological rehabilitation, restoration of motor function, detection, and diagnosis in recent years, due to the incredible advancement in the acquisition and processing of big data in neural engineering. A new area of research involving CS and neural engineering has emerged to deal with many challenges and efficiently manage substantial volumes of neurological data in an efficient, long-term, and energy-efficient approach.

Moreover, EEG signals have shown significant promise for brain–computer interfaces (BCIs), which have a broad range of applications, including neuroscience. Batteries are the primary energy source in wireless EEG devices and practical applications; they consume more power to acquire, process, and transmit signals for a long time. In addition, multichannel neural recording implants generate many data. Applying CS techniques to EEG signals can save battery life and less space storage. Generally, CS can apply to EEG signals to detect the diseases such as seizure detection [49], [50], Alzheimer's disease (AD), healthy controls (HCs), mild cognitive impaired (MCI) [51], P300 detection [33], [52], sleep stage classification [53], and motor imagery [54]. Addressing RQ1 and RQ5, this section discussed the state-of-the-art CS for EEG studies and possible challenges in sensing matrix, sparse basis or dictionary matrix, and reconstruction algorithms. A further summary of EEG studies is shown in Table III.

1) Sensing Matrices: Designing a sensing matrix is the most significant part of the CS structure since it is essential in signal acquisition at the sensor side and reconstruction at the receiving side. It is also essential for the sensing matrix to follow the RIP and should be incoherent with a fixed basis or dictionary matrix; in this regard, random sensing matrices are perfect choices, but they generate many samples. There has been a variety of sensing matrices proposed in the literature for EEG signal samplings, such as random matrices [33], [50], [52], [55], structural matrices, and deterministic matrices [56], [57]. Several random matrices have been proposed in the literature for sampling EEG signals, such as random Gaussian matrices (RGMs) with entries representing absolute values, Bernoulli matrices with entries representing 1's, and random binary matrices (RBMs) containing 0's and 1's. The RGM is commonly used [51], [58], [59] since it meets the RIP and incoherence criteria with high probability. Due to the large amount of on-chip memory used to store random floating-point matrix elements, there are several limitations related to its implementation in hardware. A further disadvantage is the high cost of on-chip matrix-vector multiplication. Because of their binary representation, the binary matrix (BM) and RBM used by [54] are preferred over RGM because the random entries are easier to generate with fewer multiplications operations but are still expensive for hardware implementation.

Studies showed that regarding the sparse BM (SBM), CS is more energy-efficient than conventional data compression [60], [61]. However, the advantage disappears with random Gaussian and other kinds of matrices because a random matrix involves many multiplication operations. According to Zhang et al. [62], the SBM is the better option for employing CS for wireless body sensor networks (WBSNs). Compared to full random matrices, SBM reconstruction performance is not as good [63]. Mangia et al. [64] and Bertoni et al. [65] introduce rakeness-based CS. This method aims to maximize the projection's ability to collect the signal energy while maintaining randomly sufficient paths to limit the signal space. In this approach, specific statistical properties of the CS sampling functions are matched with statistical properties of the input signal to significantly improve system performance by reducing the number of resources (hardware, energy, and so on) required for the signal acquisition or improving signal acquisition quality.

Furthermore, to improve the performance, there is growing interest in developing deterministic measurement matrices, as these matrices are hardware efficient, and RIP can be verified. There have been several binary deterministic matrices developed, especially quasi-cyclic array code (QCAC)-based BM [66], [67]. Zhao et al. [56] also proposed deterministic QCAC matrix and $(1, s)$-sparse RBM (SRBM) encoders as alternatives to dense random matrices used in prior literature. The proposed architecture demonstrates equivalent recovery quality for EEG and spike data compression. Signals recovered from the proposed techniques could be used for inference tasks, such as detecting epileptic seizures and sorting spikes. Despite this fact, Gaussian random matrices are commonly used. Since Gaussian random generators produce many matrix-vector multiplications (energy rigorous), they are unsuitable for wireless neural engineering applications. On signal acquisition hardware, it cannot be implemented efficiently.

2) Reconstruction Algorithms: CS signal acquisition and transmission stages are relatively straightforward, and signal reconstruction is more complex than acquisition and transmission. The initial signal can be retrieved from the compressed measurement y using a group of CS reconstruction algorithms, as shown in Fig. 5. Six broad types of CS reconstruction algorithms are presented in the previous literature. A CS

TABLE III
SUMMARY OF CS-BASED EEG STUDIES

Ref.	Application	Acquisition Strategy/ Sensing Matrix	Reconstruction Algorithm	Sparse Base	Classifier	Evaluation Matrices	Remarks
[40] 2020	EEG Seizure Detection	Random matrix	Norm-2, CSP	--	SVM	CR, Classification Accuracy	Features extracted using norm-2, and then classification using linear SVM gives better accuracy
[69]	Seizure detection	Random	Norm-2	DCT	NN, k-NN, SVM	CR, Accuracy, SNR	NN outperforms the other classifier with Norm-2
[60] 2016	Automatic detection of absence seizures	Sparse Binary	BSBL	Gabor Wavelet Dictionary	DT, KNN, DA, SVM.	TP, TN, Err, CR, CS-NMSE, CS-SSIM, SE, PE, HI	Altered compressibility can distinguish between per-seizure, seizure-free, and seizure states.
[68] 2012	Scalp EEG signals. 19-channels. 57 hours	GRM	l_1, BP, MP, OMP	Gabor, Linear, Cubic, Linear-B, and Cubic-B Spline, & Mexican hat	--	SNR, PSNR, RMS PRD, and CC	BP outperforms than MP and OMP in reconstruction but with high complexity.
[51] 2016	Alzheimer's Disease, HC & MCI	Gaussian random matrix	$l_1$norm	Gabor dictionary	Relative power and frequency thresholding	CR, RMS, SNR	CS is the complementary approach for diagnosing and controlling AD patients
[33] 2016	P300 detection and prediction of the watched character	Random	$l_1$norm minimizations	Daubechies 10 wavelet, temporal EEG signal and channel-specific	SVM	PRDN, NMSE, RMS, CR	Channel-specific dictionaries have the best results.
[52] 2016	P300 detection spelling paradigm	Random	$l_1$norm minimizations	Data Driven	SVM with linear kernel	Classification rate, PRDN, CR	The EEG signal can be accurately reconstructed with accurate results by singing the proposed dictionary.
[50] 2017	Seizure detection	Random	$l_1$norm minimizations	Gabor	Spectral-energy features, SVM with radial-basis function kernel	CR, Noise, Power, SNR	The system employs an algorithm to detect EEG biomarkers from the CS-acquired EEG signals.
[53] 2019	Sleep Stage Classification	Random Binary	Orthogonal Matching Pursuit (OMP);	DWT, DCT	A radial basis function (RBF) neural network	PDR, CR, Energy efficiency, cost, speed	Software-based implementations can achieve high classification accuracy. FPGA or ASIC implementations require moderate classification accuracy.
[61] 2014	Automatic epileptic seizure packets detection from fetal and epilepsy EEG	Binary sensing	BP, group BP, BSBL-BO, BSBL-FM	DCT, Haar, Symmlet, Daubenchies, Coiflet, & Beyklin wavelet	Binary Classifier	CR, PRD, CPU time, AUC	BSBL-FM has a similar recovery performance but is faster than BSBL, and on-chip computing resources are also reduced.
[49] 2014	Multichannel EEG-based driver's drowsiness estimation.	Binary	BP, ISL0, BSBL-BO, STSBL-EM	DCT	CCA	CR, MSE, CPU Speed, PSD, classification rate	BCI classification rate and the drowsiness estimation are the same at high CR using STSBL-EM
[55] 2018	Seizure detection	Random	Reconstruction free	Gabor, Discrete Wavelet, DCT)	SVM	CR, execution time	By using an SVM classifier, appropriate features were extracted from the compressed domain.
[63] 2019	AD, MCI, and CNT analysis	Sparse binary matrix	BSBL	DCT	PDI, λ, CC, GE	MSE, SSIM, structural similarity index	The PDI-based complex network model indicated that the parameter values (λ, CC, GE) of AD MCI & HC are substantially different.
[54] 2020	Motor imagery	Bernoulli random matrix	CNN-Based	Data-driven approach	ML classifier	CR, Accuracy	An accuracy of 91.62% has been achieved over signalscompressedat90% compression rate.
[58] 2016	Multichannel EEG signals.	Gaussian matrix	LQSP, SCLR-I, SCLR-A, SGAP, BSBL SOMP	Daubechies wavelets		MSE, MCC, CPU time	LQSP can achieve superior results with the exact measurements compared to other competing reconstruction algorithms.
[59] 2020	Application of ICA to remove an eye-blinking artifact	Gaussian Random	OMP	DCT	ICA	CR, NMSE	The proposed framework can remove interference from artifacts in a high compression ratio.
[57] 2018	Motion artifacts	channel correlation matrix	ICA analyzed using EEGLAB toolbox SPGL1 Toolbox	Daubechies-8 wavelet	--	RSNR, PRD, CR	A rakeness-based CS scheme generally performs much better than a standard CS reconstruction.
[56] 2018	EEG data compression	RBM, Deterministic QCAC, SRBM	Basis Pursuit	DCT	--	CR, SNDR, AUC	VLSI architecture designed for the given matrix

