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COLLEGE OF ENGINEERING

AN EFFICIENT PPG COMPRESSION TECHNIQUE FOR WEARABLE HEALTH DEVICES

BY

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ABSTRACT

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Title: An efficient PPG Compression Technique for Wearable Health Devices

Supervisor of Thesis: Dr.Uvais Ahmed Qidwai.

Photoplethysmography is a simple, widely used, low-cost technique to acquire important diagnostic information for assessing significant physiological parameters of the human body based on the amount of light reflected from or absorbed by the body. Photoplethysmogram (PPG) signal is recognized as one of the most powerful signals in the diagnosis of variations in heart rate, blood pressure, oxygenation saturation levels etc. With the great advancements in communication, information technology and Internet of Things (IoT), wearable health devices have been extensively used to measure PPG signals in telemedicine, remote health monitoring, ambulatory systems and in several mobile health systems. As these small wearable medical devices are battery operated and resource constrained, dedicated and efficient compression techniques are required to optimally manage energy and memory requirements, without jeopardizing the relevant clinical morphologies. The thesis deals with the study of the existing PPG compression techniques, type of the compression used, the basic implementation and a comparative analysis of these techniques, which could be helpful for choosing a suitable technique for specific applications. The thesis aims to design efficient compression techniques for the compression of PPG Signals. The proposed techniques exhibit superior performances compared to the state-of-the-art methods.

DEDICATION

I dedicate this work to my dear family for their incessant love, support, encouragement, and prayers that inspired me to complete this work.

Thank you, my beloved family

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First, I thank the Almighty Allah for all the immense blessings given to me and for granting me the strength and will power to complete the work. My heartiest thanks to my husband, Haroon Shahul, and my children, Suhail and Sahiba for their love, encouragement, understanding and support without which I would not be able to accomplish this task.

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CHAPTER 1: INTRODUCTION

1.1 Cardiovascular Diseases Detection using Wearable Health Devices

Recently, the great advancements in wireless communication and mobile technologies have brought about a spectacular change in the field of remote health care using wireless wearable health devices. The invention of wearable health devices (WHD) such as smart watches, wrist bands etc. has revolutionized the treatment pattern of life-threatening ailments such as cardiovascular diseases, respiratory diseases, arterial diseases etc. The WHD are widely used by clinicians and caretakers for physiological monitoring and to study the normal and abnormal bodily functions. These devices typically have limited energy and bandwidth and they must continue monitoring uninterrupted for a long time, without the need to recharge or to change the battery. The WHD can relay vital information such as electrocardiogram (ECG), PPG body temperature, blood pressure (BP), etc. from wearable nodes to remote equipment or cloud, which can be analyzed to administer correct and timely treatment. The therapeutic improvement through smart and intelligent healthcare has significantly improved the standard of life of the patients as well as the lifespan of elderly aged patients.

1.1.1 Impact of Cardiovascular Diseases (CVD)

Cardiovascular illnesses are the prime reason for deaths globally [1]. In 2016, CVDs caused about 17.9 million deaths that comprised about 31 % of all the global deaths, as shown in Figure 1. As heart attack and stroke causes about 85% of these deaths, as indicated in Figure 2, these fatalities may be prevented.

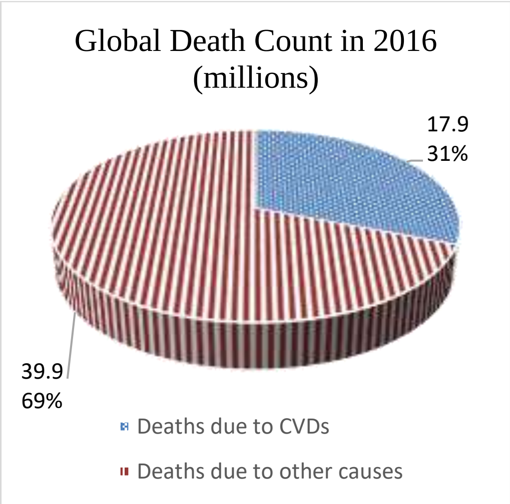

Figure 1. Global Death Count in 2016

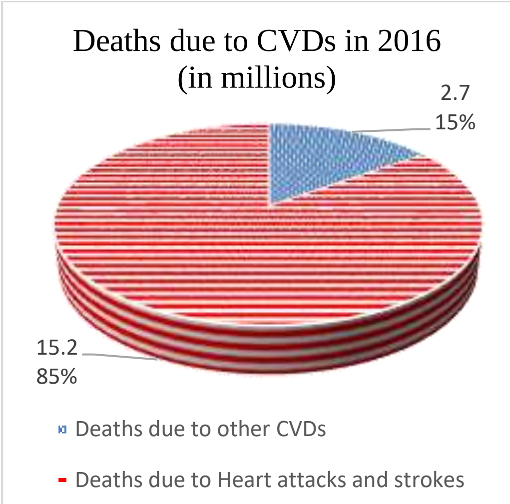

Figure 2. Deaths due to CVDs in 2016

Pervasive and continuous clinical monitoring of biomedical signals such as PPG, ECG etc. is possible through telemedicine services and remote healthcare systems. In crisis circumstances, real-time health focus is vital. As indicated by the American Heart Association, if a person encountering ventricular fibrillation is treated in the initial 12 minutes of heart failure, then the survival rate is from 48% to 75%. The rate of survival decreases to 2%-4% once the first 12 minutes expire [2]. With remote continuous clinical monitoring systems, data of patients such as PPG, ECG, heart rate, BP etc. can be acquired using the WHDs and can be instantly transmitted to clinical centres to process and store appropriately.

1.1.2 Trends in utilizing WHD for CVD management

The global WHD business is estimated to touch USD 46.6 billion by 2025 from USD 18.4 billion in 2020, with a compounded annual growth rate of 20.5% from 2020 to 2025 [3], as depicted in Figure 3. This, in turn indicates the significance of utilizing

WHDs for monitoring crucial signals such as PPG for preventive health care. The proliferating lifestyle diseases, busy work schedules, sedentary routine, technological innovations in medical care devices, and growing use of remote gadgets might be the significant factors fueling this growth [4].

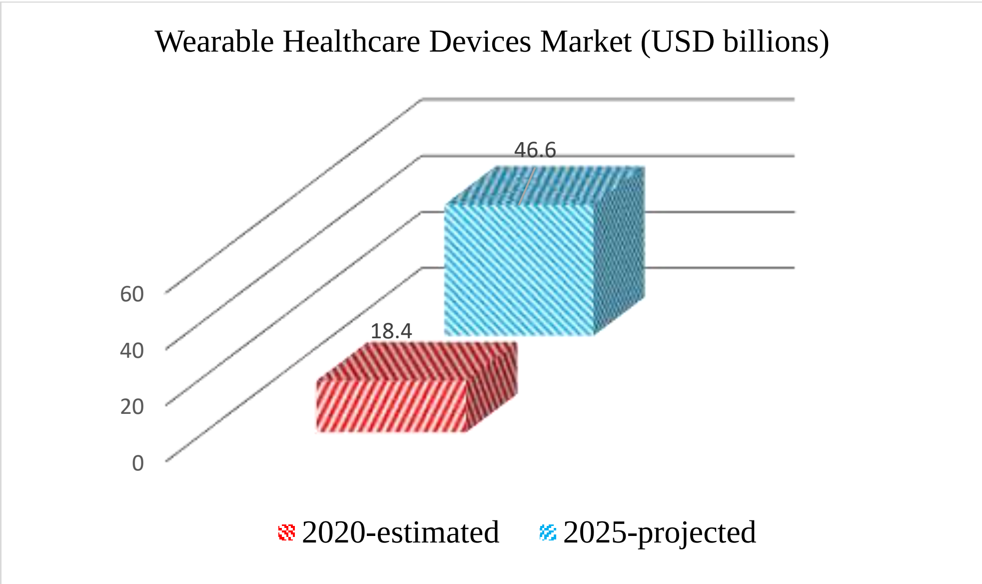

Figure 3. The growth of Global WHD Market

1.2 PPG in telemedicine and remote health care

Photoplethysmography is an inexpensive and non-invasive optical technique that measures the variations in the volume of blood flow within the blood vessels [5]. The hemodynamic changes in the microvascular bed of tissue beneath the skin, associated with each heartbeat can be detected by collecting pulse signal from the body extremities, normally the fingertips, wrist, toe-tips or earlobes [5, 6].The variations in the intensity of light transmitted through the tissues due to the blood flow in the arteries can be quantified as a voltage signal called the PPG [7]. The technique makes use of a light-emitting diode and a matching photodiode that operates in the red and/or near-infrared region attached to peripheral body sites [8]. They capture the light intensity and gather the vital data from the microvascular system underneath the skin. PPG is generally used in several applications ,for example, observing cardiovascular functions, assessing variations in heart rate (HR), estimating the respiratory rate (RR), BP, oxygen saturation levels in the blood, monitoring cardiac output, biometric recognition etc.[9]. The PPG also finds applications in several clinical physiological monitoring including vascular assessment and venous assessment [5]. The major benefit of using optical sensors for medical applications is its inherent safety as the patient has no electrical contact with the equipment and its low susceptibility to electromagnetic interference [7].

As biomedical signals are greatly subjective, the symptoms occur randomly. The presence of cardiac abnormalities is normally reflected in ECG, PPG, and HR. Nevertheless, as per the basic nature of bio-signals, this reflection appears at random time. Hence, the analysis of PPG and variations in heart rate need to be conducted for a long time, may be for 24 hours. Obviously, enormous amount of the data needs to be managed. Consequently, a method to lessen the data storage requirement is necessary while preserving the significant characteristics in the reconstructed signal and this is the exact objective of various prevailing PPG signal compression techniques[10].

Researchers use computerized measurement techniques for analyzing the PPG signals to evaluate vital clinical characteristics such as BP, HR, RR etc. Pulse oximetry, a vital parameter monitored in intensive care units and during surgery makes use of the PPG principle. Advanced compact portable devices and pulse oximetry are nowadays used in PPG acquisition due to its expediency and capability to take continuous readings. A long-time and continuous monitoring allows clinicians to remotely monitor cardiovascular system and administer timely treatment in case of emergencies [11]. Such monitoring presents major advantages such as constant patient observation, increased patient mobility and reduction in healthcare costs [12] .

1.2.1 PPG Signal Characteristics

The PPG signal encompasses a pulsatile alternating current (ac) component overlaid on a gradually varying direct component (dc) with ultra-low frequency components. The ac component relates to cardiac synchronal alterations in the blood volume with every heartbeat whereas the dc component is associated with breathing, neural activities, and regulation of body temperature [5, 13].The ac component has two phases, a rising part known as the anacrotic phase, and a falling part known as the catacrotic phase and wave reflections from the periphery, as shown in Figure 4.

The anacrotic phase indicates systole (ventricular contraction) and catacrotic phase indicates diastole (ventricular relaxation). A dicrotic notch is usually visible in the catacrotic phase, that corresponds to the transient rise in aortic pressure on aortic valve closure. Figure 4 depicts other features of the PPG waveform also such as systolic time t_s , diastolic time t_d, pulse amplitude P_h and the pulse width t_w. The interval between the consecutive systolic peaks has been utilized to analyze heart rhythm and detect variations in heart rate [8] .

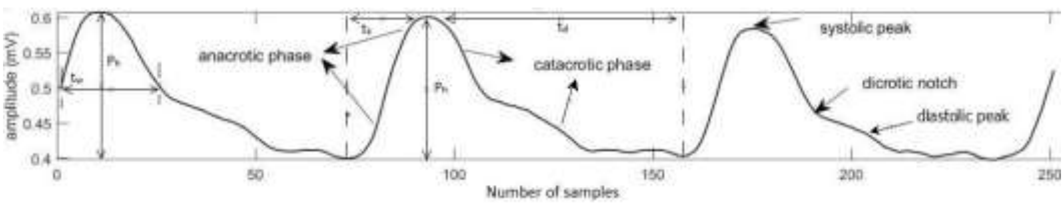

Figure 4. PPG Signal Characteristics

1.2.2 Significance of PPG as a diagnostic tool

Electrocardiogram (ECG) and PPG are the prime biomedical signals generally used for the analysis of cardiovascular functions [8, 14] . Conventional ECG based methods require connection of several electrodes to the human body for recording heart's electrical activities, whereas PPG based acquisition techniques have gained popularity as a simple, inexpensive and reliable method for monitoring the heart related functions [15]. Because of the simple and reliable acquisition process, PPG signal has been distinguished as a powerful diagnostic tool for assessing variations in HR and pulse rate during recent years [16] . Utilizing frequency analysis techniques such as Fourier transform, the power spectral density, and an adaptive notch filter, the HR can be computed from the PPG. As the respiratory component is not evidently seen in the PPG, several signal processing methods have been designed to compute RR from the PPG [17].

Multibody site PPG measurement is required in the diagnosis of vascular diseases, studies of ambulatory sleep, detection of sleep disorders, etc. [18]. The variation in the symmetry of the PPG signals acquired bilaterally from the lower extremities is used for the detection of arterial disease [8].The asymmetries such as reduction in peak amplitude, rise time etc. of the PPG waveforms can be analyzed for diagnosing cardiovascular diseases.

1.2.3 Technologies associated with PPG Signal Transmission

Wireless communication of medical data using wearable health devices requires efficient compression techniques due to the restricted channel capacity bandwidth and data transfer rate. Miniaturization of sensors and manufacture of small and compact radio frequency modules have facilitated the wireless acquisition of vital biomedical signals. Wireless technologies such as Zigbee, Wi-Fi, and Bluetooth are generally used for the acquisition and transmission of PPG signals [11]. Various mobile technologies such as GSM, 3G, 4G and 5G are also used for long distance transmission. New medical diagnostic tools have been developed utilizing the latest technologies, namely IoT, Internet of Medical Things (IoMT), artificial intelligence, genetic algorithms, biosensors etc., that led to customized advancements in e-health and healthcare. PPG associated with these tools exhibit excellent diagnostic capabilities [18].

With the technological advancements in the IoT devices, including wearable health devices, and with the bandwidth restrictions disappearing due to 5G communications becoming more pervasive, the need for compression may change. However, these advancements may take time to be available globally. The requirements of the monitoring devices may be explored to cater to the emerging trends.

1.2.4 PPG Signal Corruption and Denoising

The PPG is invariably corrupted by noise and motion artifacts (MA), regardless of its mode of acquisition, whether it is reflectance or transmittance [19]. As the PPG signals are susceptible to power line interferences and motion artifacts, specialized filtering of the data and pre- processing is mandatory for the reliable extraction of the clinical attributes. Various techniques have been experimented in denoising PPG signals using additional sensors and designing complex algorithms to enhance the PPG signal quality [19].

While PPG denoising using filters, the systolic and diastolic waves should be noticeable in the filtered output. In [20], the optimum filter and order of the filter, used for signal processing of PPG is found out using the skewness quality index. Study results indicate that the 4th order Chebyshev II filter can enhance the quality of the PPG signal more efficiently than other filter types [20].

1.2.5 PPG Signal acquisition and monitoring

Generally, a wireless PPG sensing system mainly consists of three units namely, a data acquisition unit, a processor and wireless transceiver, as shown in Figure 5 [21]. The analogue front-end unit called the data acquisition module is liable for the amplification of the weak signals obtained from the sensors, noise filtering and for converting the analogue signals to digital. A dedicated, embedded processor handles the signal processing functions such as removal of noise from the signal, signal compression, extraction of clinical data and data encryption techniques required for the PPG application. After preprocessing, the wireless transceiver transmits the sensed signals continuously to a remote medical server for clinical evaluation and hence it suffers from high power consumption.

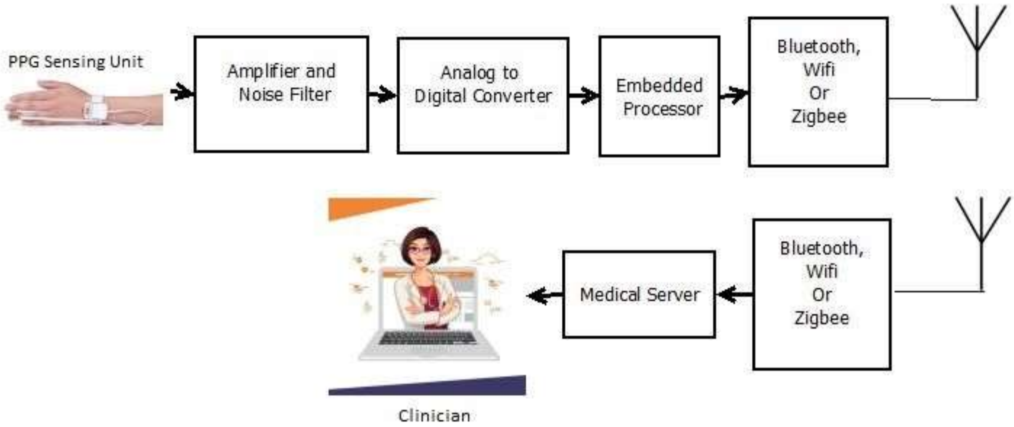

Figure 5. A PPG acquisition and monitoring system

It requires approximately 415 KB of memory to store PPG data sampled at 500Hz rate of 1-minute duration with 16-bit resolution. Due to the subjective nature of PPG signals, real time monitoring needs to be done for prolonged periods of time. As a huge volume of PPG data needs to be retained in the memory for further clinical observation, storage cost also is a matter of concern. The reduction of file size permits more information to be stored in the available storage space with less transmission time. As the PPG sensor passes light on to the skin surface and then gauges the intensity of light coming back, its power consumption and hence battery life is dependent on the sampling rate. For prolonged battery life, e-health care systems with PPG sensor should use reduced sampling rate [17].

The advancements in cloud/edge computing, the bandwidth restriction disappearing with latest communication technologies such as 5G, and the enhancements in battery life of the WHD, may in future, lead to changes on where the acquired data can be processed.