Support Vector Machine (SVM), K-Nearest Neighbor (KNN), Discriminant Analysis (DA), Decision Tree (DT), Structure SIMilarity (SSIM), Sample Entropy (SE), Permutation Entropy (PE), Hurst Index (HI), Improved Smoothed L0 (ISL0), Expectation maximization-Spatiotemporal Block sparse Bayesian learning (STSBL-EM), Area Under the receiver operation Curve (AUC), Canonical Correlation analysis (CCA), Permutation Disalignment Index (PDI), Path Length (λ), Average Clustering Coefficient (CC), Global Efficiency (GE), Independent Component Analysis (ICA), True Positive (tp), True Negative (tn), Error Rates (err), Power Spectrum Density (PSD).

reconstruction algorithm seeks an exact solution to (5) from infinitely many solutions at the receiver. The fundamental goal of these algorithms is to decrease the difference between the original input and recovered output signals through iteration. Most nonlinear reconstruction algorithms used in CS for EEG signals require a prior understanding of sparsifying ψ and C.

In most cases, authors use $l_1 -$ minimization due to its flexibility and uniformity in recovering prior information. The basis pursuit (BP) approach is a convex optimization approach that seeks a solution with an $l_1 -$ minimization. For instance, Abdulghani et al. [68] applied the BP algorithm to reconstruct the scalp EEG signals, and results show that BP outperforms MP and OMP in reconstruction but with high complexity. Morabito et al. [51] used the same approach with the Gabor dictionary to reconstruct the signal with a high CR and detect AD, MCI, and HC diseases. Other authors [33] and [52] also used the $l_1 -$ norm for P300 detection spelling. Furthermore, Zhang et al. [49], Moy et al. [50], and Liu et al. [61] used this approach to compare the performance with other algorithms. For measurements that are noise-free, $l_1 -$ minimization techniques are powerful methods for recovering CS signals. Nevertheless, noisy measurements may result in poor recovery performance, which can be solved by using $l_2 -$ norm. Few studies also used $l_2 -$ norm for reconstructing EEG signals. For example, Rani et al. [40] used $l_2 -$ norm and CS processing (CSP) techniques for detection of absence or presence of epileptic seizures in the EEG signal. Abualsaud et al. [69] also used the $l_2 -$ norm to reconstruct the singals for seizure detection. l_1 and l_2 approaches are adopted by most of the studies because they give excellent results in terms of reconstructions. Nevertheless, these norms have considerable limits since they do not consider the temporal dynamic range of EEG signals and do not recover the time courses of the signals. To overcome this issue, Gramfort et al. [70] used mixed norm l_1 and l_2 called l_{21} norm optimization for EEG signals. A greedy algorithm seeks to reduce the difference between the initial input signal and the retrieved signal in a similar manner to a convex algorithm. Many variations of BP have been proposed in the literature. For example, in [53], a system is presented for automated sleep-stage classification that incorporated the OMP algorithm to reconstruct EEG signals. The study in [71] also utilized fundamental simultaneous orthogonal matching pursuit (SOMP) and another algorithm for distributed CS used for jointly sparse signals. The BPDN is an alternative computationally capable method of reconstructing the EEG signal used in the literature [72]. Several more reconstruction algorithms have also been suggested in the literature for various applications. Shriwastav et al. [54] reconstructed motor imagery signals by applying convolutional neural networks (CNNs). The Bayesian method is also a generally used approach for signal reconstruction in CS introduced by Zhang et al. [47], known as block sparse Bayesian learning (BSBL). Bounded optimization-BSBL (BSBL-BO) outperformed state-of-the-art CS reconstruction algorithms [48]. At the same time, Zhang et al. [49] propose an energy-efficient CS algorithm called expected maximization-spatiotemporal BSBL (STSBL-EM). This algorithm exploits correlation structures within one channel signal and correlation structures within multiple channels in contrast to existing algorithms. The recovery quality of this algorithm is significantly superior to other state-of-the-art algorithms. Despite significant changes in the channel number, its speed remains relatively stable. In addition, experiments have shown that BCI classification rates and drowsiness estimations on retrieved signals are nearly identical to those on initial EEG signals, despite 80% compression of the signal. Zhu et al. [58] proposed lq norm and Schatten-p norm (LQSP) approach by utilizing cosparsity and low-rank (SCLR) properties simultaneously. Furthermore, the authors compared results with simultaneous SCLR-based on the interior-point method (SCLR-I), alternating direction method of multipliers (ADMM) method-based SCLR (SCLR-A), SOMP, BSBL, and simultaneously greedy analysis pursuit (SGAP). LQSP performance is superior regarding accuracy and speed than other algorithms. Senevirathna and Abshire [57] offered a new approach called rakeness-based CS that incorporates spatial correlations with motion artifacts. Various sensing matrix structures have been investigated on the basis of correlations between distinct channels and employed to spontaneous (unevoked) EEG data; it showed low spatial correlation, and rakeness-based CS has good performance at a high CR. A novel framework is proposed by Kanemoto et al. [59] for analyzing EEG recordings containing artifacts. This framework eliminates the need for ICA in the sensing unit, allowing the ICA block to be shifted to the data processing unit. This framework was applied to raw 16-channel EEG signals for 3 s with eye-blinking artifacts and a random matrix. The proposed framework is effective in removing artifacts with a high CR. According to Li et al. [73], longer epoch lengths result in better signal compression at the expense of longer signal reconstruction times. Furthermore, high-accuracy neural activity detection relies heavily on accurately identifying single-unit neural activities (spikes). Several recent studies [54], [74] have demonstrated that spiking neural networks (SSNs) do a strong compression of signals when they are coded as spikes.