1.3 Problem Statement

When continuous, real-time, long term monitoring of PPG signal is required, especially for telemedicine, remote healthcare monitoring services etc., enormous volume of data is generated. The huge volume of data makes the storage, processing, and communication of the data impractical. Hence data need to be effectively compressed for convenient storage, and further transmission to meet the bandwidth requirements. Reducing the data size using compression methods can reduce the transmission power and hence can extend the lifetime of wireless PPG monitoring system, provided the power expended in compression process must be less than the power saved due to compression. The limited memory size and constrained battery lifetime in WHD also necessitate a reduction in data size. Moreover, reduced data size cut down the bandwidth required to transfer the data.

Compression of PPG signals may distort them. As these biomedical signals comprise clinical data required for the diagnosis of ailments and warnings of critical conditions, any means of distortion may result in the wrong diagnosis that may prove fatal. Nevertheless, for quick and effective communication of huge volumes of medical data, a small amount of distortion is acceptable. Hence designing PPG data compression technique with tolerable distortion levels is a great task.

The compression technique chosen should be able to provide sufficient compression, as well as it should be able to preserve the clinical characteristics of the PPG signal upon reconstruction. Some medical applications require high data compression and permits tolerable distortion in return whereas certain other applications require to retain the clinical attributes of the signal on decompression.

1.4 Thesis Objective

For early detection, diagnosis, and monitoring of CVDs through tele-monitoring, large volume of PPG data is required to be transmitted to clinicians and hence, an efficient compression technique is a mandate. Although considerable research has been conducted on biomedical signal compression, the compression of PPG signals is mostly unexplored as of now. Selecting an appropriate PPG compression method for the requirements of a specific application poses a great challenge from the implementation perspective. The thesis addresses this problem.

The thesis objective can be summarized as follows: -

1. Study of different compression techniques used for efficient and reliable communication of the PPG signals.
2. A review and comparative analysis of the various existing PPG compression techniques, their implementations, advantages, and disadvantages.
3. The thesis proposes three efficient compression techniques, two lossy and a lossless compression technique is experimented.
    - The first technique is a lossy technique based on a combination of Single value Decomposition and lossless compression for effective and reliable compression of PPG Signals.
    - The second technique is a lossless compression technique based on some efficient grouping techniques.
    - The third technique is a very efficient, quality guaranteed lossy

compression technique based on the fusion of the proposed lossless compression technique with the SVD method.

1.5 Thesis Outline

The layout of the thesis is as follows. Chapter 2 discusses the types of PPG compression techniques, lossless and lossy, and the different performance metrices used for assessing the quality of compression. Chapter 3 deals with the literature review, and the implementations and analysis of some of the existing PPG compression techniques. Chapter 4 explains the implementation and the results of the lossy SVD-LAC PPG Compression technique. Chapter 5 explains the algorithm and the results of the proposed lossless PPG compression technique called IEGLC. The chapter also discusses the algorithm and performance results of a third technique formed by the fusion of SVD and the proposed lossless technique. The performance comparison of the proposed techniques with the existing PPG compression techniques is also included in this chapter. Chapter 6 concludes with the findings of the thesis and recommends some future work.

CHAPTER 2: STUDY OF BASIC COMPRESSION TECHNIQUES

2.1 Significance of Compression

Compression technique plays a significant part in prognosis, diagnosis, and analysis of various heart as well as respiratory diseases. The important considerations for selecting the right PPG compression technique are storage requirements, computational complexity of the algorithm, power consumption and communication link utilization. Generally, data can be compacted by removing redundant data. The benefits of compression include reducing the data size, storage requirement and storage costs as well as reducing the power and time requires to transmit and receive the data. The original data can be transformed to its compressed form by identifying and utilizing the patterns existing in the data.

Biomedical signal compression techniques are employed to save the memory size without losing the clinically important information, by eliminating the irrelevant data in the signal at a permissible rate. The efficiency of the compression methods relates to the fact that the algorithm used should be good enough to preserve the clinical data for analysis upon reconstruction. The authors in [22] indicate that the acceptable distortion level for the most common clinical applications is less than 10%.

Among the several methods that have been developed over decades for biomedical signal compression, Discrete Cosine Transformation (DCT), Discrete Wavelet Transformation (DWT), Fast Fourier Transformation (FFT), and Compressive Sensing (CS) are the popular methods [5, 23].

2.2 Types of Compression

Lossy and lossless type of compression techniques are used for biomedical signal compression. Existing signal compression methods for biomedical signals can be broadly classified as follows:

2.2.1 Lossless Compression

Lossless compression lessens the data volume without any information loss. The original data can be fully recovered after uncompressing the file. The compressed file produced in a lossless type will be larger in size when compared to lossy type. The reconstructed signal is identical to original signal in lossless compression [24]. In certain applications, such as medical imaging, text, military imagery, satellite imaging, law forensics etc., loss of information is not acceptable.

There is another technique called near lossless compression method that provides quantifiable guarantees about the type and amount of distortion introduced. It enables compression of videos, hyper spectral images, medical image etc. It is mainly used in medical imaging applications and for compression where the difference between the original signal and decompressed signal can be varied from the respective values in the original data by not greater than a user-defined amount known as maximum absolute distortion (MAD) [24].

2.2.2 Lossy Compression

In late 1980s, the lossy compression was first introduced [22]. In lossy compression, the file size can be permanently reduced by eliminating the redundant or irrelevant data. Such techniques are preferred in applications, where the reconstructed signal need not be precisely identical to the original signal, but an approximation of original signal is also admissible. The compression ratio (CR) for lossy compression techniques are higher in return for accepting the distortion in the reconstructed signal. Lossy compression makes use of the limitation of the perception of human ears or eyes. Likewise, in signal compression, lossy compression eliminates the redundant data from the signal segments and various channels.

Generally, such compression algorithm encompasses three processes, namely, transformation, quantization and encoding [24]. A good transform coding method removes the redundant or unwanted signal and represent the original signal in frequency domain using fewer number of coefficients. The selected coefficients undergo quantization process and are then encoded using specific methods to obtain the compressed output bit stream. The reverse process occurs during decompression, at the decoder end. The DCT and the DWT are some of the transform coding techniques [25]. Quantization is a lossy technique used to reduce a range of values to a discrete value. The DCT, the DWT, and vector quantization are the most widely used quantization methods. The final step could be executed using arithmetic encoder, Set Partitioning in Hierarchical Trees (SPIHT) or predictive coding [22].

2.3 Taxonomy of Data Compression Techniques

The existing data compression techniques may be broadly categorized into three, namely, transformation domain methods, direct data compression methods, and parameter extraction methods [15]. When employed in biomedical signal compression, direct data compression methods have more efficacy than the other techniques. This method reduces the redundancy in the data series by analyzing the neighboring samples, eg:- Delta Modulation [26] .

2.3.1 Transformation domain methods

These methods transform the signal into a suitable transform domain and send only chosen coefficients in lieu of the original data sequence. The compression performance dependent on the number of transform coefficients chosen and the representation accuracy rely on how many and which all coefficients are preserved. Transform based methods take advantage of transformations such as the DCT, the DWT, and the FFT [27]. Although these schemes have high compression capabilities, the computational burden is high for wearable devices. These methods are inherently lossy.

2.3.2 Direct Data processing methods

In this compression method, a few of the original signal samples are rejected and then linear approximation is applied to compact the data. AZTEC (Amplitude Zone Time Epoch Coding) used for real-time ECG monitoring works on this concept, whereas in LTC, the approximation of the original time sequence is done through piecewise line segments. The two endpoints of the segments are transmitted instead of the in-between points [28]. Although these methods use lightweight algorithms, their compression and reconstruction capabilities are poor when compared to transform based methods, which have high computational complexity and high memory requirements.

2.3.3 Parameter extraction methods

The rationale is to process and acquire some knowledge from the temporal series and then predict the signal morphology utilizing this knowledge. The algorithms exhibit good performance to extract the signal features. These parameter extraction methods utilize Neural networks, Compressed Sensing, Vector Quantization and Pattern Matching. Denoising encoders are also found to be used as universal approximators of biomedical signals [29].

2.4 Basic Signal Compression Techniques

The conventional method to compress a signal involves the following process:

- Sampling the signal at the Nyquist rate
- Compressing the sampled signal by employing techniques such as the DWT, DCT etc.
- Preserving and quantizing the relevant coefficients and rejecting the unnecessary ones.
- Transmission of the compressed signal following which it is decompressed.

Signal Compression techniques works on two different paradigms. Some use the correlation between subsequent patterns known as segments, while other methods take advantage of the correlation within the same segment. The first method is known as the inter-segment correlation, and the latter is termed as intra-segment correlation.

Vector quantization, online dictionary, and autoencoders are the techniques that belong to the inter-segment class, while those based on principal component analysis (PCA), LTC, DCT and DWT take advantage of intra-segment correlation properties. Figure 6 depicts the categorization of data compression techniques based on different criteria [24].

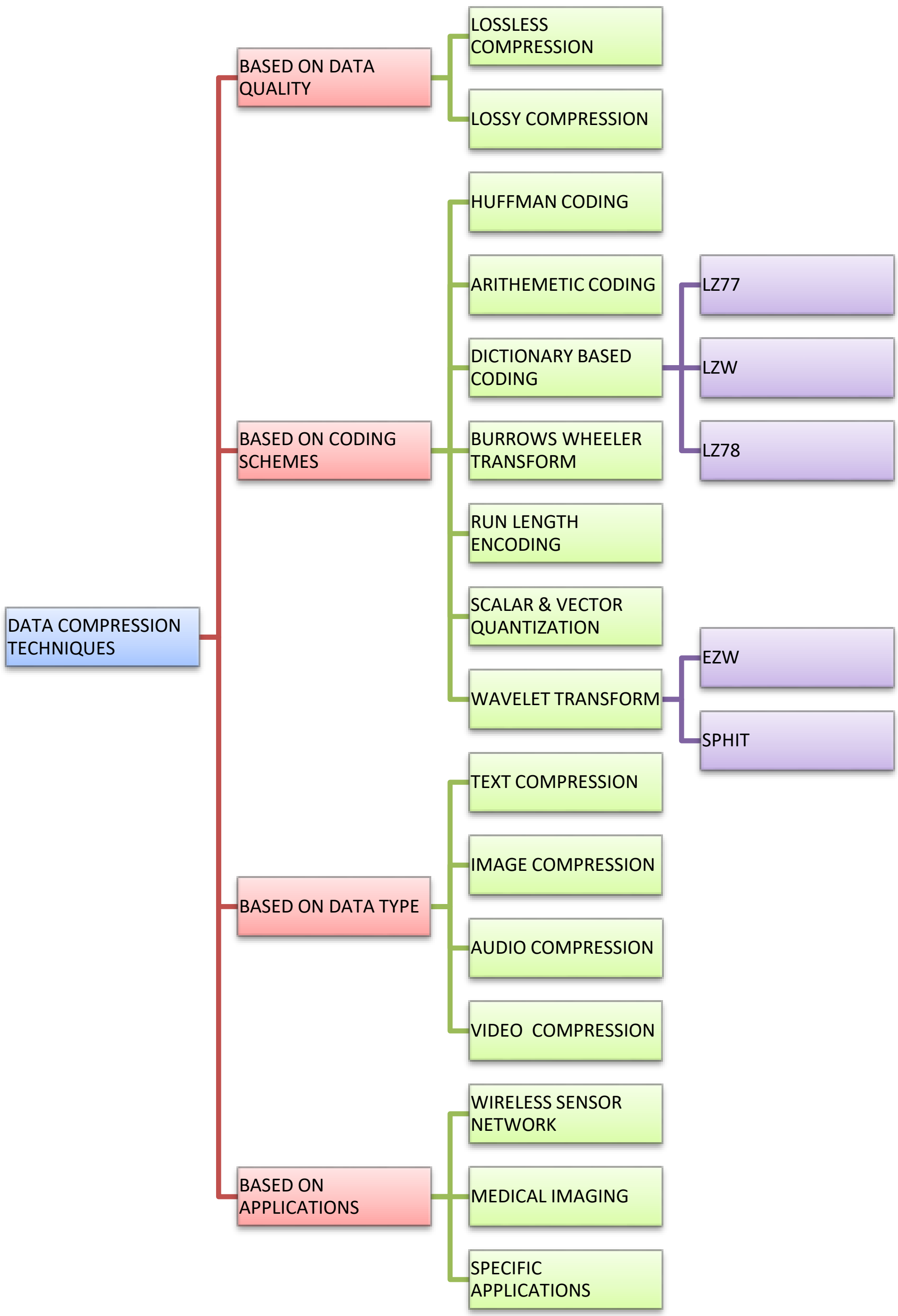

Figure 6. Classification of Data Compression Techniques

2.4.1 Discrete Fourier Transform

In digital signal processing, DFT is a powerful tool that can be utilized to trace the spectrum of a finite-duration signal. An analog continuous-time signal which may extend to positive infinity can be represented as a finite duration sequence. A time periodic signal can be considered as several harmonically related sine and cosine waves. The DFT can be used to represent a discrete sequence into its equivalent frequency domain representation. The FFT is the algorithm for computing the DFT. The FFT decreases the computational complexity required for N points from $2N^2$ to $2N \log_2 N$.

2.4.2 Discrete Cosine Transform

This method transforms a signal into its fundamental frequency components. It represents a series of finitely numerous data points as a sum of cosine functions that oscillates at various frequencies. The DCT is commonly utilized for the compression of data, especially for image compression. It gives near optimal performance for signals having high correlations within adjacent samples. It is effective in concentrating more energy to lower order coefficients than higher order coefficients.

Decomposition of signals based on DCT algorithm is a four-step process [30] .

- The signal is divided into N sub-blocks.
- DCT is computed for each block.
- The DCT coefficients undergo Thresholding and Quantization.
- The quantized DCT coefficients are encoded.

2.4.2.1 Classification of DCT

Depending on the adopted coefficient selection approach, DCT can be classified as follows:

DCT Cardinality Thresholding: In the approach, the number of coefficients to be preserved is given as input, and the coefficients are selected beginning from the lowest frequencies. Fine tuning of CR can be done using this strategy, but the error on reconstruction at the decompressor cannot be guaranteed.

DCT Energy Thresholding: In this process, the selection of coefficients is done in such a way that an energy threshold constraint is met. The coefficients that possess a fixed fraction (E_{th}), of the entire DCT spectrum energy (E), are retained. The coefficients are chosen in the ascending order of frequencies, utilizing the energy compaction property of the DCT. Hence encoding of the frequency position of the coefficients is not necessary.

2.4.3 Discrete Wavelet Transformation

DWT is applied for filtering and compressing biomedical signals. In DWT, only a subset of the transform coefficients is transmitted as majority of the signal information is contained in very few transform coefficients. The DWT algorithm selects the coefficients of signals with a considerable energy and reject the others that have a very small fraction of the total energy. This method analyzes a signal in both the domains, i.e. time and frequency. Figure 7 depicts the multiresolution decomposition of a signal into 'n' levels in different frequency bands using DWT [30]. The input signal is first decomposed into approximation coefficients that constitutes the low frequency band of processing signal and detailed coefficients that constitutes the high frequency band of processing signal. Each level further splits the signal into approximation coefficients and detail coefficients and the process repeats *n* times. The energy of different frequencies and time position corresponds to a particular coefficient in every level of decomposition [31]. DWT provides high CR with low loss of signal, but it has high computational burden, exhausts memory, and expends considerable energy [32].

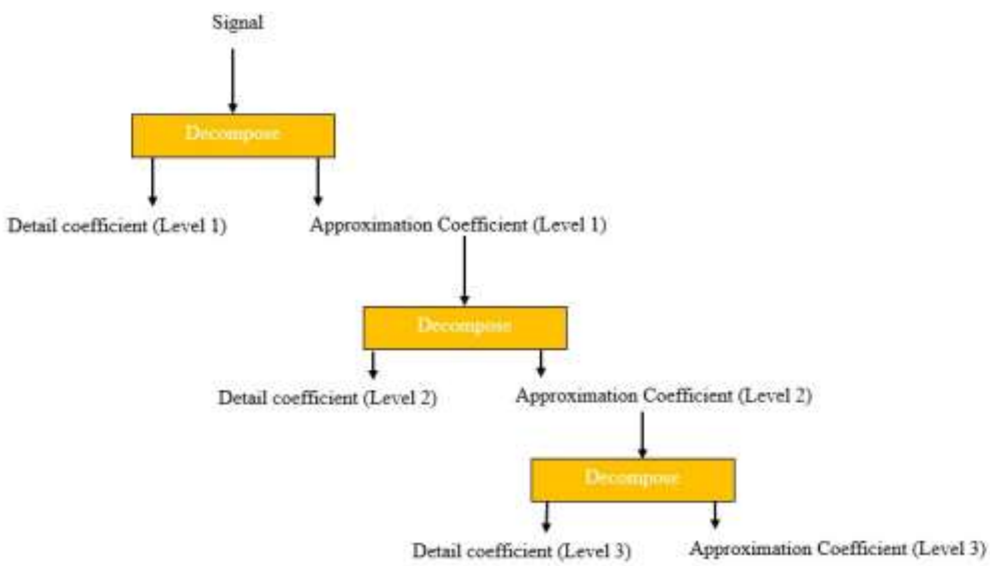

Figure 7. Multilevel Decomposition of a signal using DWT

2.4.3.1 Classic DWT Technique

In 1994, Donoho & Johnstone put forth the classic DWT technique that includes three main steps:

1. Signal decomposition

2. Identifying the coefficients with low energy and discarding it. (thresholding)
3. Reconstructing the new coefficients.

2.4.3.2 Classification of DWT

The strategy for selecting the significant coefficients for signal reconstruction is the main differentiator among the prevailing techniques. The main selection approaches are

- DWT-Level Thresholding: The rationale is to discard all the coefficients coming under a particular threshold. It is generally used for denoising. Normally, each level of decomposition has a specific threshold.
- DWT-Energy Thresholding: The method is analogous to DCT-Energy Thresholding.
- DWT-Cardinality Thresholding: The approach is like DCT-Cardinality Thresholding as it retains only a predetermined number of coefficients and rejects the ones with the lowest absolute values. Although the approach permits fine tuning the CR in DCT, it is hard to accurately control the resultant reconstruction quality in DWT.