3) Reconstruction-Free CS: As discussed above, various literature reconstruction algorithms show excellent reconstruction results. However, satisfying the speed and hardware resource constraints for real-time applications is also essential.

These algorithms are computationally complex, which limits their application, and minimizing the complexity is essential. Previous studies [38], [75] discussed the computational complexity of such algorithms. Interestingly, for some classification applications, an accurate reconstruction signal may not be necessary to extract features. It is possible to extract and classify features directly from compressed measurements. In CSP, signal features may be extracted directly from compressed measurements without reconstructing the original signal. It is a technique that eliminates the need for expensive CS reconstruction. Fig. 2 shows the block diagram of reconstruction-free CS, and it is an improvement over CS; inference problems, such as classification, detection, and estimation, can be efficiently handled by utilizing compressive measurements of the input signal [76], [77]. In this regard, Rani et al. [40] detect the presence or absence of seizure directly from compressed measurements using a binary classifier. Shrivastwa et al. [54] used a hybrid method for EEG compression at 90%, and CNN was used to reconstruct the original signals. Few other studies [78], [79] also adopted the reconstruction-free approach for real-time applications.

4) Sparse Bases: Choosing the appropriate sparse dictionary or bases matrix is critically important because signal reconstruction performance depends on the input signals' sparsity. Standard wavelet dictionaries generally do not have a high sparsity for EEG signals. As a result, the authors propose specific dictionaries tailored to the signal or database. Studies [50], [51], [55], [60], [68] used the Gabor wavelet dictionary matrix as a sparse base for EEG signals. Others [41], [49], [53], [55], [56], [59], [63] used DCT as the sparse base. Many authors observed EEG signals' sparsity in wavelet and discrete cosine transforms (DCTs). However, few studies examined the data-driven dictionaries, such [52], comparing the results obtained from the Daubechies 10 wavelet dictionary and temporal and channel-specific EEG signal dictionaries. They utilized a dataset obtained from the BCI-Competition III 2005-P300 Spelling; normalized percent of root-mean-square difference (PRDN), normalized mse (NMSE), root mse (RMSE), and Percentage Root-mean-square Difference (PRD) are evaluated for given dictionaries. Based on the results, a channel-specific dictionary and a single-specific dictionary for the temporal ECG perform considerably better than standard wavelet dictionaries. Another work from the same author [52] proposed a data-driven dictionary, which is not patient-specific but a universal mega dictionary for EEG signals.

5) State-of-the-Art Hardware Implementations: From the hardware design perspective, a lot of attention is focused on developing efficient CS-based architectures for EEG signals suitable to be integrated within wearable devices. Moy et al. [50] described a flexible, thin-film system for acquiring and extracting EEG biomarkers. Furthermore, an algorithm is incorporated into the design that extracts EEG biomarkers, such as spectral-energy features directly from compressed signals, and α waves from epileptic patients are recorded. Signals were successfully reconstructed from compressive measurements at up to $8\times$ compression.In addition, spectral features were extracted for seizure detection using seven channels of compressively sampled EEGs, with superior performance up to prominent compression factors (e.g., an error rate of 8% at $64\times$ compression). Software implementation using CPU or GPU provides high accuracy and flexibility for various applications. However, field-programmable gate array (FPGA) and application-specific integrated circuit (ASIC) platforms provide high-level energy efficiency and speed with average classification accuracy [53]. In [61], the CS and wavelet-based compression process implemented on Xilinx Spartan 6 FPGA shows that the dynamic power and energy consumption of CS-based compression is only 68.7% and 23.7%. Aghazadeh et al. [55] used STM32F4-DISCOVERYkit (ARM Cortex M4) to implement reconstruction-free CS for automatic seizure detection using an SVM classifier with an accuracy of 95.4% and a sensitivity of 96.6%. In [57], an ADC chip (TI ADS1299), in addition to a sampling rate of up to 16 kHz and a microcontroller (Atmel SAM G55), is used in the system for motion artifacts removal from EEG signals. Furthermore, EEG signals have been collected from the following databases: Physionet CHB-MIT [40], [50], [61], scalp EEG provided by the IRCCS [51], dataset II of BCI Competition III 2005 [33], and cyclic alternating pattern (CAP) sleep dataset [53].

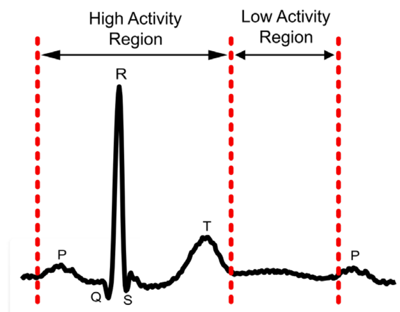

Fig. 7. ECG signal low and high information regions.

B. Compressed Sensing for ECG Signals

According to the World Health Organization (WHO), cardiovascular disease globally accounted for 32% of deaths in 2019 [80]. The continuous measurement of ECG signals is essential for detecting various cardiac abnormalities, including arrhythmias [81]. Wireless sensor nodes consume approximately 60% of the battery's energy, requiring continuous charging or replacement of the battery [82]. For body area networks (BANs), low energy consumption is essential [83]. To overcome this problem, CS is the only technique that can simultaneously compress and sense the ECG signal. It has been observed previously that sparse signals are highly redundant [84]. For example, there is no information in ECG signals in the isoelectric region (region of low activity), while the PQRST region (high activity region) contains important information, as shown in Fig. 7. It is possible to reduce the amount of data sampled by applying CS to ECG signals, reducing energy consumption in wearable devices by reducing data transmission. The use of CS in ECG expends to a range of applications, for instance, detection and classification of fetal and maternal beats [85], arrhythmia [86], QRS detection [87], telecardiology application [88], WBAN gateway [89], and heart rate estimation [90]. The CS theory can facilitate feature extraction from the ECG signal in several ways. In this section, we will address RQ1–RQ5 regarding ECG physiological signals and discuss the approaches in detail.