2.4.4 Compressive Sensing

The main concept behind Compressive Sensing is to directly capture data in a compressed form. The CS method takes benefit of the sparseness of the signal in a specific domain to reconstruct the signal with significantly lesser number of samples. As per Nyquist sampling theorem, when a signal is sampled, the rate of sampling should be greater than the Nyquist Rate , which is double the signal bandwidth [12]. Normally, this method works with lesser number of samples than Nyquist rate. The CS also takes advantage of the incoherence principle i.e. measurement matrix used for signal acquisition must be incoherent with the dictionary which sparsely characterizes the signal. Incoherence extends the duality between time and frequency and communicates that objects that have a sparse representation must be spread out in the domain in which they are acquired. Generally, data consist mostly of relatively small numbers, rather than being mostly zeroes. Smaller coefficients can be zeroed out and the large ones can be used to get a compressed or de-noised version of the data.

In compressive sensing also called compressed sensing, a given signal, ‘z’ is k-sparse in the standard basis, implies that it has maximum ‘k’ non-zero coordinates. For a signal of sparsity level ‘k’ and length ‘n’, let A be an m × n matrix with $m = \Theta(k \log \frac{n}{k})$ rows, with each of its mn entries, independently selected from the standard Gaussian distribution. With high probability over the selection of A, each k-sparse signal ‘z’ can be effectively retrieved from b = Az [33].

The compressive sensing method can be mathematically explained as follows: The objective is to design a small number of linear measurements in a manner that their results enable the unique and effective reconstruction of an unknown sparse signal.

- Design ‘m’ linear measurements $a_1, \ldots, a_m \in \mathbb{R}_n$
- Consider an unknown signal, say, an n-vector $z \in \mathbb{R}_n$
- Get the measurement results $b_1 = (a_1, z_i)$, $b_2 = (a_2, z_i)$, . . . $b_m = (a_m, z_i)$.
- From the m-vector b, restore the n-vector z.

From the available ‘m’ samples of data, ‘n’ data samples of the original signal, can be reconstructed on solving a convex optimization problem, by finding the minimum L1-norm solution. Other methods such as subspace pursuit, NESTA etc. can also be used for signal recovery[28].

The CS is suitable to WHD, mobile, or low power devices since it lessens the data volume as well as the resources needed in the microcontroller and the Analog-to-Digital Converter (ADC). It also offers power reduction during signal acquisition, compression process and the wireless transmission. Nevertheless, there is a trade-off, as the computational needs of CS reconstruction and power consumption is considerably higher comparative to other compression methods [12].

2.4.5 Online Dictionary/Codebook based compression

This is a lightweight procedure based on the idea of motif extraction. The technique works for biometric signals such as PPG, ECG, respiratory signals etc., that exhibits recurring patterns. The principle is to identify recurring patterns and a runtime codebook is built based on the most representative among them. For every single input pattern, the related index in the codebook is sent instead of the initial data series. To enable faithful signal reconstruction, the codebook must be in synchronization with the decompressor. Figure 8 explains the whole compression processes.

2.4.5.1 Processes involved in Codebook based Compression

The processing functions involved in this method include

- Passband filtering: The process removes high frequency noise, artifacts, and the DC component

- Peak detector: It identifies the peaks of the signal.
- Frame extractor: The data samples between successive peaks is extracted as segments and these form the input segments to the compressor algorithm. The codebook is then constructed using machine learning algorithms.
- Pattern Matching: It checks whether the current input segment matches with any of the codewords in the codebook, that is created and updated at runtime. A matching criterion called Dynamic Time Warping (DTW), is widely used for comparing patterns of varying length. It can be executed in linear time.
- Codebook manager: It has two major tasks.
    - A well representative and updated codebook must be maintained
    - Input patterns must be encoded to the related indices from the codebook.

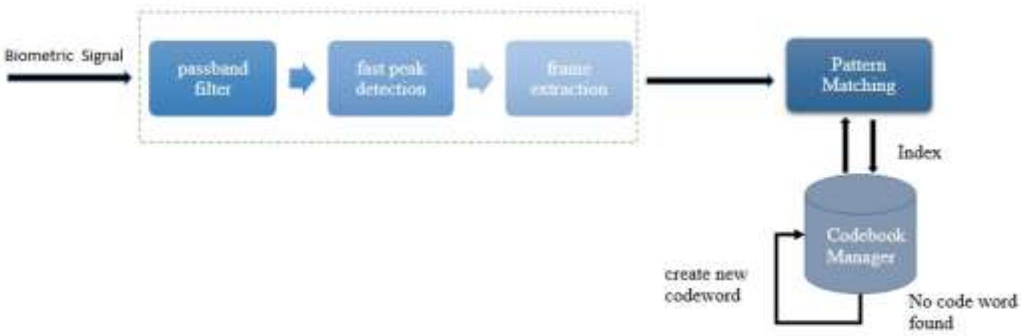

Figure 8 Codebook-based compression algorithm

This method is somewhat based on vector quantization. Consider z_t denotes a segment obtained from the frame extraction unit, at the generic time t = 0, 1, 2, … assuming discrete time, relating to the new segment arrival. Let the codebook at time t, be $C_t = \{c_1, , , , c_N\}$ and the codewords be c_i, i = 1, , ,N. The segment z_t of length 'W' is remapped into another segment x_t of the same size. For i = 1, , , N, size(c_i) = size(x_t) = W. The new segment, x_t is got through linear resampling and eliminating offset o_t and gain g_t from z_t. For all codewords c_i in the codebook, an appropriate distance function d (x_t ,c_i) is calculated. Then the codeword c_i, with index i*, that has the least distance, is selected. Then, if the distance function <= ε, then the codeword c_i* is considered as the best representative of the current segment z_t, else x_t is included as a new codeword in the codebook, with i* as the related index. The parameter 'ε' can be used to control the fidelity of signal reconstruction during decompression. Finally, instead of sending the entire segment, the index i* is sent along with the original segment length, l_t , o_t and g_t . If a match for z_t is obtained from the codebook, as per the criteria, the associated index is sent, along with l_t, , o_t and g_t. Thus, the entire signal is processed to get a compressed bitstream. The decompressor reconstructs the initial time sequence from this bitstream, using the reverse process.

The decompressor specifically applies some transforms to codeword i* from the codebook:

- Renormalizes it with respect to offset and gain
- Resamples as per the original segment length l_t.

If z_t has no match in the codebook, then it is included as a new codeword in the codebook. Then, its normalized form along with the related index are sent to the decoder to keep the dictionaries at the compressor and the decompressor always in synchronization. ‘ε’ influences the codebook size and hence, the required memory. If the codebook exceeds the permissible memory space, implementation of codeword removal from it can be done according to last used timestamps.

2.4.6 Gain Shape Vector Quantization

The technique takes advantage of the redundancy of information among neighboring samples. Figure 9 shows the processes involved in GSVQ compression. The signal is divided into segments and the period is normalized to a fixed length and amplitude. Then using this normalized data, a codebook, that has a fixed number of codewords K, is built. GSVQ creates the codebook or dictionary via an offline training phase. The codebook is created from previously collected datasets and a stream of residuals is sent to recompense for the changes in the signal statistics at runtime. A GSVQ compression system has two parts an encoder and a decoder. After dictionary formation, the technique relates every normalized data to the closest codeword, transmits the index of the codeword in lieu of the original time sequence. The offset, the gain, and the length of the original segment is also encoded. In the final step, the encoder computes the difference between the current data and the codeword chosen, and utilizes the AREA algorithm, an adaptive sampling method for single dimensional signals that acquires added information, to enhance the reconstruction quality. The residual encoding phase encodes and transmit a smaller number of significant coefficients to limit the error on reconstruction. On receival of an encoded packet, the decoder, regains the associated codeword from its local dictionary copy, does a denormalization using the gain, the offset, and the length, and add up the remaining stream to the regenerated signal. The performance of GSVQ is mostly dependent on its residual encoding phase as the threshold used for residual encoding is mainly responsible for the transmitted data volume.

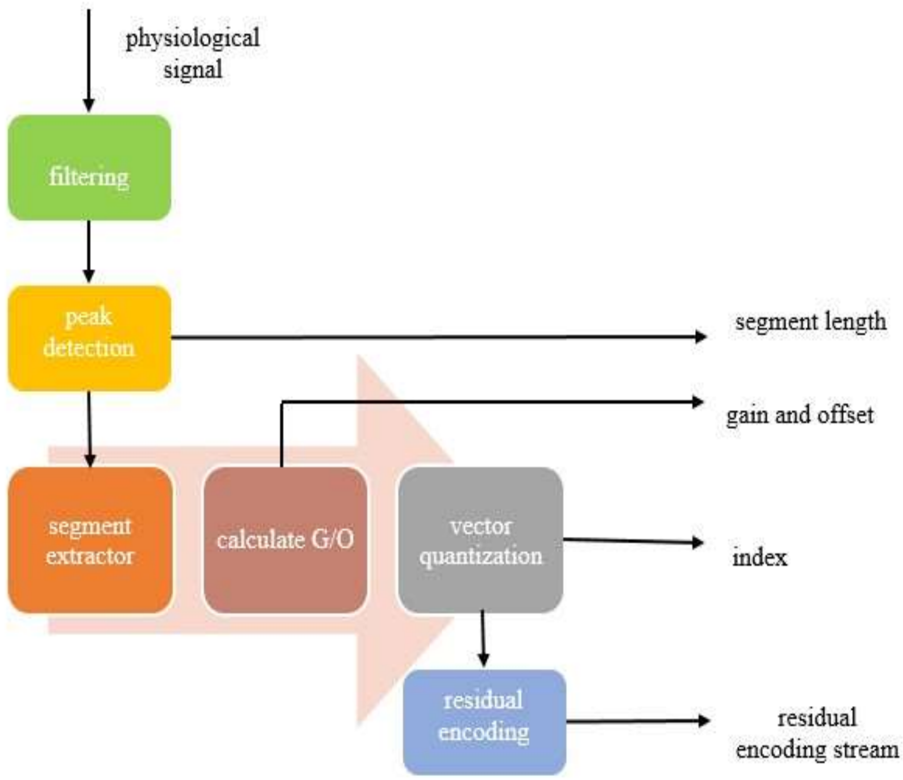

Figure 9. Illustration of the GSVQ compression method

2.4.7 Lightweight Temporal Compression

It is a simple and fast technique that requires very little storage. It is based on method based on linear approximation. Data can be sampled at high rate with this compression scheme. Let x[i], i = 0, 1, 2, . . . be the original time sequence. First, x[0] is selected as the left endpoint of the current approximating segment. The resulting points x[i], with i > 0 are converted into vertical intervals x[i]- ε, x[i]+ ε], ε > 0 . Here, ε is an error margin on the regenerated signal. On considering point i > 1, LTC takes the segment with boundaries (x[0], x[i]) and examines if this segment is within any of the previously obtained vertical intervals between x[1], x[2], ,x[i -1]. In that case, the algorithm takes the vertical interval for the current point 'i' and does the check for (i + 1). Or else, the procedure stops, considering x [i -1] as the right endpoint of the present segment. Then, along with the segment length 'í', x[0] and x[i -1] are sent as the left and right endpoints of the current segment as an approximation to values {x[0],x[1], , , , x[i-2], x[i-1]}.The process repeats by taking another approximating segment, and using x[i -1] as the left endpoint. In LTC, the maximum error margin (ε) between an original and reconstructed data point can be arbitrarily set. ε works as a regulator to fine-tune the tradeoff between compressed data size and accuracy. [34].

2.4.8 Principal component Analysis

It is a statistical technique that aims to compact the data presented by a huge set of mutually related variables into a few variables with lower dimensionality called principal components. Every principal component is calculated as a linear combination of the initial variables, and the combination weights are selected such that the components are not correlated mutually. The method proved successful in a lot of applications, that include PPG and ECG etc. In PCA, there is no previous information of the basis in which the signal is sparse. The rationale of the method is to scrutinize the data set and find out the "best" basis for approximately representing it as linear combinations of a small set of k orthonormal vectors. The estimation of the original data points onto the top k principal components can be regarded as a sparse approximation of the original data set, with only k non-zeros per data point in the new basis. Determining the singular value decomposition (SVD) of a matrix, which is a low-rank matrix approximation, that retains only its top k singular vectors and values can also be considered in this manner[28] .

2.4.9 Autoencoders

Autoencoders are neural networks (NN), that can work as universal approximators [35]. The dimension of the input and output layers of the network are the same, say, W. The layers between them are called hidden. The deepest hidden layer has a lower dimension h, where h < W. w_{ij}^1 and w_{ij}^2 denote the autoencoder weights from neuron i to neuron j of the input to the output layer. The information in the original segments, of size W can be compressed to a much smaller space, h neurons, using autoencoders as a non-linear dimensionality reduction technique. Figure 10 shows the graphical representation of an autoencoder

The NN is trained through an unsupervised learning algorithm that utilizes several training examples, $x \in \mathbb{R}^W$ that are fed as the autoencoder input. The backpropagation is accomplished by fixing the output y = x and the NN weights w_{ij}^1 and w_{ij}^2 are corrected for the autoencoder to work as an identity function. Figure 10 graphically represents an autoencoder. After the autoencoder is trained, the weights w_{ij}^1, and w_{ij}^2 fully specify the compressor and the decompressor, respectively. After preprocessing, each segment is fed as autoencoder input and the values of ‘h’ related to the neurons in the compression layer is obtained in return. The ‘h’ values along with the original segment length and are sent to the receiver. Lastly at the receiver, the decompressor utilizes the values of these h inner neurons, along with weights w_{ij}^2, to get back’ y’ through the decoder.

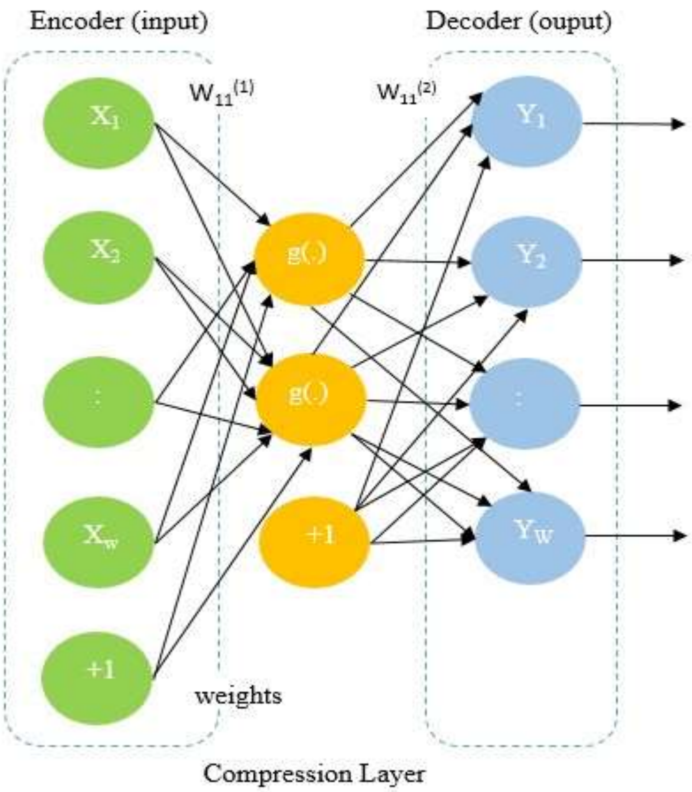

Figure 10. Graphical representation of an autoencoder

The aim of an autoencoder is to learn an efficient coding for a set of data, usually for reducing the dimensionality, by training the network to ignore signal noise. The output of the autoencoders would be more accurate if denoised data is fed to autoencoders. Denoising autoencoders can be used to approximate the input biomedical patterns. Contrary to traditional linear dimensionality reduction methods, for example PCA, neural networks depend on non-linear functions which makes them more attractive.

The thesis implements a very efficient compression technique for compressing the PPG Signals. It is based on a combination of Singular Value Decomposition and lossless compression using some grouping techniques. These techniques will be explained in detail in Chapter 1V. The work also proposes a lossless compression technique based on some extensive grouping techniques. Finally, the proposed lossless technique is combined with SVD to form a reliable and efficient lossy technique.

2.5 Performance Metrices

Various metrices are defined for analyzing the performance of signal compression algorithms. The complexity of the algorithm, the memory used for computation, the computational speed, the volume of compression and the quality and the fidelity of regenerated data are considered for performance evaluation. For better understanding of the metrices, consider a PPG signal compression of N samples, where x[i] is i^{th} sample of the original PPG signal, $\hat{x}[i]$ is the i^{th} sample of the decompressed signal, μ_x and $\mu_{\hat{x}}$ is the mean of the original signal and decompressed signal respectively. Then, the performance metrices can be defined as follows:

Compression ratio (CR)

CR is the most popular metric used to calculate the efficacy of a compression technique and it is calculated as the ratio of total number of bits needed to represent the data prior compression and total number of bits needed to represent the data after compression. A higher CR means algorithm performs better [36].

$$CR = \frac{Uncompressed\ data\ size}{Compressed\ data\ size} \tag{2.1}$$

The CR can also be calculated related to file size. The file CR is computed as the ratio of the uncompressed file size to compressed file size. File CR is also used as a performance metric to evaluate the compression performance by researchers.

Percentage root-mean-squared difference (PRD)

It is a popular metric used to quantify the distortion between two signals [5]. PRD can be viewed as a quality controlling metric of the decompressed signal. It gives a quantitative estimate of the sample to sample squared reconstruction error [8] .

$$PRD = \sqrt{\frac{\sum_{i=1}^{N}(x_i - \widehat{x}_i)^2}{\sum_{i=1}^{N}(x_i)^2}} \times 100 \tag{2.2}$$

To prevent the effect of mean value in computing the rate of distortion , the PRD is calculated by subtracting the mean of the signal from the original signal [36]. The efficiency of the decompressor can be better assessed by analyzing the PRD and PRD normalized (PRDN).

$$PRDN = \sqrt{\frac{\sum_{i=1}^{N}(x_i - \widehat{x}_i)^2}{\sum_{i=1}^{N}(x_i - \mu)^2}} \times 100 \tag{2.3}$$

Root Mean Square Error (RMSE)

It is determined by computing the standard deviation of the differences between original data and the reconstructed data and normalizing it with respect to the peak-to-peak amplitude (App) of the signals [36]. It gives a direct indication of the reconstruction fidelity of the signal [29].

$$RMSE = \frac{100}{A_{pp}} \times \sqrt{\frac{\sum_{i=1}^{N}(x[i] - \widehat{x}[i])^2}{N}} \qquad (2.4)$$

Quality score (QS)

It is a numeric representation of the general performance of a compression technique [37] .

$$QS = \frac{CR}{PRD} \qquad (2.5)$$

The higher values of QS, the better the compression [38].

Cross Correlation (CC)

CC is a metric used to define the similarity between the original and decompressed PPG signal. The range of CC varies between 0 and 1 [36].

$$CC = \frac{\frac{1}{N}\sum_{i=1}^{N}(x[i] - \mu_x)(\widehat{x}[i] - \mu_{\widehat{x}})}{\sqrt{\frac{1}{N}\sum_{i=1}^{N}(x[i] - \mu_x)^2}\sqrt{\frac{1}{N}\sum_{i=1}^{N}(\widehat{x}[i] - \mu_{\widehat{x}})^2}} \qquad (2.6)$$

Signal to Noise ratio (SNR)

The Signal to Noise ratio is calculated as

$$\text{SNR} = 10\log_{10} \frac{\sum x([i]^2}{\sum |x[i] - \hat{x}[i]|^2} \tag{2.7}$$

The performance metrices such as CR, PRD, CC, RMSE and QS were mainly used for the evaluation in this thesis. The CR in PPG signal compression denotes the efficiency of the compression algorithm. It indicates the amount of data reduction possible, and hence can be used to assess the bandwidth and the power required to transmit the data. In PPG Signal compression and regeneration, the PRD can be used as a standard quality controlling metric as it is a measure of the distortion between the original and the regenerated PPG signal. The CC indicates the similarity between the original and the reconstructed PPG signal. The RMSE is an indication of the reconstruction faithfulness of the PPG signal. The QS is a quantitative measure that is used to evaluate the overall performance of a PPG compression algorithm.

On analyzing the above performance metrices, the overall quality and fidelity of the reconstructed signal can be assessed.

CHAPTER 3: LITERATURE REVIEW

3.1 Existing Compression Techniques of PPG Signals

Compression of biomedical signals has two advantages in monitoring vital physiological parameters: low storage requirements and efficient utilization of communication channel bandwidth. Very few techniques have been designed for dealing with the compression of PPG data. Compressive Sensing (CS), DCT, DWT, Lightweight Temporal Compression (LTC) and Gain Shape Vector Quantization (GSVQ) are some of the prevailing methods used by researchers for PPG Compression [35]. While data compression, tradeoffs exists between various factors such as the extent of compression, the level of distortion occurred, and the computational resources needed to compress and reconstruct the data. An efficient algorithm compresses the bio-signals acquired by the smart devices, with high CR and good reconstruction fidelity [29] .

In [39], Malgina et al discusses an amplitude threshold compression (ATC) algorithm that is suitable for compressing real-time bio-signals. In ATC, the amplitude difference between the previous and succeeding neighboring samples is compared with a chosen threshold value. If the difference is larger than the threshold, then the sample is stored, else it is eliminated. The first sample is automatically retained. The compressed signal is constituted by the stored samples. Signals are regenerated using the Cubic spline approximation algorithm.

In [8], Gupta, R. presents a lossless, real-time compression technique for PPG signals using a fusion of second order delta and Huffman encoding (HC) with the objective of creating a compression algorithm of low complexity. The encoding for this algorithm is done using the delta values representing the difference between two successive data samples. Two delta arrays are created and are biased in a way suitable for efficient compression by Huffman coding. The modified arrays are then made to undergo Huffman coding where in, initially the number of occurrences of each distinct element called the Huffman symbol, is computed along with its probability to construct a Huffman tree. Then the Huffman symbols, the number of bits used to denote each symbol along with the Huffman code are compressed. Then compressed Huffman coded bit stream are zero padded and converted into bytes. This encoded data along with header bytes that contain vital information regarding the data within the data packet, are used to form PPG data packets which are then saved into the memory. For decompression, the exact reverse sequence is followed.

Systolic upstroke time, pulse width and systolic amplitude are the three vital clinical features that are used for analyzing the impact of compression on diagnostic quality of the signal. The technique has a CR of 2.223, PRD of 0.127 and PRDN of 0.187. It has a low time complexity that makes it an inexpensive, real-time PPG measurement technique for health monitoring.

Reddy et al, in [21] introduces a unique approach that employs a cycle-by-cycle Fourier Series analysis (CFSA) , to eliminate MA from corrupted PPG signals along with data compression with the aim of reducing the impact of MA on pulse oximeter readings. The acquired data is filtered utilizing the Savitzky–Golay (SG) smoothing filter to eliminate the noise at high frequencies. Using CFSA, the PPG signals are regenerated in a cyclic manner. Results suggest that the technique is insensitive to HR variation and causes only negligible processing error. Moreover, this technique retains all the morphological features of PPG and achieves and overall reduction of 35 dB in MA and a total data compression factor of 12. The error caused while selecting the pulse periods reduces the performance of this technique.

A distinct method of delta modulation for efficient PPG signal compression for use in real-time measurements and monitoring applications was described in [40] . Another method in [26] also uses Delta modulation for achieving higher compression.

A novel approach for reducing power consumption, using an integrated data compression and pulse rate measurement technique, for wireless IOT enabled PPG monitoring devices was presented by Reddy et al, in [36]. The PPG signals are compressed using a combination of differential pulse code modulation (DPCM) and Huffman coding techniques. Once the differential signals are generated, the pulse rate, is extracted from it in a timely manner. IIR Chebychev type-1 filter is used to filter out all the noise. Henceforth DPCM is used to perform compression by correlating the samples with the focus on reconstructing the PPG signal without any slope overload error. Then, Huffman Encoder is used to encode the error signals by assigning code words to the signals based on their frequency of occurrence. The decompression stage consists of a Huffman decoder that receives the binary sequence and produces a quantized error signal, a predictor to reconstruct the signal, and a moving average filter to denoise the data. The method achieves an average CR of 4.76, PRD of 0.19%, SNR of 27.9 dB.

The PPG Compression technique put forth by Sadhukhan D., et al in paper [41] makes use of the inherent signal redundancy in the frequency domain. Besides achieving high CR, the technique is noise robust and adopts simple computation for its adaptation in portable monitoring devices. Depending on the characteristics of each signal, an adaptive estimation of the useful bandwidth required for faithful reconstruction of the signal is chosen, to optimize compression. The significant frequencies of the blocks of PPG data are represented with DFT coefficients. To reduce the Gibbs oscillation effect at the ends of the segment, an overlapping data segmentation method is selected. The calculated DFT coefficients are subjected to adaptive quantization ensuring that most of the coefficient energy is retained. These coefficients are finally encoded utilizing optimum bit allotment scheme to enhance compression.

Elimination of the redundant frequency components makes the scheme noise robust and hence minimal data preprocessing is sufficient. A header that comprises the details about the adaptive bandlimits, the quantization level and the number of bits needed for encoding the coefficients is generated for appropriate decompression. During decompression, the entire coefficient set is recreated by replacing zero in lieu of the insignificant coefficients and the data blocks are reconstructed using the coefficients.

Paper [9] introduces a quality controlled, lossy PPG compression technique that is capable of keeping the global and local distortion of data within pre-specified limits using PCA approach to select the dominant principal components (PC) required for compression. The algorithm normalizes the whole data array to the magnitude from 0 to 1.

The algorithm first detects the foot and systolic peaks from the first derivative of the scaled dataset called the velocity photoplethysmogram which in turn is smoothed using cubic spline interpolation technique. Then a beat matrix which is a multivariate time series data is generated. Eigen value decomposition is done on the covariance matrix of the beat matrix, after which the PC are selected in a recursive manner. The levels of quantization are adjusted till the reconstructed signals attain the desired quality. This is done using a convergence test algorithm with the minimum quantization level for PC as 7 bits. The PC and eigenvectors are quantized using a linear formula. The output of this test is a quantized PC array, quantization level for PCs, quantized eigenvectors array and extrema of the PC and eigenvectors. After this the quantized PC and eigenvectors are encoded in a specific format to form data packets.

The eigenvectors and PC obtained here are compressed in the next stages. If the number of PC selected is greater than 2, the quantized eigen vector matrix is compressed using a differently formatted delta encoder, else they are contained directly in the packet along with the obtained extrema values. The method however obtained lower CR and PRDN with PPG applications corrupted with MA and Gaussian noise but managed to maintain an acceptable quality. This method preserves the fidelity in reconstruction and can be used to construct an embedded system that can act as standalone PPG monitoring application.

Dhar, S., et al. in [37] proposes a lossless, high performing and reliable PPG signal compression and encryption method comprising of several steps. Initially, the signal noise is eliminated using a Butterworth low-pass filter of order 9 with a 25 Hz cut off frequency and then down-sampling is done to eliminate all the high frequency noise. The signal is amplified after truncation to second decimal places and computing the second difference. The algorithm operates on a block of 8 samples each and sign byte is generated for each block. To enable efficient compression, the amplified integers are categorized into different groups using various grouping techniques. The grouped integers are encrypted to cipher text using a symmetric key. The reduced dataset is encoded and stored in the form of American Standard Code for Information Interchange (ASCII) characters in the output file. The reverse algorithm is used to regenerate the PPG signal. The technique is highly efficient and robust and do not depend on complex mathematical transforms. An attractive CR and low PRD indicates the compression efficacy, and the encryption ensures better data security. The algorithm has a limitation that if the amplitude-range is greater than a threshold, say 15 mV, it cannot process the PPG signals in a proper manner.

A PPG compression and tele-monitoring technique based on ASCII character encoding- was put forth by Mukhopadhyay et al. in [42] whose CR is greater than that of the techniques described in [8, 21, 26, 40].But the algorithm has the same amplitude-range limitation as in [37]

Mukhopadhyay et al presents a highly efficient quality guaranteed PPG signal compression technique called StePPGcomp, based on single value decomposition (SVD) and lossless ASCII character coding in [38]. It can be used to reduce steganographed PPG signals as well, that contains patient information also. The PPG signal is preprocessed by denoising it through a zero phase, fourth order Butterworth bandpass filter with cutoff frequencies in the range 0.05 Hz and 25 Hz. The signal is amplitude normalized to maintain it in the range from -1 to 1 and then downsampled so that the sampling frequency does not fall below 100Hz. The systolic peaks are detected to calculate the HR. The beat lengths are extracted and normalized using FFT based interpolation technique. The signal is then subjected to SVD to get the left singular matrix(U), singular value matrix (S) and right singular matrix(V). The singular values in the S matrix is arranged in decreasing order and most of the signal information is contained in the first few rows of the matrix.

Depending on the user defined value of signal distortion, the S matrix is truncated by selecting an optimum number of singular values. Truncation of singular values leads to reduction in the dimensions of the matrices U, S and V, which in turn aids data reduction and better compression. The ASCII values private data of the patient is concatenated with the U matrix and the U matrix is subjected to a lossless compression, which uses a low complexity algorithm The algorithm uses various grouping techniques for data reduction and has high compression performance. The grouping techniques are completely reversible to enable proper separation of coefficients during signal reconstruction. The truncated V matrix undergoes a near lossless compression through quantization process and ASCII character encoding. Finally, a dynamic security key is generated using crucial information and transmitted along with the data. At the other end, the PPG signal is regenerated, and all crucial data is recovered using the reverse of StePPGcomp algorithm. The algorithm exhibits higher values of CR, QS and CC and lower values of PRD and RMSE.

Paper [12] introduces Compressive Sensing, which is a representative method beyond the Nyquist Shannon sampling Theorem. It makes use of the sparseness of the signal in a specific domain to substantially reduce the number of samples required to recreate the original signal. It can faithfully reconstruct the initial signal from a compressed signal sampled at a rate lower than the Nyquist sampling rate. CS can only be applied to a sparse signal or when the signal can be transformed to a sparse signal. Trials reveal that the performance is insufficient when CS is applied to non-sparse bio signals [12].

Paper [43] put forth an approach where cardiac signal identification of an individual is performed using a compressed sensing method where in signals are reconstructed with very few measurements and performs sampling and data compression in a synchronous manner. The method is suitable for portable cardiac acquisition devices. In order to determine the sparse representation that is better in representing cardiac signals, a comparative experimental analysis was done on the effects of the cardiac signals reconstructed using DCT and KSVD when they are combined with a reconstruction procedure such as orthogonal matching pursuit (OMP) and a Gaussian measurement matrix. It is observed that the pulse compression and reconstruction algorithm formed by combining DCT and OMP led to serious distortions while the K-SVD and OMP compression and reconstruction algorithms displayed less distortion and hence was adopted for this approach.

To ensure better stability in reconstruction and higher accuracy, a modification of OMP algorithm, known as stagewise weak orthogonal matching pursuit (SWOMP) was used along with a Gaussian measurement matrix to reconstruct the signals. Since the SWOMP algorithm has some defects and is unstable, an improved version of this algorithm called sparsity weak adaptive matching pursuit (SWAMP) which has relatively more stability and better accuracy is used. The filtered cardiac signals are further denoised using wavelet transform method based on coif3 function. After preprocessing the signals, feature vectors are extracted for identification, which is done using signal derivative method for the PPG signals. The extracted feature vectors undergo a normalization process and then a recognition training is performed. Finally, these vectors are classified using a one-to-one Support Vector Machine (SVM) Classifier. Analysis results indicate that the rate of recognition is almost similar prior and after reconstruction, thus proving the efficacy of this technique.

A Subject-Adaptive coMpression technique for biomedical quasi-periodic signals called SAM was proposed by Vadori et al in [35]. The method utilizes a subject-adaptive dictionary, that is learned and updated at runtime using the time-adaptive self-organizing map (TASOM) unsupervised learning neural networks. The technique also exploits vector quantization (VQ) and motif extraction techniques along with TASOM for real time learning. Quantitative results reveal that the technique can achieve a CR of up to 35 for PPG and hence considered much superior when compared most of the state-of-the-art techniques.

In [28], an online dictionary (OD) based compression method that involves several functions such as passband filtering, peak detection, segment extraction, pattern matching and a codebook manager. The period of the extracted segments is normalized using linear interpolation. The PPG signal compression utilizing autoencoders (AE) is also explored in [28].

Table 1 presents a comparison of the existing works in PPG Compression.

Abbreviations used in Table 1

MR- Memory requirement; NS-Noise Sensitivity; CB-Computational Burden

Table 1. Comparison of existing works of PPG Compression

Authors [Ref.]	SF	CR	PRD	PRDN	MR	NS	CB
R. Gupta et al [8]	125	2.223	0.127	0.187	H	H	H
S. Mukhopadhyay et al [38]	125	30.27	0.22	0.33	M	H	H
K.S. Chong et al [26]	1000	16	0.392	-	L	H	L
Reddy et al [21]	200	12	1.67	-	M	L	H
S. Alam et al [40]	125	3.84	5.82	7.57	H	H	H
Alam, S., Gupta, R., and Bera, J [9]	60	13.5	-	-	-	H	H
Dhar et al [37]	500	122.24	0.02	0.03	M	-	H
Sadhukhan, D, Pal, S. and, Mitra, M [41]	125	35.95	3.88	6.21	L	L	L

3.2 Analysis of Different Compression Techniques

The lossless, low complexity compression process based on Huffman coding of second order delta proposed in [8] is suited for short range, real-time applications. It exhibits poor performance, and the CR is low. The delta modulation technique detailed in [26] to compress PPG signal is advantageous only if the sampling rate of the signal is high. The method offers good CR and a low PRMSE and is appropriate for low data rate and low power wireless protocol. Improper step size selection will change the signal characteristic. Adaptive Delta Modulation (ADM) can solve this issue by varying the step size continuously to adapt to the changes in signal variations. In [11], suitable step size selection enabled the reconstruction incorporating the real time changes of the PPG signal as well as by retaining the signal morphology. The paper [44] details the effect of the step size in DM technique on the PPG signal under different scenarios: with MA and without MA. Although both methods have similar CR values, there is a difference in the quality of reconstructed signals. As the step size becomes smaller, the percentage RMSE increased due to the slope overloading effect. The CSFA data compression method in [21] attenuates MA from the noise corrupted PPG signals. The method can faithfully regenerate the PPG Signal with its main clinical features using the initial seven significant Fourier coefficients. The method reduced the computational error of oxygen level in blood (SpO2) from 37% to 2%. The compression performance is low owing to the error in identifying the pulse periods.

In [37], a reliable, high performing PPG compression and encryption technique that utilizes the grouping techniques is presented. The method provides a high CR of 122.24 and a PRD of 0.02%, which is superior to most of the other techniques. The algorithm is easier to implement on real time systems, has a low computational burden and further, encryption is done to increase the data security.

StePPGcomp algorithm proposed in [38] can also be used for steganographed PPG signals that contains patient's personal data. The highlight of the algorithm is that it can precisely control the clinical quality of the regenerated signal and it has a superior CR when compared to other algorithms. The reconstruction error is independent on the steganographic process and on the size of the patient's personal information. Also, the restored patient's data shows no error. The method in [28] proved very effective, exhibiting excellent approximation capabilities, high compression performance and low computation burden.

The different techniques were analyzed to assess the compression performance, the reconstruction fidelity and clinical importance of the reconstructed signal. The computational burden, memory requirement and noise sensitivity of these techniques were also examined. When power consumption of the device is a concern, the compression technique with low computational burden will be the better option. When effective memory utilization is prime need, the compression method with higher CR will be the best option [15]. Most of these compression techniques mainly aim to maximize the compression ratio and a few techniques attained good CR. Very few methods talk about the clinical acceptability of the regenerated signals, even though it is mentioned that the error is low. Majority of the techniques had no control over the required quality of the regenerated data. More works need to be done in future for introducing quality control in PPG compression algorithms.