1) Measurement Matrices: It is important to construct measurement matrices that prevent the signal information from being damaged during the compression process. CS techniques usually do not consider the signal structure when applying compression. An ECG signal has a specific structure, as shown in Fig. 7. Compression results can be improved by using this structure. In this regard, Ansari-Ram and Hosseini-Khayat [91] provide a new approach for the sensing matrix that samples the ECG signal at the location where most of the information is contained. In this manner, the CR value for a given PRD can be further improved. In the study [92], the QRS complex of the ECG is estimated during the preprocessing stage, and the DWT sparsifying matrix is used to compress the resulting signal after subtracting the approximate QRS complex from the initial ECG signal. Furthermore, Zhang et al. [42] used an RGM sensing matrix for ECG acquisition. Mitra et al. [81] also used random Gaussian and deterministic binary block diagonal (DBBD) matrix and the recovered signal with Kronecker-based recovery; results show that DBBD outperforms with reconstruction. Most of the studies [42], [83], [86],

[90], [93], [94] used the random Gaussian and Bernoulli sensing matrix, which is excellent regarding satisfying the RIP and accuracy at the reconstruction edge, but it requires more measurements and consumes more energy. In hardware, it is challenging to generate random numbers due to memory limitations, and it is even impossible to store all random numbers. Therefore, pseudorandom sensing is preferred in practice over a full random matrix. While Da Poian et al. [85] and Liu and Wu [95] used to binary sensing matrix for acquiring data from abdominal multichannel f-ECG signals and using this sensing matrix, ECG signals can be encoded efficiently, resulting in fast computations and low memory requirements, thereby minimizing the encoder's energy consumption. Such matrices are very time-consuming and inefficient processes to implement hardware. In [83], a minimal mutual coherence pursuit (MMCP) algorithm was proposed and compared with the random SBM (R-SBM) method for encoding ECG signals. Unlike the R-SBM, the proposed algorithm optimizes entry locations and achieves minimal mutual coherence. Ravelomanantsoa et al. [96] proposed a deterministic sensing matrix for reconstructing EEG and EMG signals and also implemented it on the MSP-EXP430G2 LaunchPad development board.

2) Reconstruction Algorithms: The signal compression methods aim to achieve the maximum compression rate with the minimum error at the reconstruction step. A maximum allowable reconstruction error rate for ECG signals must be determined to produce a signal of satisfactory quality to utilize further for diagnostic procedures. According to Zigei et al. [97], cardiologists rate the reconstructed ECG signals as follows: "very good with PDR 0%–2%," "good with PDR 2%–9%," "not good with PDR 9%–19%," and "bad with PDR 19%–60%." The success of the reconstruction algorithm relies on the number of measurements, and they should be as less as possible in this regard. A restricted Boltzmann machine (RBM) is presented by Rezaii et al. [87] to reduce the number of measurements needed in order to achieve a faithful reconstruction by utilizing the representational power of RBMs to model the probability distribution of sparsity patterns in electrocardiogram signals. Mitra et al. [81] used the Kronecker-based approach and proved that noisy signal recovery is possible using the DBBD sensing matrix. Zhang et al. [42] presented new CS reconstruction algorithms for undersampled signals; an ECG signal was first subsampled randomly and mapped into 2-D space utilizing Cut and Align (CAB). The model proposed by Ravelomanantsoa et al. [96] is a fast and straightforward DCT thresholding approach, faster than OMP and StOMP. In most CS-based ECG compression schemes, only sparsity is exploited.

However, preliminary knowledge about the signals is usually accessible for a particular application. Polanía et al. [86] proposed the model-based IHT and CoSaMP reconstruction technique for applying CS to ECG. Appropriately incorporating prior information into the reconstruction procedure can achieve more accurate reconstructions, and compression rates can be higher. Zhang et al. [48] and Zhang and Rao [98] reconstructed fetal ECG and EEG signals using BSBL. Most research has focused on node efficiency, neglecting the CS decoder energy consumption. Sometimes, ECG signals are transmitted from the sensing node to the WBSN gateway, such as a smartphone, to reconstruct or extract features online; in such cases, both gateway and sensing node are battery operated, and it is difficult to reconstruct or extract features in power constraint in such a case. Kadrolkar et al. [82] proposed the rakeness-based CS and demonstrated it to be more effective than standard CS, attaining a greater compression rate at a similar quality level, thus lowering the transmission of data within the node. Moreover, Da Poian et al. [90] propose a method for detecting QRS complexes directly from CS measurements; results are comparable to those taken from the initial signal for CRs of around 60%–70%. Moreover, even with a CR of 75%, positive predictivity and sensitivity values average about 95%. CS for ECG acquisition in the Internet of Medical Things (IoMT) was proposed [94] using a novel reconstruction algorithm to denote distinct types of ECG structures compactly; massive overcomplete dictionaries are first trained on predefined QRS morphologies.

3) Sparse Bases: CS incorporates the sparsity of signals, but ECG signals are not much sparser in the original domain; however, the wavelet representation of a signal is usually reasonably sparse. There are several wavelet families available in the literature. It is, therefore, necessary to compare them to determine which wavelet family is most suitable. Previous studies [83], [88], [89], [90] used wavelet transform as the sparse base for ECG compression. Thus, it shows promising results with a high CR. Zhang et al. [42] used a Fourier dictionary matrix and reconstructed the signal at a 30% CR. However, the studies in [81], [94], and [96] used DCT as a sparse base, which also shows promising results. Indeed, wavelet, Fourier, and DCT are the suitable sparse basis for ECG signals, but, still, more active components are available, so perfect CS condition signals need to be as sparse as possible. To overcome this, in [42], the ECG signal is randomly subsampled and mapped into 2-D space utilizing CAB to deal with the sparsity. Contrasting the patient-specific dictionary for CS approaches, a beat-type dictionary may provide high-quality signal recovery for individual ECG recordings without the need for training [88]; Ravelomanantsoa et al. [96] used the thresholding approach in DCT. In other studies, Craven et al. [93] used an adaptive dictionary scheme based on multiple dictionaries created using the deep learning (DL) technique to improve performance. In addition, there is no prior knowledge of the order of sparsity of the signal.

Therefore, Rezaii et al. [87] proposed an optimal sparsity order selection (OSOS) method that minimizes the reconstruction error when calculating the sparsity order. In addition, the authors have demonstrated that the basis matrix based on raised cosine kernels is more efficient in compression than Gaussian basis matrices. Simulation results confirm the efficiency of their method in terms of CR and robustness to observation noise. Liu and Wu [95] proposed self-training dictionary approaches called STDS-AL0CM, achieved better performance results in terms of percent norm difference (PND) and reconstruct signal-to-noise ratio (RSNR) compared to DCT-BSBL, WT-BSBL, WT-OMP, DCT-OMP, and STDS-L1 method, and also provided a further precise approximation of the original signal even when CR = 0.2. A well-known orthogonal basis, such as DCT, DWT, and FT, can be applied to the reconstruction of CS. They are orthogonal, the signal's dimension is equal to the number of atoms, and each signal can be represented uniquely by a vector of coefficients. It has been shown that orthogonal transforms (basis) effectively represent natural signals though they might present challenges for physiological signals [99]. It is essential to construct alternate dictionaries for certain physiological signals in this scenario. In such dictionaries, the number of atoms outstrips the dimensions of the signal, known as overcomplete dictionaries, since it is necessary to represent the concerned signals more compactly [94]. In compressive sensing, many sparsifying matrices are available, but certain types of signals may not respond well to these matrices. Using training data, dictionary learning is an efficient method of finding the sparse mapping matrix.

4) State-of-the-Art Hardware Implementations: Due to the constraints of wearable devices and a large amount of information coming from sensor networks, the CS paradigm has been widely exploited in the recent past to design real-time and low-energy IoT nodes for remote ECG monitoring [45], [100], [101], [102], [103]. Particularly, most of the recent prior art focused on accelerating the reconstruction algorithms through either innovative hardware architectures or hardware-oriented computational paradigms. An optimized architecture of the OMP approach is presented in [45] for biometric identification using the ECG signal; the proposed method also integrates a CS decoder and the biometric identification unit into heterogeneous reconfigurable hardware. The authors obtained 98.88% identification accuracy with 30% CR. The heterogeneous hardware/software implementation based on the Zynq FPGA-based system-on-chip platform accelerates the overall processing time by a factor of 7.73 with a cost of 2.318-W PC, which offers much better performance per watt compared with the pure software solution.