3.3 Basis of the proposed Compression Techniques

The lossy SVD-LAC compression technique proposed in the thesis will be a variation of the compression method proposed in [38].The lossless compression technique based on iterative extensive grouping introduced by this thesis will be an enhancement on the Grouping methods employed in the compression methods used in [37] .

CHAPTER 4: IMPLEMENTATION OF THE PROPOSED SVD_LAC TECHNIQUE

4.1 Singular Value Decomposition and Lossless ASCII character encoding-based Compression

The proposed lossy compression technique is based on a combination of Singular Value Decomposition and lossless ASCII character encoding-based quality guaranteed PPG compression (SVD-LAC). The lossless compression is done using some grouping techniques.

The algorithm of SVD-LAC technique consists of six steps.

1. Preprocessing
2. Singular Value Decomposition of the preprocessed signal
3. Truncation of Singular Values
4. Estimating the optimal number of Singular Values
5. Lossless Compression of the truncated Left Singular Matrix
6. Near Lossless Compression of the truncated Right Singular Matrix

Figure 11 demonstrates the schematic of the proposed SVD-LAC technique.

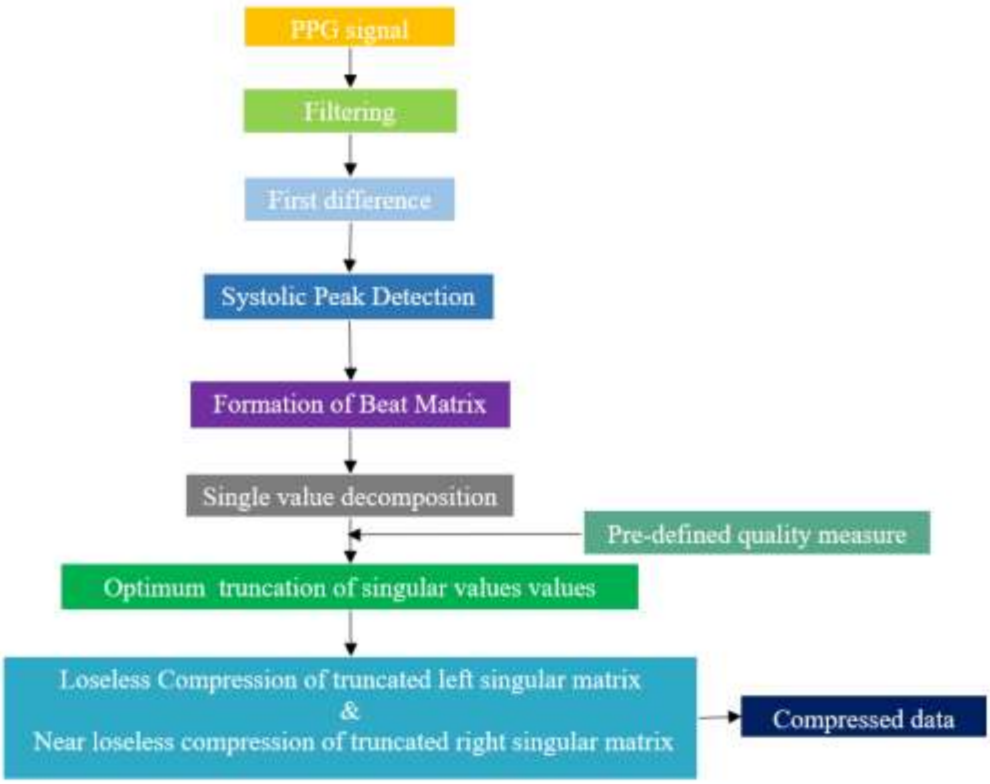

Figure 11. Schematic of the proposed SVD-LAC algorithm

4.1.1 Preprocessing

The preprocessing involves filtering, down-sampling, finding first difference and identifying systolic peaks. The bandwidth of the PPG signal that contains useful clinical information ranges from 0.05Hz to 25 Hz. The filtering of the PPG signal is done using a fourth order Butterworth band pass filter having lower cut off frequency of 0.05Hz and higher cut off frequency of 25Hz. Hence, sampling frequency (SF) of the signal should be greater than 50 Hz. Figure 12 shows the original PPG signal, the signal after filtering and the signal after finding the first difference.

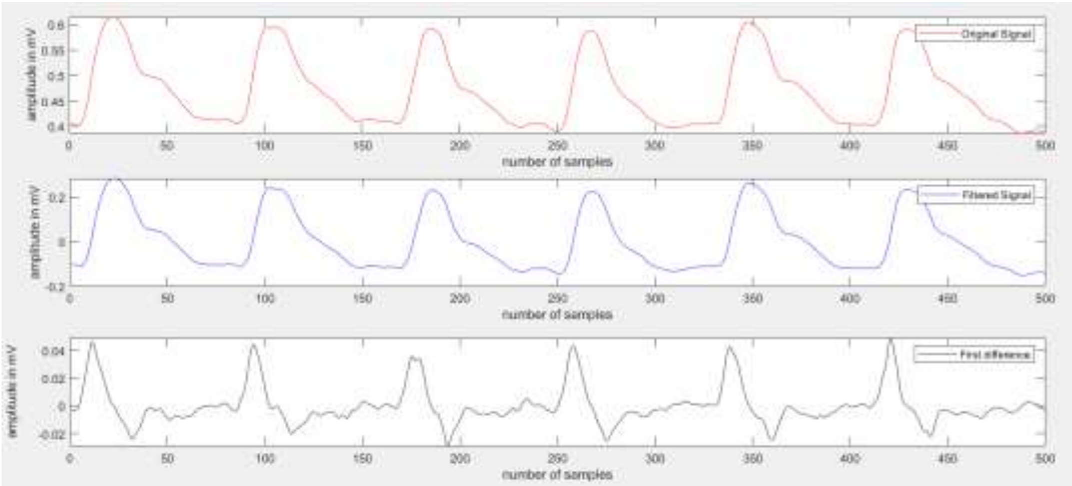

Figure 12. Original PPG signal, the filtered signal and the signal after first difference

If the SF is very high, say, 500 Hz, then it should be down-sampled so that the SF should not come below 100 Hz. Down-sampling process involves the following steps. Let DF denote the down-sampling factor.

1. DF= (SF of the original PPG Signal)/100
2. if DF<2, down-sampling factor =1
3. else down-sampling factor=DF
4. Down-sample the PPG signal by DF.

Now for enhancing the high slope regions, the first difference of the down-sampled signal is calculated. The highest amplitude can be obtained after the first difference computation. The samples that have an amplitude within 30% of the highest amplitude are identified and their indices are marked. The identified samples indicate the rising edges of the PPG beat. The slope reversal events in the time domain of the signal which follow the identified marked samples are detected as systolic peaks. The

HR is computed by dividing the number of detected systolic peaks by duration. The beat locations are identified. The heart rate can be computed from the number of identified systolic peaks. Then the peak to peak interval is split into two halves and the PPG beat is separated. Because of the high quasi-periodic nature of the PPG signals, the PPG beat lengths might not be the same and therefore the number of samples per PPG beat also might not be equal. Hence, the beat length needs to be normalized.

The normalized beat length, N_s is obtained using the calculation.

$$N_s = \frac{60\text{xSF}}{\text{HR}} \tag{4.1}$$

Let 'B' be the number of PPG beats. All the PPG beats are length normalized and they are positioned to form a beat matrix of dimension, N_s x B.

4.1.2 Singular Value Decomposition

The SVD is a most popular and broadly applied matrix factorization technique that factorizes a matrix into the product of three other matrices: an orthogonal matrix, a diagonal matrix and the transpose of an orthogonal matrix [45] [46]. A non-zero, real, rectangular matrix P of dimension, N_s x B can be decomposed into three other matrices of the form,

$$P_{\text{Ns x B}} = U_{\text{Ns x Ns}}\, S_{\text{Ns x B}}\, V^{\text{T}}_{\text{BxB}}. \tag{4.2}$$

Here, U and V are orthogonal matrices and S is a diagonal matrix. The SVD of a matrix P comprises of computing the eigen values of PP^T and P^TP. The eigen vectors of PP^T and P^TP are the columns of the left singular matrix, $U_{Ns\ x\ Ns}$ = $=[u1,u2,.....u_{Ns}]$ and right singular matrix, $V_{BxB}=[v1,v2,.....v_B]$ correspondingly. The singular values (μ) are the square roots of the eigen values from either PP^T or P^TP. The 'μ' values are real and positive and are placed in descending order. Mathematically, the total information-energy of $P_{Ns\,x\,B}$ may be written as

$$\chi = \sum_{i=1}^{B} \mu_i^2 \ \ \textbf{where} \ \ \mu_1^2 \geq \mu_2^2 \geq \sigma_B^2 \geq 0 \tag{4.3}$$

Since μ is placed in descending order, the term, $u_i\mu_i v_i$ with smaller 'i' values contains majority of the information. The data size can be reduced by truncating the μ values to an optimal number of coefficients, thus the compression performance can be increased. The percentage of information-energy preserved in the truncated singular values can be represented as

$$\chi_{TE} = \frac{\sum_{i=1}^{\gamma} \mu_i^2}{\chi} .100\% \tag{4.4}$$

4.1.3 Truncation of Singular Values

The compression performance is based on the singular value truncation factor, γ. The lower the γ value, the higher the compression performance, and vice-versa. Depending on a user defined threshold value of the signal distortion measure, called UDPRD (User Defined Percentage Root mean square Difference), an optimum number of singular values (γ_{opt}) are chosen. The size of S matrix decreases from N_s x B to γ_{opt} x γ_{opt}. Subsequently, the dimensions of the $\bar{U}$ matrix reduces from $N_s \times N_s$ to $N_s \times \gamma_{opt}$ and V matrix reduces from $B \times B$ to $B \times \gamma_{opt}$.

4.1.4 Estimation of an optimal number of singular values

When a PPG signal is compressed and regenerated, there will be small data loss, mainly due to three reasons.

- Down-sampling
- Normalization of beat-length

- Truncation of singular values.

The overall loss of data due to the operations can be assessed beforehand, which enables to precisely control the quality of the regenerated PPG signal. For measuring distortion, PRD is used as the standard metric for controlling the quality of the regenerated signal. To meet the predefined Quality measure, a user-defined threshold value, $UDPRD$ is fixed. The optimal number of singular values, γ_{opt} to meet the UDPRD needs to be estimated. The algorithm to estimate the value of γ_{opt} based on $UDPRD$, is as follows:

Step 1: Set γ=1

Step 2: Reconstruct the signal using the truncated $U_{Ns\times\gamma}$, $S_{\gamma\times\gamma}$ and $V_{B\times\gamma}{}^{T}$

Reconstructed signal, $R_{\mathrm{Ns\ x\ B}} = U_{Ns\times\gamma}\ S_{\gamma\times\gamma}\ V^{T}{}_{B\times\gamma}$ (4.5)

Step 3: One dimensional (1D) PPG signal is approximately recreated from $R_{Ns\times B}$ by restoring the length of each PPG-beat., In case, if the PPG signal was down sampled in the preprocessing stage before compression, up-sampling operation must be performed.

Step 4: Computation of PRD.

If the computed $PRD>UDPRD$

$\gamma=\gamma+1$

Step 5: $goto\ Step$ 2

$else$

$\gamma_{opt.} = \gamma$

$PRD_e = PRD$ (PRD_e is the estimated PRD upon regeneration)

end

4.1.5 Lossless Compression of the truncated Left Singular Matrix using Grouping Techniques

LAC is used to compress the truncated Left Singular Matrix ($\bar{U}$ matrix) coefficients. LAC is a low-complexity compression algorithm that compacts the signal in a lossless manner with a high compression performance. The process runs on a set of 8 coefficients at a time. The algorithm starts with the computation of the first difference of the $\bar{U}$ matrix coefficients. The first 8 consecutive coefficients are taken together. Then, it computes the sign bit of each of the 8-coefficients by marking a binary 0 and 1 for the positive and negative coefficients, respectively. The 8 binary bits is converted into its decimal equivalent and thus the sign-byte, ***sb***[] for the first 8 samples is generated. All the 8-coefficients are made positive post sign-byte generation. Then, the neighboring coefficients are combined by employing different grouping techniques for reducing the size of the data. The grouping is a fully reversible technique and therefore the grouped coefficients can be fully retrieved during data reconstruction. The grouping techniques are described in 4.1.5.1.

4.1.5.1 Grouping Techniques

Grouping is an efficient technique to decrease the size of the PPG data file.

Technique I: If all the 8 samples are the same, then only a single integer needs to be sent.

Technique II: If *Technique 1* is not applicable, i.e. if all the 8-coefficients are not identical, then two neighbor coefficients are taken and examined whether both the coefficients are less than 10 or not. If two neighbor coefficients are ≤ 10, then the first one is multiplied by 10 and added with its next. Thus, a single integer is obtained by grouping the two neighbor coefficients.

Technique III: While grouping, if all the coefficients in a set belong to Grouping *Technique II* and if each of those grouped integers are ≤15, then once again they are grouped in their binary domain. Each regrouped integer is transformed into corresponding 4-bit binary (4bits =1 nibble). An 8-bit string is formed by concatenating two such neighbor nibbles and converted into its decimal equivalent. Thus, from 8-coefficients, using *Technique III*, the data is reduced to 2 integers.

Figure 13 illustrates an example of *Technique II* and *Technique III.*

<table>
<tr><td>Coefficients</td><td></td><td>1</td><td>4</td><td>1</td><td>1</td><td>1</td><td>2</td><td>0</td><td>9</td></tr>
<tr><td>Technique II</td><td></td><td colspan="2">14</td><td colspan="2">11</td><td colspan="2">12</td><td colspan="2">9</td></tr>
<tr><td>4-bit binary</td><td rowspan="3">Technique III</td><td colspan="2">1110</td><td colspan="2">1011</td><td colspan="2">1100</td><td colspan="2">1001</td></tr>
<tr><td>8-bit binary</td><td colspan="4">11101011</td><td colspan="4">11001001</td></tr>
<tr><td>Decimal equivalent</td><td colspan="4">235</td><td colspan="4">201</td></tr>
</table>

Figure 13. Illustration of *Technique II* and *Technique III*

Technique IV: If both *Technique I* and *Technique II* are not valid for a pair of nearby coefficients, then those coefficients are sent unchanged along with an extra byte,

e[] that is used to indicate their index. Figure 14 illustrates *Technique IV* and the implication of the ***e***[]. If the extra byte associated with a coefficient, ***e***[]=0, then it implies that the coefficient corresponding to this index has already been grouped. Else, if ***e***[]=1, then it means that the coefficients are sent unaltered. After grouping of every 8 coefficients of the $\bar{U}$ matrix, the length of the grouped integers is computed and stored in the length byte, say ***l*[]**. The compressed data is accompanied by the length byte, sign byte and extra-byte.

Coefficients	1	6	4	5	15	7	12	89
Reduced data	16		45		15	7	12	89
Extra byte e[]	0	0	0	0	1	1	1	1
Decimal equivalent of e[]	15							

Figure 14. Illustration of *Technique IV*

The grouping technique is used repeatedly till the entire $\bar{U}$ matrix coefficients are compressed. Ultimately, the grouped, non-grouped and regrouped coefficients are transmitted along with their associated overheads such as length byte, sign-byte, and extra byte. The workflow of the lossless compression of $\bar{U}$ matrix using Grouping Techniques is shown in Figure 15.

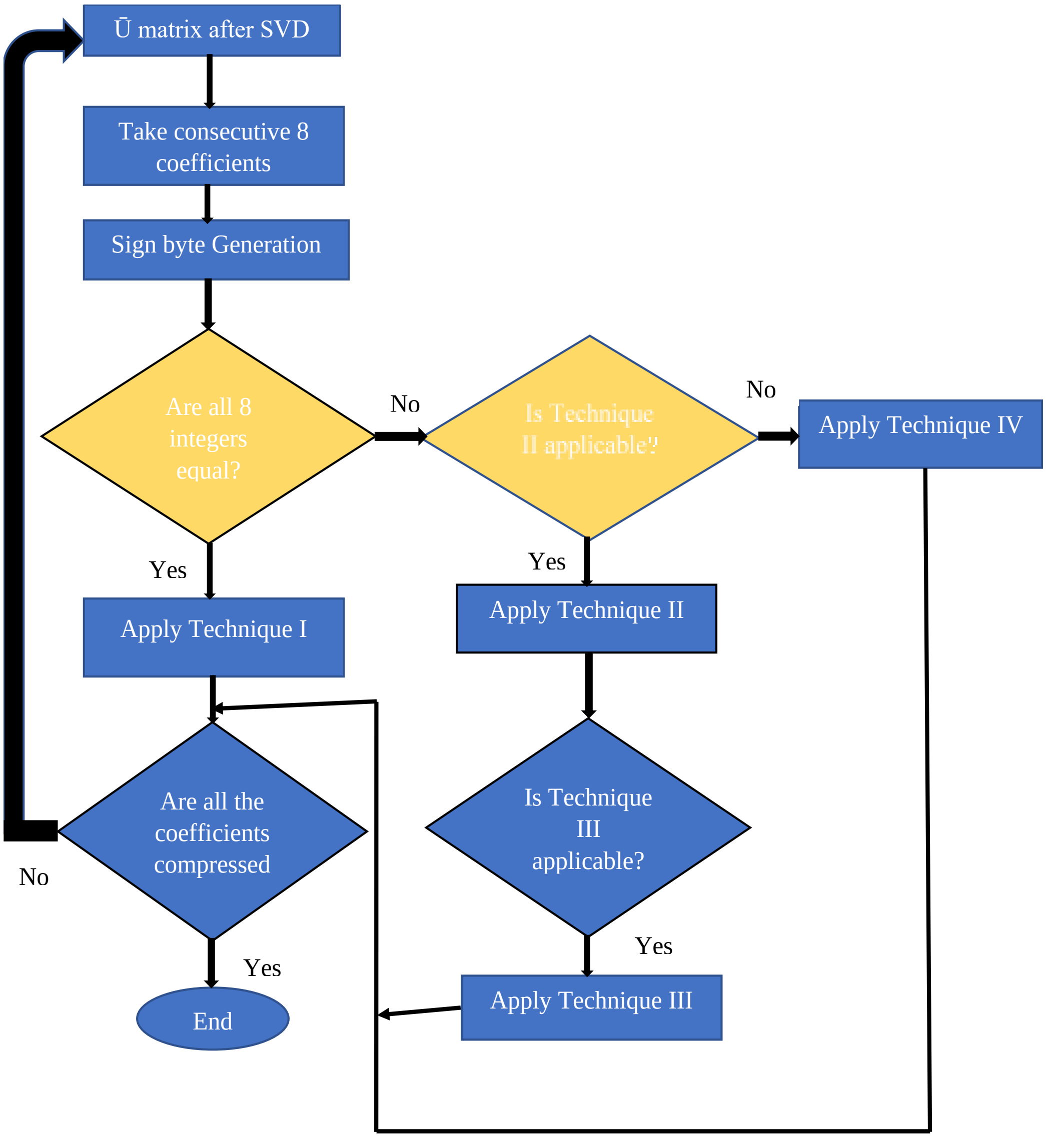

Figure 15. Workflow of Lossless Compression of Ū matrix using Grouping Technique

4.1.6 Near-lossless compression of the truncated right-singular matrix coefficients

The coefficients of the truncated right singular matrix ($V_{B\times\gamma opt}$) are quantized using a uniform quantizer of 2^{16} levels and the quantized values are encoded using 16-bits.

4.1.7 Formation of compressed data file

Finally, the compressed data file encompasses the following

- starting location of each of the PPG beats
- Compressed truncated $\bar{U}$ matrix coefficients in the form of ASCII characters
- Compressed $V_{B\times\gamma opt}$ coefficients as ASCII characters
- Optimally truncated singular values

The file containing the above information is transmitted for enabling PPG signal reconstruction at the receiving end.

4.2 PPG Signal Reconstruction

The PPG signal is regenerated, utilizing the reverse process of the SVD-LAC algorithm. The reconstruction algorithm comprises of 3 steps:

- Decoding the $\bar{U}$ matrix coefficients
- Decoding the $V_{B\times\gamma opt}$ matrix coefficients
- Reconstructing the PPG signal.

4.2.1 Decoding the $\bar{U}$ matrix coefficients

The lossless compression is a fully reversible technique and so, the $\bar{U}$ matrix coefficients can be decoded with no loss. The received data file contains the grouped and non-grouped integers along with the length byte, *l*[], sign byte, *sb*[] and extra byte, *e*[]. Grouped and regrouped integers are segregated properly applying the reverse grouping techniques.

From the received input stream, *l*[], *sb*[] and *e*[] are extracted and the depending on the length in *l*[], corresponding bytes are taken as retrieved data, which is in the compressed form. Figure 16 shows the format of one set of the data retrieved from the compressed file.

Length byte *l*[]	Sign byte *sb*[]	Extra byte *e*[]	Compressed data based on different Grouping Technique
1 byte	1 byte	1 byte	Data length specified by *l*[]. *l*[] value depends on the Grouping Technique

Figure 16. Data format of one set of retrieved data

To decompress this data, reverse grouping techniques are employed. If there is only one integer in a set in the retrieved data, i.e., *l* [] =1 it implies that the data was grouped employing Technique1 and all the 8- integers are same, hence reconstruction is easy in this case. If a retrieved set contains two integers i.e., *l* [] =2, it indicates that the data belong to Grouping Technique III. Next, the two integers are converted to the 8-bit binary equivalent form. Each 8-bit string is separated into two nibbles. The four nibbles thus obtained are converted into their decimal equivalents. Then, applying the reverse algorithm of Grouping Technique II, these four integers are ungrouped into eight integers.

If there are four integers, i.e., *l* [] =4, it indicates that grouping was done utilizing Technique II. Every integer is divided by 10. The quotient and the modulus constitute the two ungrouped integers. Thus, eight integers are got by ungrouping the four grouped integers. If there are more than 4 integers in a set, then they are ungrouped based on the value of *e* []. If the value of *e* [] =1, then the retrieved integers form the ungrouped data. If *e* [] =0, then depending on the length in *l* [], corresponding ungrouping methods are used to get back the eight integers. The 8-integers are ungrouped using the reverse algorithm of Grouping Technique IV. The ungrouping can be illustrated with the following example in Figure 17.

Decimal equivalent of e []	15							
Binary equivalent of e []	0	0	0	0	1	1	1	1
Retrieved Grouped data	16		45		15	7	12	89
Ungrouped data	1	6	4	5	15	7	12	89

Figure 17. An example of Ungrouping data from retrieved compressed data

The sign-byte of each set is reverted into its corresponding 8-bit binary equivalent using which the 8 reconstructed integers are changed to its signed form. If any sign bit is found to be 1 in the binary bit stream, the ungrouped integer in the corresponding position is made negative.

Figure 18 shows the Original $\bar{U}$ matrix coefficients obtained after SVD decomposition, Decoded $\bar{U}$ matrix coefficients, using which signal is reconstructed and the error between them. The data is obtained while compressing and decompressing PPG signal of id no: s01182 of bidmc_data.mat. Details of the database is given in section 4.3.1.

4.2.2 Decoding the $V_{B\times\gamma opt}$ matrix coefficients

The highest and lowest values of the $V_{B\times\gamma opt}$ matrix coefficients are taken and using these two values, the V matrix coefficients are restored by decoding the 16-bit data words. Lastly, the $V_{B\times\gamma opt}$ matrix is reconstructed by arranging the regenerated coefficients.

4.2.3 Reconstructing the PPG signal

The following equation is used to form the two-dimensional (2D) PPG beat-matrix

$$P_{approx}=U_{Ns\times\gamma opt}\,\mathrm{x}\,S_{\gamma opt\times\gamma opt}\,\mathrm{x}V_{B\times\gamma opt}. \tag{4.6}$$

Every column of the PPG beat-matrix, P_{approx} comprises a length-normalized PPG-beat. The real lengths of all the PPG beats are obtained from the received data file,

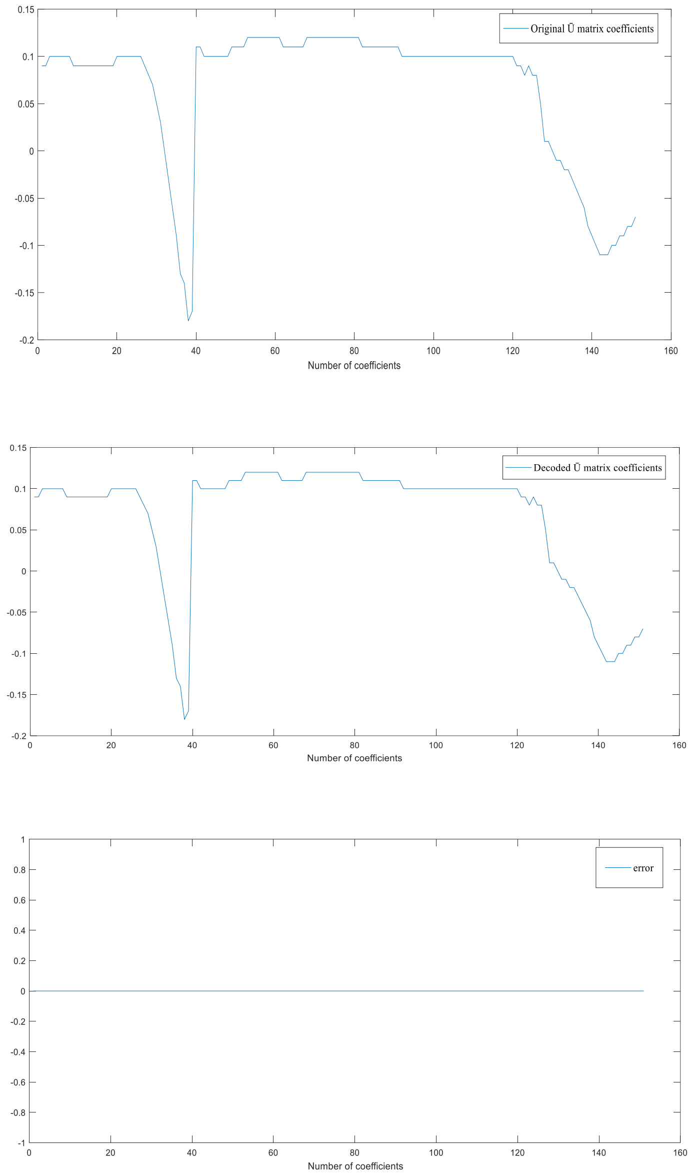

Figure 18. Original Ū matrix coefficients, Decoded Ū matrix coefficients and the error between them

Then, the length-normalized PPG-beats are reinstated to their original lengths by resampling.

The 1D PPG signal is recreated by the concatenation of all the length- reinstated PPG-beats. In case, if down-sampling was done before compression, then the 1D PPG signal is up sampled applying the linear interpolation method to return it to its initial sampling rate.

4.2.3.1 Calculation of Compression ratio.

In this study, the CR is computed in 2 different ways, namely CR and File CR. Let 'd' denote the duration of the PPG signal in minutes, 'Nb' be the number of beats in the signal, 'n' the number of optimum singular values, 'Un', the number of elements in truncated U matrix and 'Vn' ,the number of elements in the truncated V matrix .Let CR be the bit-level compression ratio taking resolution of the signal into account. The dataset A has a resolution of 16 bits. As the truncated U matrix coefficients have only 8-bit resolution, CR is calculated as

$$\mathrm{CR}=\frac{16*60\mathrm{xdurationxSF}}{(24*\mathrm{n})+(16*\mathrm{Nb})+(8*\mathrm{Un})+(16*\mathrm{Vn})} \tag{4.7}$$

The file CR is calculated as the ratio of the size of the original PPG file to the size of the compressed output file.

$$\text{File CR} = \frac{Uncompressed\ File\ Size}{Compressed\ Filesize} \tag{4.8}$$

4.3 Datasets used for simulating the SVD-LAC Algorithm

Two datasets are used for testing the SVD-LAC algorithm.

4.3.1 Dataset 1

The dataset used for testing the Compression and Reconstruction algorithm was taken from the publicly physionet database available in https://physionet.org/content/bidmc/1.0.0/bidmc_data.mat. [47-49] . Figure 19 shows the physionet database link.

Figure 19. Physionet Database link

This dataset consists of signals and numeric obtained from the bigger MIMIC II matched waveform Database. The dataset consists of 53 PPG recordings, each of 8-minute duration, sampled at 125 Hz.

Figure 20 shows the Physionet Database downloads of the file, bidmc_data.mat of size 29110 KB. 20 recordings from this dataset is taken to form the Database 'A' in this study.

Figure 20. Physionet Database download link of the file, bidmc_data.mat

4.3.2 Dataset 2

Another dataset was also used for testing the different compression techniques. It was also taken from the publicly available database, Capnobase. available in the link https://www.capnobase.org/index.php?id=857. [50, 51].

The TDBME2013-PPGRR-BENCHMARK_R3.zip was downloaded from the link shown in Figure 21. The data is the Benchmark data for RR estimation from the Photoplethysmogram used in [51] .The data set contains raw PPG signals of 42 cases each of 8 minutes duration, sampled at 300 Hz. 20 recordings from this dataset were used to form the Database ’B’ in this work.

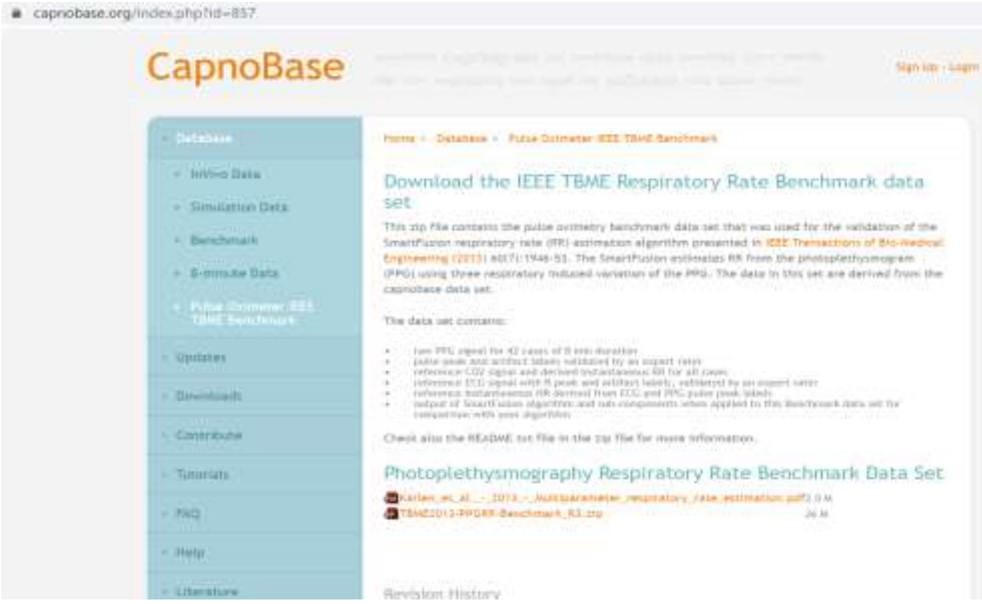

Figure 21. Capnobase Database download link

4.4 Implementation Environment

The PPG signal compression and reconstruction procedure were implemented on MATLAB(R2018a) platform in a laptop computer with 64-bit Windows 10 Operating system, Intel (R) Core™ i7-8550U CPU @ 1.80 GHz, 16.0 GB RAM. Table 2 details the implementation environment.

Table 2. Implementation Environment

Property	Type
Processor	Intel(R) Core™ i7-8550U CPU
RAM	16 GB
Operating System	Windows 10
Platform	MATLAB(R2018a)
System Type	64-bit

The algorithm is coded in MATLAB. The compression and decompression algorithm were tested using Database and Database B. 20 PPG Signals from Database A, each sampled at 125 Hz for a duration of 8 minutes and consisting of 60000 samples i.e. (125x8x60). were used for testing. The algorithms were also tested for 20 PPG signals from Database B, each sampled at 300 Hz for a duration of 8 minutes and comprising of 144000 samples.

4.5 Results and Discussion

Figure 22 depicts the original signal, the reconstructed signal and the error of a PPG Signal, Id: s01795, third recording of bidmc_data.mat.

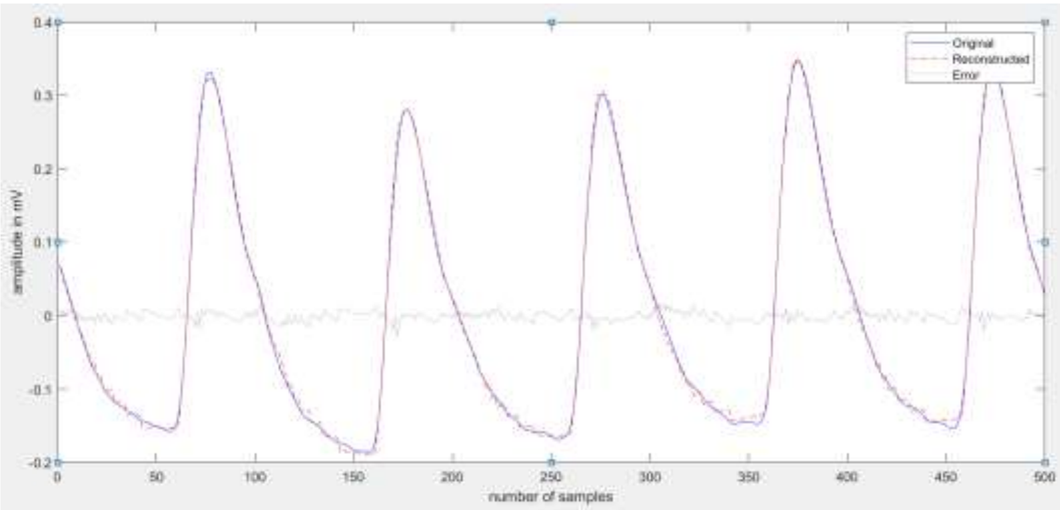

Figure 22. Original signal, the reconstructed signal, and the error

According to the globally considered standard [52], the quality of the reconstructed biosignal is considered to be ‘very good’ if the PRD values lie in within the ranges 0 to 2% and ‘good’ if it is within the range 2% to 9%.

Abbreviations used in Table 3

Id-Corresponding file Id in the database.

PRDr -Actual PRD value upon PPG signal reconstruction

PRDe -Estimated PRD based on a user defined quality measure (UDPRD)

Table 3 and Table 4 shows the performance of the proposed SVD-LAC technique on Database A for UDPRD values of 9 and 8. The technique works for efficient signal reconstruction for UDPRD values of 9 and 8. The reconstructed signal quality degrades for UDPRD value, 7.

Table 5 depicts the performance for UDPRD=7.For lower values of UDPRD, the performance is not consistent.

Abbreviations used in Table 3

Id-Corresponding file Id in the database.