Starting from the observation that in remote ECG monitoring, most of the changes between the original and reconstructed signals are distributed in the QRS region; Tseng et al. [102] proposed an adaptive method integrating the near-precise compressed (NPC) and CS algorithms: the former is used to process the ECG signal regions with great changes, while the latter elaborates on the remaining signal portions. This approach allows simultaneously improving the SNR and CR, achieving an area occupancy of 2.69 kgates and PC of just 2.1 mW on a TSMC 0.18-μm standard CMOS process.

The framework demonstrated in [103] merges the CS and approximate computing paradigms to reduce the volume of data to be stored/transmitted and the number of arithmetic operations to be performed according to the target diagnosis accuracy required by the specific healthcare application. Experiments conducted on a 65-nm ASIC technology show that such a framework saves about 60% of energy compared to the accurate CS counterpart without significantly degrading signal quality. Recently, compressive learning has been exploited to bypass the reconstruction process and extract features of interest directly from the compressed ECG signals [100], [101].

By removing the decoding stage, a significant amount of energy is saved because of the reduced number of operations; in addition, custom DL models can be trained to classify possible cardiac arrhythmias by processing the compressed data having a reduced size. Finally, since DL models rely on simple arithmetic functions, such as multiply-and-accumulate, they are well suited to be accelerated through hardware platforms, such as ASIC and FPGA. Just as an example, the 1-D CNN proposed in [100] realizes on-device multiclass classification of ECG signals by an adaptive architecture: according to the desired CR, accuracy and energy efficiency can be traded off by modifying the model size and, as a consequence, the number of multiply-and-accumulate operations. At CR = 0.2, the hardware accelerator [100] synthetized on a UMC 40-nm technology achieves an energy efficiency of 0.83 μJ/classification under a 1.1-V power supply at a frequency of 5 MHz. Each classification is performed within 7.08 ms at 5 MHz.

C. Compressed Sensing for EMG Signals

Electrical activity in muscles is measured by EMG in response to nerve stimulation. Neuromuscular abnormalities can be detected using EMG testing. It is possible to analyze the biomechanics of human or animal movement using an EMG signal. An EMG signal has three main characteristics: amplitude (varying from 1 V to 50 mV), phase, and frequency. It can monitor muscle function and activity during sports, fitness, and daily life. Existing EMG systems have the following main drawbacks: first, they cannot provide continuous monitoring; second, they are slow and take a long time to process; and finally, they are too power-hungry for wireless healthcare systems. For this purpose, CS theory is an optimal solution. In CS, sparse signals are compressed by a few incoherent linear measurements, reducing the number of samples required for signal reconstruction by a significant amount. Some common applications of CS for EMG signals are fatigue analysis [104], cyclic movement analysis [104], posture control [105], musculoskeletal disorder analysis [105], hand gesture recognition [62], and prosthetic control [62]. Despite this, PC poses a significant challenge to these devices' design and widespread use. The device consumes significant power to wirelessly transmit signals captured from multiple channels at high sampling rates. To overcome this constraint, Balouchestani and Krishnan [44] proposed a wearable wireless surface EMG (sEMG) biosensor architecture designed and implemented using Analog-based CS theory according to three novel algorithms. Based on the proposed architecture, the sampling rate has been reduced to 25% of the NR, the consumption of power has been reduced to the amount 40%, the PRD has been reduced to 24%, and the RMSE has been reduced to 2%, which provides an excellent background to establish wearable wireless healthcare systems.

1) Measurement Matrix: As discussed previously, the sensing matrix should be chosen wisely and mainly depends on computational complexity and encoder efficiency [106]. Many measurement matrices proposed in the literature for sensing EMG signals are random sensing matrices. Authors in [44] proposed the sensing matrix selection (SMS) method to select the most suitable RSM for the CS situation. According to [107], just a 1-bit Bernoulli Measurement Matrix can produce up to 16x compression for the EMG signal. The study [108] also used the random measurement matrix and concluded that 6-bit Gaussian random coefficients could be used for compression aspects up to 18x.

Further studies have shown that 6-bit uniform random coefficients are preferable for some biosignals. Park et al. [109] used CCS with various linear sparse ruler (LSR) samplings, and length-20 LSR shows favorable results regarding CR and classification accuracy. A deterministic measurement matrix is proposed in [43] and easily implemented in hardware. The proposed measurement matrix is implemented in a digital CS encoder, which is then utilized to compress and recover EMGs and ECGs at a 75%–87% CR, further saving energy consumption up to 75% and 87.5%. In [110], a random structural matrix is adopted, while, in [113], a sparse binary measurement matrix is proposed due to its lower execution resources and accelerated hardware performance. Most presented studies rely on optimizing the sensing matrix to improve performance. In particular, Pareschi et al. [111] adopted the newly introduced rakeness approach to CS. The study [112] utilized a DBBD sensing matrix, the Daubechies wavelet kernel as a sparse dictionary, and an OMP reconstruction algorithm. The performance of the reconstructed signal was assessed by sEMG signals' envelope detection and collected while walking ten healthy subjects. In light of the results obtained, it appears that the proposed technique is reliable for detecting envelopes.

2) Sparse Base: CS outcome highly depends upon the sparsity of EMG signals, but many artifacts mixed with original EMG signals in wireless devices make them nonsparse. Time and frequency domains of healthy EMG signals are sparse [108]; however, neuropathy signals are sparse only in time, while myopathy signals are sparse only in frequency [107]. Compressive sensing cannot be applied when there is no sparsity in the signals, either in the frequency or time domain. Due to the nonsparsity of EMG, compressive sensing is ineffective [113], [114]. Therefore, a new EMG compression scheme is needed that offers both good compression performance and low computation costs during the compression process. To overcome the sparsity constraint in EMG signals, compressive covariance sensing (CCS) is proposed by Romero et al. [115]; rather than reconstructing the original signal itself, CCS reconstructs its covariance, which is not a significant fact since several signal processing methods use covariance as a signal (e.g., power spectrum density, multiple signal classification, and machine learning covariance features). Park et al. [109] use a CCS compression scheme for EMG signals for gesture classification. It is a good compression technique, but it cannot recover the original signal. In some applications, such as real-time monitoring and artificial arm control, it is important to recover the original signal. For real-time applications, CCS should have a better temporal resolution to improve classification accuracy; more work is needed, and PC analysis is not done yet. Wilhelm and Massoud [110] used a symlet-4 wavelet as a sparse base with a structural random measurement matrix; the simplicity and efficiency of Symlet-4 are well balanced with respect to L1 norms.

EMG recordings are frequently masked by ECG signals, which is the major problem. An ECG signal is produced by activity in the heart, which expands and attaches to the diaphragm. Due to this, the ECG signal is unavoidably contaminated by the diaphragmatic electromyogram (EMGdi) signal. In order to address this issue, Wu et al. [114] proposed a novel framework to address the sparsity problem in EMG signals and reconstruct compressible information data in various systems, including wireless sensor networks (WSNs) and the IoT. AL0 performs well for compressible signals. A new wavelet threshold (NWT) technique is intended to remove ECG interference from EMGdi recordings. It is evident from the experimental results that wavelet-based methods perform better than other methods. Therefore, AL0 and new wavelet thresholding methods are promising for the compression, transmission, reconstruction, and denoising of EMGdi data based on WSNs and IoTs.