PRDr -Actual PRD value upon PPG signal reconstruction

PRDe -Estimated PRD based on a user defined quality measure (UDPRD)

Table 3. Performance of the SVD-LAC technique on Database 'A' for UDPRD=9%

Id	OSV	File CR	CR	PRDr	PRDe	CC	RMSE	QS
s01182	6	39.72	11.36	8.73	8.72	0.9962	0.011	1.24
s01241	6	38.87	11.11	8.19	8.14	0.9966	0.017	1.29
s01795	4	65.31	18.68	8.74	8.54	0.9962	0.017	2.02
s03386	2	102.39	29.30	8.53	8.46	0.9964	0.019	3.30
s03386	2	93.09	26.64	7.73	7.61	0.9970	0.018	3.32
s03386	2	84.54	24.19	8.37	8.26	0.9965	0.021	2.80
s03386	3	80.74	23.10	7.65	7.48	0.9971	0.016	2.87
s08452	4	46.71	13.36	7.69	7.70	0.9971	0.018	1.69
s08936	6	43.64	12.48	8.40	8.40	0.9965	0.021	1.40
s09483	4	55.23	15.80	8.20	8.20	0.9966	0.013	1.85
s11342	7	37.98	10.86	8.71	8.66	0.9962	0.011	1.17
s17497	5	47.44	13.56	8.92	8.67	0.9960	0.019	1.45
s17735	7	37.37	10.68	8.52	8.43	0.9964	0.013	1.18
s22348	3	83.63	23.93	9.25	8.88	0.9957	0.023	2.46
s24455	5	46.02	13.16	9.08	9.00	0.9959	0.026	1.38
s25323	6	46.57	13.32	8.40	8.32	0.9965	0.022	1.48
s29093	2	100.29	28.70	8.45	8.39	0.9964	0.021	3.27
s29125	5	45.73	13.07	8.41	8.22	0.9965	0.018	1.49
s29622	7	48.08	13.75	8.74	8.71	0.9962	0.023	1.44
s31400	3	69.87	19.99	7.32	7.18	0.9973	0.018	2.63

Table 4. Performance of the SVD-LAC technique on Database 'A' for UDPRD=8%

Id	OSV	File CR	CR	PRDr	PRDe	CC	RMSE	QS
s01182	8	30.81	8.81	7.80	7.81	0.9970	0.010	1.07
s01241	7	33.97	9.71	7.44	7.37	0.9972	0.016	1.24
s01795	5	54.21	15.50	8.00	7.98	0.9968	0.016	1.83
s03386	3	76.32	21.83	6.93	6.87	0.9976	0.016	3.01
s03386	2	93.09	26.64	7.73	7.61	0.9970	0.018	3.32
s03386	3	63.20	18.08	6.51	6.43	0.9979	0.016	2.68
s03386	3	80.74	23.10	7.65	7.48	0.9971	0.016	2.87
s08452	4	46.71	13.36	7.69	7.70	0.9971	0.018	1.69
s08936	7	38.11	10.90	7.22	7.20	0.9974	0.018	1.42
s09483	5	45.90	13.12	7.27	7.27	0.9974	0.011	1.73
s11342	9	30.29	8.66	7.91	7.91	0.9969	0.010	1.03
s17497	7	35.45	10.13	7.53	7.52	0.9972	0.016	1.27
s17735	8	33.20	9.49	7.93	7.92	0.9969	0.012	1.13
s22348	4	66.40	18.99	7.97	7.96	0.9968	0.020	2.25
s24455	7	34.42	9.84	6.85	6.67	0.9977	0.019	1.37
s25323	7	40.69	11.63	7.84	7.84	0.9969	0.021	1.38
s29093	3	74.77	21.39	6.57	6.42	0.9978	0.016	3.12
s29125	6	39.11	11.18	7.44	7.31	0.9972	0.016	1.44
s29622	10	34.78	9.94	7.97	7.96	0.9968	0.021	1.14
s31400	3	69.87	19.99	7.32	7.18	0.9973	0.018	2.63

Table 5. Performance of the SVD-LAC technique for UDPRD=7%

Id	OSV	File CR	CR	PRDr	PRDe	CC	RMSE	QS
s01182	14	18.42	5.26	6.91	6.90	0.9976	0.009	0.72
s01241	8	30.17	8.62	6.70	6.67	0.9978	0.014	1.22
s01795	14	21.43	6.13	7.00	7.00	0.9976	0.014	0.82
s03386	3	76.32	21.83	6.93	6.87	0.9976	0.016	3.01
s03386	3	69.55	19.89	6.22	6.19	0.9981	0.014	3.08
s03386	3	63.20	18.08	6.51	6.43	0.9979	0.016	2.68
s03386	5	53.41	15.27	6.84	6.84	0.9977	0.015	2.11
s08452	5	38.84	11.10	6.76	6.59	0.9977	0.016	1.59
s08936	8	33.85	9.68	6.58	6.51	0.9978	0.016	1.38
s09483	6	39.28	11.23	6.62	6.52	0.9978	0.010	1.62
s11342	15	18.85	5.39	6.94	6.94	0.9976	0.009	0.73
s17497	9	28.30	8.09	6.99	6.99	0.9976	0.015	1.09
s17735	14	19.83	5.67	6.98	6.98	0.9976	0.011	0.76
s22348	6	47.15	13.48	6.55	6.49	0.9979	0.016	1.93
s24455	7	34.42	9.84	6.85	6.67	0.9977	0.019	1.37
s25323	15	20.20	5.77	7.00	7.00	0.9976	0.018	0.77
s29093	3	74.77	21.39	6.57	6.42	0.9978	0.016	3.12
s29125	7	34.17	9.77	6.80	6.80	0.9977	0.015	1.37
s29622	120	3.12	0.89	7.57	7.57	0.9971	0.020	0.11
s31400	4	55.70	15.93	6.71	6.66	0.9978	0.016	2.28

From the above 3 tables, it is clear that, as UDPRD is reduced the CR decreases, but there is an increase in cross correlation and a reduction in reconstruction error. Table 6 shows the performance of the proposed technique on the second database Database B for UDPRD values of 9.

Table 6. Performance of the SVD-LAC method on Database B for UDPRD values of 9

Id	OSV	File CR	CR	PRDr	PRDe	CC	RMSE	QS
0029	4	185.30	48.28	11.17	8.32	0.9938	0.046	4.08

Id	OSV	File CR	CR	PRDr	PRDe	CC	RMSE	QS
0031	4	182.89	48.38	10.11	8.24	0.9949	0.033	4.51
0035	3	156.97	41.65	11.70	6.50	0.9931	0.058	3.46
0103	3	157.42	42.01	13.08	7.35	0.9914	0.055	3.13
0104	2	196.56	51.28	12.81	8.93	0.9918	0.060	3.91
0122	2	299.25	77.75	11.50	8.49	0.9934	0.049	6.47
0125	3	211.91	54.82	12.29	7.90	0.9924	0.046	4.27
0128	5	160.44	41.47	11.72	8.39	0.9931	0.040	3.33
0133	4	184.31	47.63	10.96	8.13	0.9940	0.041	4.13
0134	3	228.20	59.02	10.47	7.93	0.9945	0.043	5.36
0148	3	209.08	54.20	10.93	8.01	0.9940	0.046	4.72
0311	2	310.32	81.77	10.51	8.57	0.9945	0.051	7.38
0312	7	142.61	37.56	9.97	8.60	0.9951	0.018	3.41
0313	3	117.19	31.17	13.73	6.72	0.9905	0.056	2.24
0322	2	294.24	77.29	10.73	8.62	0.9942	0.048	6.86
0325	1	450.13	118.81	18.49	8.85	0.9830	0.078	6.21
0329	3	188.06	49.43	11.16	8.01	0.9938	0.048	4.27
0330	1	440.60	116.04	20.08	8.12	0.9799	0.100	5.60
0331	4	192.93	50.27	10.27	7.71	0.9948	0.035	4.62
0332	2	296.46	77.86	11.10	8.37	0.9939	0.049	6.73

The Database A is having a mean CR of 17.35 and PRD of 8.40 whereas database B has achieved a mean CR of 60.33 and PRD of 12.14, for a UDPRD of 9.The SVD-LAC technique exhibits a very good CR with tolerable distortion.The performance comparison of SVD-LAC Technique with other existing techniques is shown in Table 7.

Table 7. Performance comparison of SVD-LAC method with other existing techniques

Algorithms	SF(Hz)	FileCR	CR	PRD (%)	QS	CC	RMSE
Gupta et al [8]	125		2.223	0.127	17.5	-	
Alam et al [40]	125		3.84	5.82	0.7	-	

Algorithms	SF(Hz)	FileCR	CR	PRD (%)	QS	CC	RMSE
CFSA [21]	200		12	1.67	-	-	
Delta modulation [26]	1 K		16	0.000392	40816	-	
Dhar et al. [37]	500	122.24		0.02	7228.41	0.9988	
Mukhopadhyay et al. [38]	125	60.78		2.34	24.21	0.9966	0.03
	250	114.92		0.05	1159.58	0.9970	0.02
	500	471.02		1.94	100.92	0.9973	0.006
Mukhopadhyay et al. [42]	125	28.77		2.34	24.21	0.9966	0.03
	250	30.52		0.05	1159.58	0.9970	0.02
	500	30.852		1.94	100.92	0.9973	0.006
Proposed SVD-LAC Technique	125	60.66	17.35	8.40	1.99	0.9965	0.018
	300	230.24	60.33	12.14	4.73	0.9923	0.050

CHAPTER 5: IMPLEMENTATION OF THE PROPOSED ITERATIVE EXTENSIVE GROUPING LOSSLESS COMPRESSION TECHNIQUE

5.1 Lossless Compression based on Iterative Grouping Techniques

The proposed compression technique is an efficient and reliable lossless technique based on iterative extensive grouping techniques. This technique is an enhancement on the grouping technique implemented in [37] where five grouping techniques were used to group the PPG data samples and reduce the data. Although the method achieved good compression ratio, there was a limitation that it could process signals that are only within a specific amplitude range (less than 15mV). The proposed method overcomes that limitation.

Figure 23 shows the schematic of the proposed Iterative Extensive Grouping based Lossless Compression (IEGLC)Technique.

5.1.1 Processes involved in lossless compression

The technique constitutes the following steps.

- Filtering the signal
- Down-sampling (if the sampling frequency is very high).
- Second difference and amplification
- Sign byte Generation
- Grouping

5.1.1.1 Filtering

Most of the useful information in a PPG signal is contained in frequencies below 15 Hz. Hence, to eliminate the high frequency noise and power line interferences, the signal is filtered using a low pass order 9 Butterworth filter with a cutoff frequency of 25 Hz. If the PPG signal obtained from the database is sampled at a very high frequency eg: 400Hz, then it must be downsampled to 100 Hz.

5.1.1.2 Down-sampling

Down-sampling reduces the data size and hence the computational time complexity. In 1978, W.C.Mueller first introduced down-sampling in biomedical signal compression[53].

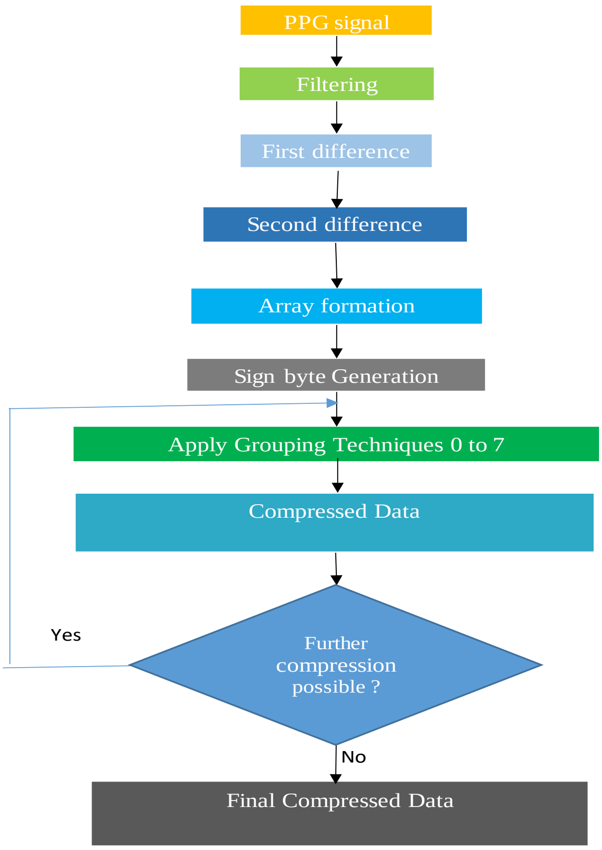

Figure 23. Schematic of the proposed Iterative Extensive Grouping based

5.1.1.3 Second difference and amplification

The down sampled PPG signals are truncated to 2 decimal places, which in turn boosts compression. After truncation, the second difference of these signals are computed (SDPPG) and are amplified by 100 to make them integers. The SDPPG samples are experimentally observed to be always less than 0.150mV [37]. Figure 24 shows the original signal, filtered signal and the signal after first difference and second difference.

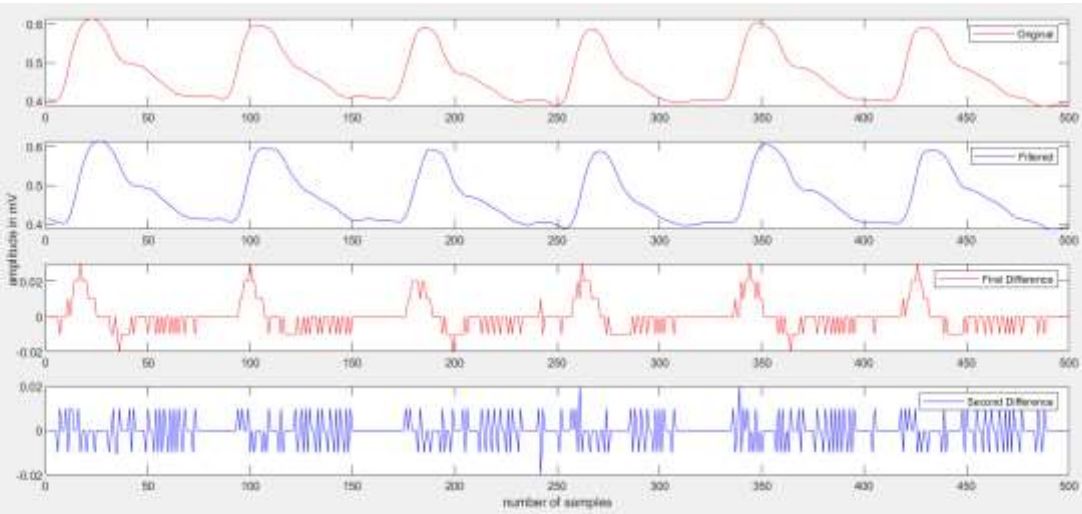

Figure 24. Original signal, filtered signal, signal after first difference and second difference

5.1.1.4 Sign byte Generation

The algorithm works on 8 samples each. After amplification, the sign byte of the amplified integers is created in the same way as in SVD -LAC technique. After sign byte generation, all the integers are made positive and categorized into different groups.

5.1.1.5 Grouping

Grouping is the most significant procedure in compacting the PPG data. In the proposed method, extensive grouping techniques are applied in an iterative manner to reduce the number of integers required to reconstitute the signal. In [37], four different grouping types, Type I to Type V are applied to classify the data and compress it. The proposed method is based on extensive grouping that employs 8 different grouping types, Type 0 to Type 7 to categorize the 8-bit samples.

The new extensive grouping procedure can significantly reduce the data size of these samples than the method used in [37]. The reduced samples obtained after extensive grouping is subjected to further grouping using the same extensive grouping procedure. The extensive grouping technique is applied to the data samples in an iterative manner till the data size reaches a limit, further which no reduction is possible. On reaching this limit, the algorithm stops, and the output data then obtained will be the minimum possible reduced data.

The algorithm of Iterative Extensive Grouping Technique is as follows:

The grouping algorithm starts by fetching 8 integers at a time from the input array, for example, a[], as in

13	24	10	8	15	12	5	11

Figure 25.

a[1]	a[2]	a[3]	a[4]	a[5]	a[6]	a[7]	a[8]
13	24	10	8	15	12	5	11

Figure 25. Input array

Each of the eight integers are grouped using the Grouping Types defined below. Checking initially starts with Grouping Type 0. Checking continues through Group 0 to Group7 until the integers are grouped and sent to the output array.

5.1.1.5.1 Grouping Type 0

If all the 8 integers are same, then the data can be represented by a single integer and it goes to the output array as shown in Figure 26.

a[1]	a[2]	a[3]	a[4]	a[5]	a[6]	a[7]	a[8]
3	3	3	3	3	3	3	3

b[1]
3

Figure 26. Grouping Type 0

5.1.1.5.2 Grouping Type 1

If Type 0 is not valid, then Type1 is to be checked. It primarily checks if first 6 elements are the same and the last 2 elements are the same. Next it verifies whether all elements are less than 16 or not.

a) if all elements are less than 16, then the then first element is multiplied by 16 and added with the last element.
b) If not, the first and last elements are sent unchanged.

5.1.1.5.3 Grouping Type 2

If Type 1 is not valid, then Type 2 is to be checked. It primarily checks if first 2 elements are same and the last 6 elements are same. Then it verifies whether all elements are less than 16 or not.

a) if all elements are less than 16, then the then first element is multiplied by 16 and added with the last element.
b) If not, the first and last elements are sent unchanged.

5.1.1.5.4 Grouping Type 3

If Type 2 is also invalid, then type 3 checking is done. In type 3, the initial step is to check whether the first 4 integers are the same and the last 4 integers are the same. Case a: if all of them are below 16, then first integer is grouped with the last integer. i.e., the first integer is multiplied by 16 and added with the last integer to get a single integer output, as shown in

Figure 27.

a[1]	a[2]	a[3]	a[4]	a[5]	a[6]	a[7]	a[8]
5	5	5	5	7	7	7	7

b[1]
87

Figure 27. Grouping Type 1, Case a

Case b: But in the same case, if the first four integers and the last four integers are greater than 16, then the first integer and the last integer is sent to the output array as shown in Figure 28 .

a[1]	a[2]	a[3]	a[4]	a[5]	a[6]	a[7]	a[8]
25	25	25	25	17	17	17	17

b[1]	b[2]
25	17

Figure 28. Grouping Type 1,Case b

5.1.1.5.5 Grouping Type 4

Type 4 checking is done if Type 3 is also invalid. In Type 4, out of the 8 integers, it is checked whether the first 4 integers are the same, the next 2 integers are the same, the last 2 integers are the same. Once this condition is satisfied, the algorithm goes for the second level checking and further grouping is based on that.

a) If all the integers or the first six integers are below 16, then the first one is multiplied by 16 and the fifth integer is added to it. The last integer is sent unchanged.

b) If the first four integers and last two integers are below 16, then first one is multiplied by 16 an added with the last integer. The fifth integer is sent unchanged.

c) If last four integers are below 16, then the fifth one is multiplied by 16 and added to the last integer. The first integer is sent unchanged.

d) If none of the above, the first, fifth and last integer is sent unaltered.