3) Reconstruction Algorithms: The EMG signal should be reconstructed at the receiving end from compressed measurements to extract the features. Multiple algorithms are proposed in the literature based on accuracy and complexity. Balouchestani and Krishnan [44] recovered the original sEMG biosignals, used reconstruction techniques considering a combination of L1–L1 optimizations, and applied the BSBL structure to the receiving end. In addition, the suggested algorithms have been examined over a number of hours of experimental sEMG biosignals obtained from the PhysioBank ATM, the EMG Bank, and the EMG project lab databases. Dixon et al. [107] employed BP convex, CoSaMP, and normalized iterative hard thresholding (NHIT) to achieve high SNRs at high sparsity (>95%), while OMP and BPDN convex were unable to reconstruct EMG signals successfully, and BP algorithms are more complex than the greedy algorithms. Salman et al. [108] reconstructed healthy signals sparse in time and frequency domains with the L1 approach. Park et al. [109] used CCS with the least square method; it showed effective compression techniques for EMG. Even though the original signal cannot be recovered, most applications do not need to retrieve it.

CCS study is still in the early stage, so the temporal resolution of real-time applications needs to be improved. In addition, broad work is required to improve the classification accuracy, and PC has not yet been analyzed. Cisotto et al. [116] proposed a novel method for combining EEG and EMG biosignals based on cortico-muscular coherence, a function that simultaneously considers brain and muscle activity changes and can classify different movements. This method increases the compression rate compared to separately transmitting EEG and EMG samples. Furthermore, smoothed L0 (SL0) and subspace pursuit (SP) were used for reconstruction [110]; the SP reconstructions have smaller artifacts than SL0, but SP yields a slightly lower SNR. This approach is insufficient for personal medical care in WSN and IoT applications. To meet the constraints of applications involving personal medical care in WSNs and the IoT, an approximated

L0-norm (AL0)-based approach is proposed [114] to seek the solution through the gradient descent method and then projects the solution to an approximate reconstruction reasonable set to maximizing the performance and reducing hardware complexity. Furthermore, to improve the performance and reduce the hardware complexity, Pareschi et al. [111] contributed to the design of hardware for acquiring and reconstructing EMG signals by exploiting the rakeness-based CS approach to boost the compression factor; as a result, fewer data are required to represent the signal information. An interesting comparison of the most commonly used algorithms for reconstructing EMG signals via CS, namely, OMP, L1-minimization, NIHT, and CoSaMP, can be found in [117].

EMG biosignals from a wide range of sources were used in this study. All algorithms exhibit a marked peak in SNR near Sparsity = 0.4–0.5. Whereas OMP, NIHT, and CoSaMP exhibit a rapid decline in SNR, the L1 algorithm maintains a nearly constant SNR over a wide range of sparsities. CS reconstruction shows almost no impact of noise on L1-minimization, which shows a behavior independent of sparsity. Elmantawi et al. [118] use a random matrix with a K-SVD dictionary and L2 minimization for muscle fatigue monitoring. A novel 96-channel ASIC simultaneously records, compresses, and transmits sEMG signals to monitor muscle fatigue. An ASIC provides a dedicated channel for signal conditioning and amplification, and compresses the sEMG signal by a factor of 10 with a 1.61% median frequency error, allowing wireless transmission of all channels. The CR can be increased when EEG and EMG signals are compressed jointly [116], [119]. It can be used in BSN and IoT health applications where multiple signals are monitored simultaneously.

D. Compressed Sensing for EDA/GSR

EDA measurement and analysis have applications in various fields, ranging from market research to seizure detection, content valence classification, and audience cohort analysis to human stress assessments. The superposition of numerous components in an EDA signal can often obscure a user's response to a stimulus. Using CS-based decomposition, unwanted noise components can be mitigated, and physiological signals can be revealed. The conductance typically measures a person's EDA over the skin near the sweat glands (e.g., the palms of their hands). Very few research works have been conducted in CS for GSR signals due to sparsity constraints. We found only two articles in the selected time period; therefore, this section is more compact.

Jain et al. [120] proposed a novel CS-based framework for processing EDA signals; the authors used simple preprocessing followed by CS-based decomposition; in the proposed framework, the baseline signal is explicitly modeled, and the user's responses can be recovered. As a result of their approach, SCR events can be accurately recovered from simulated data. In addition, the recovery procedure outperforms other existing recovery procedures for event detection of SCR. This approach includes high computational complexity. Therefore, a modified CS decomposition (MCSD) is proposed [121] for EDA signals that may vary the impulse response over time and with variable noise models. The primary objective of this model is to improve the accuracy of the recovery of EDA signal decomposition and to improve the monitoring system for human stress. In addition, a computationally effective decomposition approach is developed by using matrix-free convex-optimization modeling. This method utilizes the Toeplitz structure to enable the decomposition of EDA signals with guarantees of reconstructing actual SCR events.

IV. Discussion, Challenges, and Future Recommendations

Monitoring physiological signals wirelessly in healthcare applications is exciting and profoundly impacts people's health. It is certainly possible to improve our health further by integrating possible technologies with future healthcare technology. A wireless device based on CS can address the challenges encountered in low-power applications, such as battery-operated sensors. However, no simple solution is available in CS techniques for physiological signals. In other words, there is no sensing strategy; the sparsest bases and reconstruction algorithms work well for every problem and cannot be relied upon for every application. We can use various techniques to achieve optimum results. This review paper discussed the key research components of CS for physiological signals. This section discussed the challenges, new research directions, and future recommendations.

Considering the (RQ1), multiple sensing matrices available for CS have been discussed in Section II-C.3. Research papers reviewed in this article utilized different measurement matrices and are discussed accordingly. EEG, ECG, and EMG are discussed in Sections III-A.1, III-B.1, and III-C.1. Most studies used random sensing and sparse binary matrices, showing high reconstruction accuracy and satisfying RIP but requiring more storage space, and are not energy efficient. It is possible to overcome these disadvantages using the deterministic construction of sensing matrices, and only a few studies used deterministic matrices. There are great advantages to using a deterministic matrix, including simplicity in the sampling and reconstruction stages and reduced computational complexity. Further research is needed on CS measurements for physiological signals under deterministic sensing matrices.

Replying to the (RQ2), reconstruction algorithms perform differently depending on the parameters. Further reconstruction algorithms used for physiological signals are discussed in Sections III-A.2, III-B.2, and III-B.3 for EEG, ECG, and EMG. It can, however, be concluded that BSBL and BPDN are more suitable choices for most applications where accurate reconstruction is required and computation time is not critical. Threshold-based reconstruction could benefit most real-time applications where computation time is not the primary concern. In addition, BPDN achieves better reconstruction accuracy in noisy measurements than OMP and BSBL. OMP is recommended when computational complexity is a design concern. During the recording of data, human movement can cause significant artifacts. Wireless telemonitoring is intended to provide people with freedom of movement. Physiological signals are always contaminated by strong artifacts generated from muscle movements and electrode movements. Thus,

TABLE IV
SUMMARY OF CS-BASED ECG STUDIES

Ref.	Application	Acquisition Strategy	Reconstruction Algorithm	Sparse Base	Evaluation Matrices	Remarks
[42] 2019	ECG Signal reconstruction	Random Gaussian	OMP, CoSaMO Bo-BSBL, EM-BSBL	Fourier domain	PDR, CR	Faithfully reconstruct with 30% acquisition
[96] 2015	ECG Signal reconstruction	Deterministic	OMP, StOMP, thresholding DCT	DCT	SNR, CR, PC, Speed, PDR, RMS, QS	Proposed Algo is 23 & 12 times faster than the OMP and Stagewise OMP
[85] 2016	Detection and classification of fetal and maternal heartbeats using abdominal multichannel ECGs	Sparse Binary	BP denoising, SL0	Overcomplete Gaussian Dictionary	S, P+, PRDN, HRMeas(bpm^2), RRmeas(ms), ICA, FN, CR, TP PDR, RMS, & FP,	Compression of abdominal f-ECG signals and appropriate solution for low power devices.
[86] 2015	Arrhythmia ECG reconstruction using prior information	Bernouli, Matrix I Matrix II	IHT, CoSaMP, SPIHT, BPDN, BSBL-BO, MMB–IHT, MMB–CoSaMP	--	PRD, CR, PRDN, QS, SNR	MMB–CoSaMP and MMB–IHT outperforms s-o-a algorithms
[93] 2017	AD for EEG Reconstruction and QRS detection	Bernoulli Random matrix	SD-Q7, AD-Q6,, SPIHT, MMB-CoSAMP, MMB-IHT, and BSBL	Data-Driven/Adaptive	PDR, CR, SNR, PC, Speed,	Improved the tradeoff between CR and distortion.
[83] 2015	On-node ECG compression	RGM, R-SBM, and MMC-SBM	OMP, IHT, GP, BCS, BP, BSBL, WLM (MMCP)	Wavelet	PDR, CR, PC,	MMCP shows superior sensing performance and ultra low energy consumption
[95] 2021	Compress and reconstruct ECG	Binary matrix	Al0CM frameworks	Self-training dictionary scheme (STDS)	SNR, PND, Speed, PDR, QS	Self-training provides a more accurate sparse representation
[87] 2018	ECG reconstruction for QRS detection	Cosine, Gaussian, OSOS	OMP algorithm	Dictionary-based	CR, SNR, PDR, Speed,	OSOS calculates sparsity order by minimizing the reconstruction error
[88] 2019	Telecardiology application	Non Uniform Random sensing matrix	Beat Type dictionary-based Reconstruction	Adaptive, Standard, Wavelet and Beat type dictionary	CR, SNR, PDR, RMSE, PC, QS	Proposed BTD outperforms then others
[81] 2020	EEG Arrhythmia detection	Bernoulli and Gaussian Random, DBBD deterministic	Kronecker based recovery	DCT and 76 others	CR, PDR, PDRN, SNR, RMS, CC, QS	DBBD allows Kronecker-based ECG signal recovery.
[89] 2018	ECG reconstruction at WBAN gateway	rakeness-based antipodal sensing matrix	OMP, CoSaMP, FOCUSS	Wavelet	CR, SNR, Speed, QS	Reconstruction time and CR are better with Rakeness
[90] 2018	Estimation of heart rate from compressed sampling ECGs	Random sensing	BPDN, OMP, SL0, and reconstruction-free CS	wavelets (WT), Daubechies− 4, and Gaussian dictionary (GD) with matched filter	TP, FM, TN, S, P+ CR	Calculate heart rate and R-peak positions from CS measurements
[94] 2021	ECT Acquisition & reconstruction in IoMT	Bernoulli, Gaussian, Rparse Toeplitz, Circulant matrix	BP, OMP, Irls, SP, CoSaMP, BSBL-EM, BSBL-BO, and Reconstruction free	DWT, DCT, FT, and AODMF	CR, PDR,	Selected dictionary fits the current frame well & improves the reconstruction

Model-based CoSaMP (MMB–CoSaMP), Model-based IHT (MMB-IHT), Set Partitioning in the Hierarchical Tree (SPIHT), Adaptive Dictionary with quantization of the difference values at 6 bits (AD-Q6), Sparse Dictionary with quantization of the difference values at 6 bits (SD-Q6), Random Sparse Binary Matrix (R-SBM), Weighted L1 Minimization (WLM), Approximated ℓ0 Norm Constraint Method (AL0CM), the Deterministic Binary Block Diagonal (DBBD), FOCal Underdetermined System Solver (FOCUSS), Adaptive Overcomplete Dictionary and Matched Filter (AODMF), Subspace Pursuit (SP), Iteratively Reweighted Least Squares (Irls)

sparse signals can become nonsparse in time and transform environments. As a result of the nonsparsity, CS algorithms are severely degraded, failing to recover the signal. CS algorithms generally need to remove artifacts prior to compression to prevent artifacts from being compressed. It will result in a dramatic increase in circuitry complexity and a conflict with the energy constraint. Studies [47], [48], [49], [122] proposed a novel algorithm based on the BSBL framework for CS of nonsparse physiological signals, which was successful in telemonitoring fetal ECGs and single-channel EEGs. The studies suggested recovering nonsparse signals directly without resorting to preprocessing or optimal dictionary matrices as an alternative to preprocessing or using optimal dictionary matrices.

However, BSBL is designed to recover signals from single channels. As a result, BSBL cannot be used for real-time multichannel signals as it recovers the signals channel by channel, which can be time-consuming. In addition, there is a strong correlation between physiological signals from different channels, and exploiting interchannel correlation is crucial and very beneficial. As a result, BSBL ignores this issue. It is essential to note that most CS algorithms are not energy efficient for wireless telemonitoring. Thus, the compression process should be simple as possible and its recommended to use the reconstruction-free CS.

It is important to note that not all physiological signals are sparse; therefore, CS techniques do not apply to all physiological signals. Typically, wearable devices are capable of collecting multiple signals. If they are sparse, then they can be acquired using CS techniques; if not, traditional techniques can be used. Multiple algorithms can be used at the receiving

TABLE V
SUMMARY OF CS-BASED EMG STUDIES

Ref.	Application	Sensing Matric	Sparse Base	Reconstruction Algorithm	Performance Evaluation matrices	Remarks
[44] 2014	Healthy, neuropathy, and myopathy	Random	Sparse coding based on OMP and SVD	L1, BSBL	SEN, SPE, CR, PDR, RMSE, SNR, SL, PC, CT	The proposed architecture has reduced SL, PC, PRD, RMSE, and CT.
[107] 2012	Healthy, myopathy, and neuropathy patients	BRM	Adaptive	BP, BPDN, OMP, CoSaMP, NIHT	CR, PDR, SNR, SL, CT	1-bit Bernoulli measurement matrix can produce up to 16x compression for EMG.
[108] 2011	Healthy EMG	GRM	Original and frequency domain	L1	CR, PDR, SNR, SL	Healthy signals are sparse in time, and the freq. domain reconstructed well with the L1 norm
[109] 2019	Gestures Classification using CCS EMG	Liner Sparse Ruler (LSR)	CCS	CR, Accuracy	CR, PDR	The proposed technique demonstrated a high classification rate and superior compression rate
[116] 2018	Jointly compression of EEG & EMG based on CMC	Cortico-Muscular Coherence (CMC)	CMC	CR, PDR	CR, PDR	EEG and EMG signals can be compressed together for higher compression ratios
[43] 2017	CS encoder for EMG for power constraint application	Deterministic	DCT	IDCT	PDR, SNR, SL, PC	Signals recovered at 75% compression with the proposed encoder
[110] 2012	Classification of Intramuscular	Structural Random	Walsh-Hadamard transform and symlet-4 wavelet	SP, L1	CR, PDR, SNR	The sampling rate reduce by 10x, while classification accuracy > 95%
[114] 2018	Telemonitoring of EMGdi	Sparse binary	New wavelet threshold	Approximated l0 (AL0) norm	CR, NMSE, PSD, Central Frequency (CF)	EMGdi compression, transmission, reconstruction, and denoising with AL0 and NWT methods are up-and-coming for WSNs and IoT
[111] 2016	EMG Analog-to-Information Converter (AIC) based on CS	Rakeness based sensing	Symmlet-6 Wavelet	Rakeness based approach	CR, RMSE, CT	AIC obtained in this study outperforms previous approaches
[117] 2019	Biceps, Deltoideus, Triceps.	Random Bernoulli	DCT, Haar, and DB4.	L1, OMP, CoSaMP, and NIHT	PDR, RMSE, SNR, SL, CT	L1-minimization outperforms the other algorithms
[112] 2022	sEMG envelope detection	Deterministic Binary Block Diagonal	Daubechies12 wavelet kernel	OMP	CR, CT	The proposed method is reliable for a given application
[118] 2018	96-channel ASIC for fatigue monitoring	Random Gaussian, Bernoulli, and Binary	Data-driven using K-SVD dictionary learning	L2 norm	CR, PDR, SL	The proposed architecture is suitable for wireless data to transmit

end for signal reconstruction, but this process will increase the computational complexity. To reduce the computational complexity, it is recommended to use reconstruction-free CS because signal reconstruction is not always necessary; certain features can be indeed extracted directly from the compressed measurements.

Considering (RQ3), generally, evaluation matrices used for CS performance evaluation are discussed in Section II-C.5. Furthermore, a few previous review papers highlighted the evaluation matrices mentioned in Table I. In addition, we highlighted the performance evaluation matrices used in the CS framework for EEG, ECG, and EMG in Tables III–V. It is noted that CR is commonly used, and most authors used only CR, RMSE, PDR, and SNR to judge the performance, but it is not enough. Other parameters are also important to check the success of CS for physiological signals in wireless applications, such as computation time, PC, computational complexity, and sparsity level. It is recommended to evaluate all possible parameters.

Answering (RQ4), all physiological signals are not sparse in the original domain, and finding a basis or dictionary matrix that represents the signal to be acquired in the sparsest possible manner is challenging. For EEG, ECG, and EMG, various sparse basis or dictionary matrices are discussed in Sections III-A.4, III-B.3, and III-C.2. Identifying the sparse basis will facilitate faithful reconstruction from further reduced

CS measurements. Therefore, it is necessary to develop a system capable of identifying the sparse basis of a signal. In addition, only a few studies observed that data-driven dictionaries could be used as a sparse basis, which has excellent benefits, such as high sparsity and incoherence. It is recommended in the future to use the data-driven dictionary matrices as the sparse basis for physiological signals.

Replying to (RQ5), different features can be extracted for physiological signals, such as the presence or absence of seizure, AD, HC, MCI, sleep stage classification, driver's drowsiness estimation, and motor imagery, which can be extracted from EEG using CS. Detection and classification of fetal and maternal heartbeats, arrhythmia and QRS detection, and heart rate estimation can be done from the ECG signal using CS. Furthermore, the following features can be extracted from EMG signals; healthy, neuropathy, and myopathy patient detection; gesture and intramuscular classification; and biceps, deltoideus, triceps, and fatigue monitoring. In addition, CS for GSR can be used for seizure detection, content valence classification, and audience cohort analysis for human stress assessments. Tables III–V discuss a detailed review of such applications.

Referring to the (RQ6), four physiological signals were reviewed in this article. It is found that EEG, ECG, and EMG singles are more suitable for applying CS techniques. However, EDA/GSR signals are unsuitable for CS techniques due to nonsparsity characteristics. Furthermore, GSR studies are discussed in Section III-D. Future work is required to find the sparse bases for such signals.

Preprocessing techniques, such as filtering, peak detection, and dynamic thresholding, increase the circuit complexity and energy consumption, and CS techniques should efficiently handle such issues.

Even though the latest developments in hardware technologies and the practicability of performing on-chip signal processing, most of the CS research for physiological signals reviewed in this article demonstrated the digital implementation of the CS framework, which depends on various hypotheses. Future CS implementations are expected to be analog with built-in hardware for minimizing energy consumption under real-life conditions.

CS techniques for wearable devices represent an exciting opportunity in view of both power and latency savings, in contrast to traditional techniques, which acquires the raw data first and then compresses it, while the compressed information is directly extracted at the acquisition time in CS. Consequently, such a framework requires much less memory storage capacity while significantly improving both the speed rate and the energy efficiency of data transmission. Several articles have been published in this context to save power and latency. WSN, proposed by Al Disi et al. [123], increases the battery lifetime by more than two times with respect to the conventional approach. Zhang et al. [124] proposed a quantized deep CS network (QDCS-Net) for both linear and nonlinear measurements to help better compress the data to reduce the transmission volume of data and achieve good reconstruction performance. Zhang et al. [124] proposed deep CS for edge cloud collaborative industrial IoT networks to reduce the latency of networked control systems. In addition, CS-based encryption methods can be used in IoT applications to enhance security and privacy.

In healthcare, advances in the acquisition of physiological signals and processing of large datasets have enabled a broader understanding and observation of patients with various diseases. Despite this, most current research does not yield a personalized data-driven approach to treatment. Current research lacks a quantitative integrative tool to translate these understandings and clinical observations to the individual level to build a platform for personalized treatment. Research in this area is important and should be considered in the future.

CS is used in acquiring and reconstructing physiological signals, but, in real-time applications, it would not be helpful. In such cases, reconstruction-free learning may be beneficial for several machine learning-based applications. It is expected that this type of reconstruction-free learning will be more prominent in the future for a wide range of healthcare applications.

V. Conclusion

Many wireless sensors are used to acquire physiological signals in wireless healthcare applications, and most are facing challenges, such as PC, transmission, and storage space, which may require long-term and energy-efficient computational approaches and suitable compression techniques. In this regard, the CS framework is a novel approach that can deal with such challenges. In this article, we have reviewed existing literature in the CS framework for four physiological signals, namely, EEG, ECG, EMG, and GSR signals, in terms of sensing matrices, sparse bases or dictionary matrices, reconstruction algorithms, and performance evaluation matrices. This article also notably highlighted the hardware implementation of CS techniques and reconstruction-free CS for healthcare applications.

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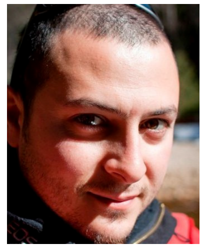

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