5.1.1.5.6 Grouping Type 5

The algorithm does the Type 5 check if Type 4 cannot be applied. In Type 5, the primary check of the 8 integers is done at first. i.e. if first 2 integers are the same, the next 2 integers are same and the last 4 integers are same. Then comes the second level checking that evaluates and groups the integers in the following manner.

a) if all the integers or the last six integers are below 16, the third integer is grouped with the last one, whereas the first one is sent unaltered.
b) If first two and last four integers are below 16, then first integer is multiplied by 16 an added to the last one. The third integer is sent unchanged.
c) If the first four integers are below 16, then the first integer is grouped with the third. The last integer is sent unchanged.
d) If none of the above, the first, third and last integer is sent unaltered.

5.1.1.5.7 Grouping Type 6

If Type 5 also fails, the algorithm proceeds to check for Type 6. The type 6 primary check is that if first 2 integers are same, the next 4 integers are same, and the last two integers are same

a) if all the integers or the first six integers are below 16, then the first integer is grouped with the third integer. The last integer is sent unchanged.
b) if last four integers are less than 16, then the third integer is grouped with the last integer. The first integer is sent unchanged.
c) if first two integers and last two integers are less than 16, then first integer is grouped with the last integer. The third integer is sent unchanged.
d) if none of the above, the first, third and last integer is sent unaltered

5.1.1.5.8 Grouping Type 7

Two categories come under Type 7.

a) If the integer set taken does not fall in any of the group types, Type 0 to Type 6.

b) If the length of the last set of integers is less than 8, then those coefficients also come under Type 7. In that case , the last set of integers are sent unchanged.

The grouping is then done in the following way.

If the first pair of integers is below 16, then first integer is grouped with its next. If not, the two integers are sent unchanged. Similar check is done for the second, third and fourth pair and they are grouped in the same manner.

Thus, all the integers in the input array are fetched and grouped to form the output array. The output array is further reduced by reapplying the same grouping Techniques. The newly formed output array is subjected to iterative looping for further compression until a point is reached where further compression is impossible. The reduced output thus obtained forms the final compressed data.

During compression, the sign byte and a type byte is also generated and sent along with the output array for enabling easy ungrouping. The number of iterations involved during compression is also sent.

The first 4 bits (MSB) of the Type byte are the extra bits that carry information whether the 4 pairs of data fetched at a time are less than 16 or not. Each bit corresponds to a pair. The last four bits (LSB) of the type byte denote the Grouping type of the fetched integers. Example of a type byte is shown in Figure 29.

t[1]	t[2]	t[3]	t[4]	t[5]	t[6]	t[7]	t[8]
1	1	0	0	0	1	0	0

Figure 29. Example of a Type byte

In this example, the 4 extra bits in the type byte indicates that the first two pairs of integers are greater than 16 and the last 2 pairs of integers are less than 16. The last 4 bits denotes that the set belong to Type 4 Grouping. The type byte is converted to decimal and sent along with the compressed data.

Finally, the compressed data file comprises of the compressed integers, the sign byte, the type byte, and the number of iterations as shown in Figure 30.

Encode -Frame nth frame n-1 frame... ...first frame

Iteration variable	Extra byte	Type byte	Compressed data	Extra byte	Type byte	Compressed data	.	.	Extra byte	Type byte	Sign-byte	Compressed data
	4bits	4bits	X bytes	4bits	4bits	X bytes			4bits	4bits	8bits	X bytes

Figure 30. Data format of the compressed data after performing IEGLC

5.1.2 PPG Reconstruction.

The reconstruction process involves the following steps.

- Ungrouping.

- Sign byte regeneration
- Interpolation

5.1.2.1 Ungrouping

From the received output array, the number of iterations required for ungrouping is first extracted. Then the exact reverse operations are performed on the grouped data to get back the original integers. The last 4 bits of type byte is used to identify the grouping type and then the data is segregated into different groups. Depending on the retrieved group type, the reverse grouping process is applied to ungroup and get back the original integers.

5.1.2.2 Sign byte regeneration

After the final iteration of ungrouping, the 8-bit binary equivalent of the sign byte is retrieved to revert the ungrouped integers to its signed form.

5.1.2.3 Signal regeneration

The ungrouped signed integers are then de-amplified by dividing the integers with the amplification factor to get back the SDPPG signals. The second difference data is manipulated to get back the original PPG samples.

5.1.2.4 Interpolation

In case of down-sampled signals, the original signals are regenerated by linear interpolation.

5.2 Results and Discussion

The algorithm was able to reconstruct the signal with very low PRD, very high correlation, and a good CR and a very good file CR. The performance of the proposed

IEG LC technique while compressing PPG signals in Database ‘A’ is shown in Table 8

and Database ‘B’ is shown in

Table 9.

Abbreviations used in Table 8 and Table 9

Id-Corresponding file Id in the database.

Table 8. Performance metrices of IEG- LC technique for Database ‘A’

Id	File CR	CR	PRD	CC	QS
s01182	12.63	3.16	0.615	0.9990	5.14
s01241	11.21	2.80	0.586	0.9998	4.78
s01795	11.36	2.84	0.637	0.9998	4.46
s03386	11.50	2.87	0.649	0.9998	4.43
s03386	11.25	2.81	0.581	0.9998	4.84
s03386	11.25	2.81	0.587	0.9998	4.80
s03386	11.22	2.81	0.595	0.9997	4.71
s08452	11.96	2.99	0.564	0.9998	5.31
s08936	11.35	2.84	0.612	0.9998	4.64
s09483	11.29	2.82	0.645	0.9995	4.38
s11342	12.11	3.03	0.588	0.9992	5.15
s17497	11.10	2.78	0.647	0.9998	4.29
s17735	11.32	2.83	0.581	0.9996	4.88
s22348	11.59	2.90	0.629	0.9998	4.61
s24455	11.22	2.80	0.590	0.9998	4.75
s25323	11.54	2.88	0.588	0.9998	4.90
s29093	11.01	2.75	0.155	1.0000	17.77
s29125	11.35	2.84	0.569	0.9998	4.98
s29622	11.06	2.76	0.145	1.0000	19.12
s31400	11.20	2.80	0.608	0.9998	4.61

Table 9. Performance metrices of IEG- LC technique for Database 'B'

Id	File CR	CR	PRD	CC	QS
0029	25.34	6.34	11.15	0.9938	0.57
0031	25.96	6.49	9.18	0.9958	0.71
0035	28.29	7.07	7.27	0.9973	0.97
0103	29.51	7.38	6.38	0.9980	1.16
0104	26.96	6.74	9.89	0.9951	0.68
0122	24.67	6.17	8.66	0.9953	0.71
0125	26.76	6.69	6.78	0.9971	0.99
0128	26.95	6.74	8.14	0.9957	0.83
0133	26.49	6.62	7.52	0.9963	0.88
0134	28.43	7.11	6.51	0.9969	1.09
0148	28.40	7.10	5.86	0.9976	1.21
0311	29.34	7.33	5.93	0.9974	1.24
0312	32.10	8.02	6.11	0.9982	1.31
0313	33.23	8.31	5.47	0.9985	1.52
0322	32.15	8.04	6.88	0.9977	1.17
0325	32.06	8.01	6.56	0.9979	1.22
0329	32.17	8.04	7.81	0.9970	1.03
0330	32.03	8.01	6.76	0.9977	1.18
0331	32.08	8.02	7.16	0.9975	1.12
0332	32.03	8.01	7.21	0.9974	1.11

The IEG LC algorithm attained a mean file CR of 11.43, CR of 2.86, PRD of 0.56, CC of 0.9997 and a QS of 6.13 for Database A whereas it could achieve a file CR of 29.25, CR of 7.31, PRD of 7.36, CC of 0.9969 and a QS of 1.03 for database B. The sampling rate of Database B was 300 Hz and hence it was downsampled by a DF of 3.

Figure 31 and

Figure 32 shows the original signal, the reconstructed signal and the error occurred while using IEGLC technique, for file id:s31400 of Database A, and file id: 0332 of Database B respectively.

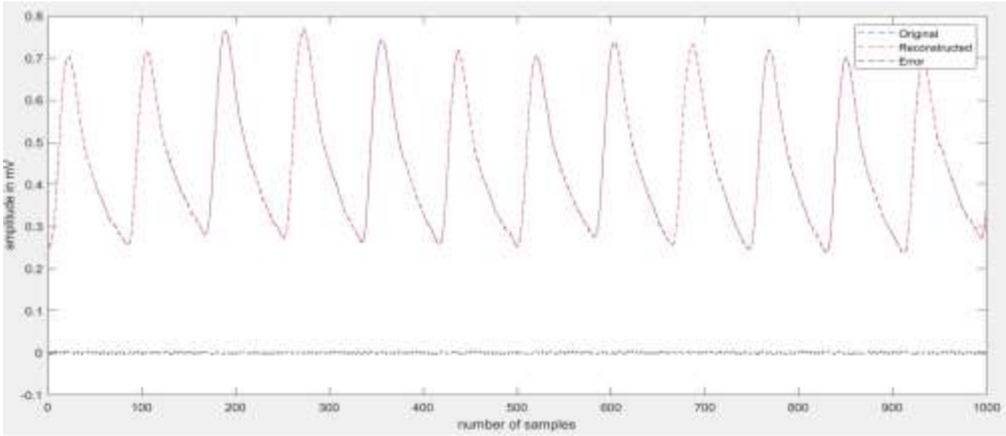

Figure 31. Original signal, reconstructed signal, and the error for IEGLC, Database A

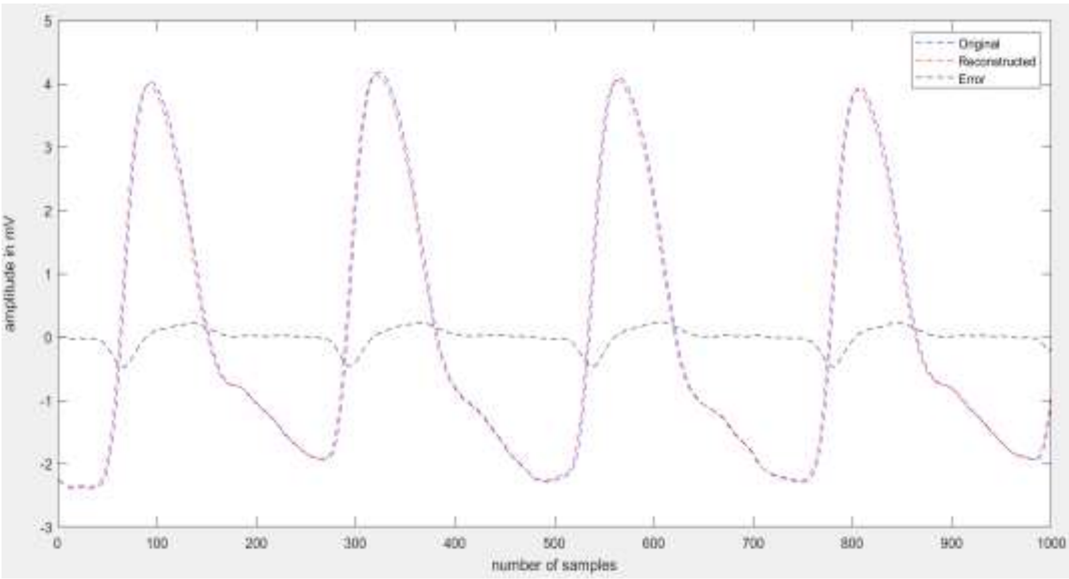

Figure 32. Original signal, reconstructed signal, and the error for IEGLC, Database B

5.2.1 Advantages of the IEG-LC Technique

IEG-LC is a lossless compression-based technique that can deliver a reasonably good CR with very low PRD and high correlation coefficient. The original PPG signal is regenerated with minimum distortion, thereby preserving the clinical characteristics of the original signal. The algorithm imposes no amplitude limitation on the input signal when compared to other algorithms which uses Grouping techniques for lossless data reduction. It can process input PPG signal of high amplitudes without normalization, hence the error on reconstruction will be the minimum. This can be used to provide lossless compression for all 1D signals. The algorithm can process digitized PPG signals regardless of their sampling frequencies. Table 10 shows the performance comparison of the IEGLC technique with prevailing techniques.

Table 10. Performance Comparison of the IEGLC technique with prevailing techniques

Algorithms	SF(Hz)	FileCR	CR	PRD (%)	QS	CC
Gupta et al [8]	125		2.223	0.127	17.5	-
Alam et al [40]	125		3.84	5.82	0.7	-
CFSA [21]	200		12	1.67	-	-
Delta modulation [26]	1 K		16	0.000392	40816	-
Dhar et al. [37]	500	122.24		0.02	7228.41	0.9988
Proposed IEG-LC	125	11.43	2.86	0.56	6.13	0.9997
Technique	300	29.25	7.31	7.36	1.03	0.9969

5.3 Implementation of some Basic Compression Techniques

Some basic compression techniques were also implemented in this study to understand the performance of these techniques.

5.3.1 DCT Compression

The DCT compression was implemented using the Database A. In this technique after filtration, DCT is applied. All the non-zero samples are identified and those samples within the range 0.22 and -0.22 were discarded and transmitted. At the receiver, inverse DCT operation is performed to retrieve the signal.

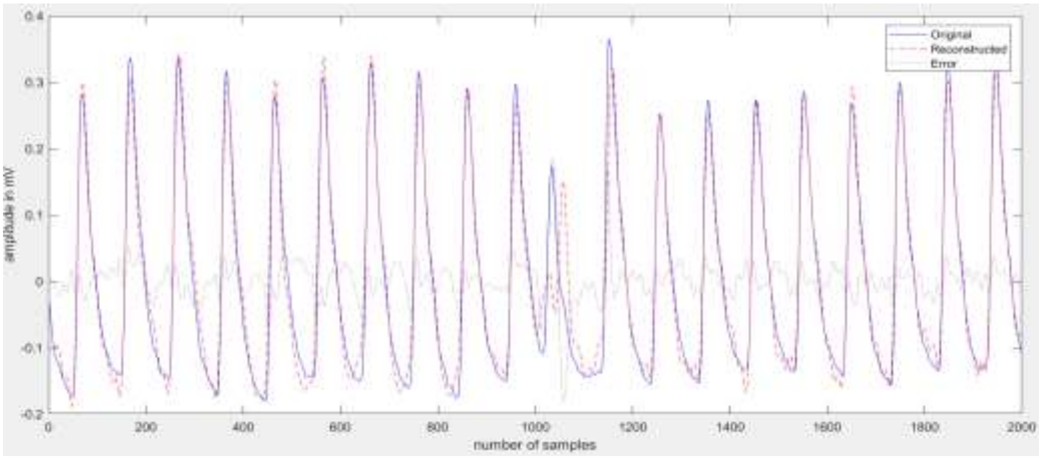

Figure 33 illustrates the DCT compression. The original signal, the reconstructed signal from DCT Compressed data and the error on reconstruction of a PPG Signal are shown. Even though the CR obtained is very high, the signal is regenerated with significant distortion and there is no guarantee on preserving the clinical characteristics of the PPG signal. Table 11 shows the performance metrices of DCT Compression using Database ‘A’.

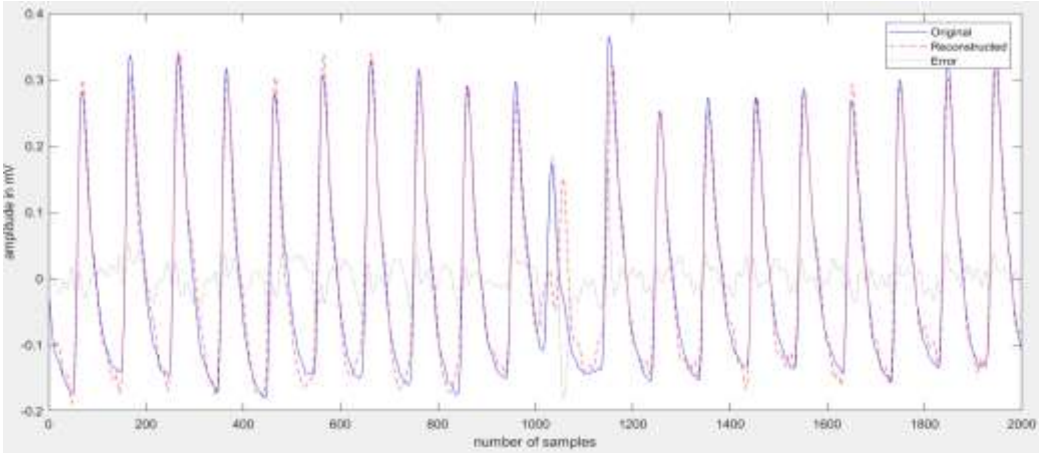

Figure 33. DCT Compression- Original Signal, Reconstructed Signal and error

Table 11. Performance of DCT Compression

Id	CR	PRD	CC
s01182	99.30	125.81	0.9621
s01241	97.74	100.46	0.9864
s01795	98.46	92.37	0.9874
s03386	99.00	64.28	0.9916
s03386	99.34	41.30	0.9946
s03386	99.09	70.54	0.9911
s03386	98.96	73.34	0.9885
s08452	98.69	71.93	0.9903
s08936	96.15	107.06	0.9857
s09483	99.11	81.07	0.9826
s11342	99.07	142.32	0.9605
s17497	98.06	113.04	0.9843
s17735	98.83	94.69	0.9816
s22348	98.07	86.08	0.9892
s24455	98.42	90.39	0.9872
s25323	97.74	74.68	0.9895
s29093	96.76	33.09	0.9990
s29125	96.95	139.15	0.9816
s29622	92.60	25.12	0.9992
s31400	98.89	59.33	0.9918

5.3.2 FFT Compression

The filtered PPG signals were compressed using FFT Compression Technique. Figure 34 demonstrates the FFT Compression. The error on reconstruction due to FFT compression of a PPG Signal is presented. In this technique, although the CR is very high, the reconstructed signal is significantly distorted. It is evident that some peaks are missed during reconstruction and the error is also high. So accurate recovery of clinical characteristics is not possible. The performance metrices of FFT Compression using Database A is given in Table 12.

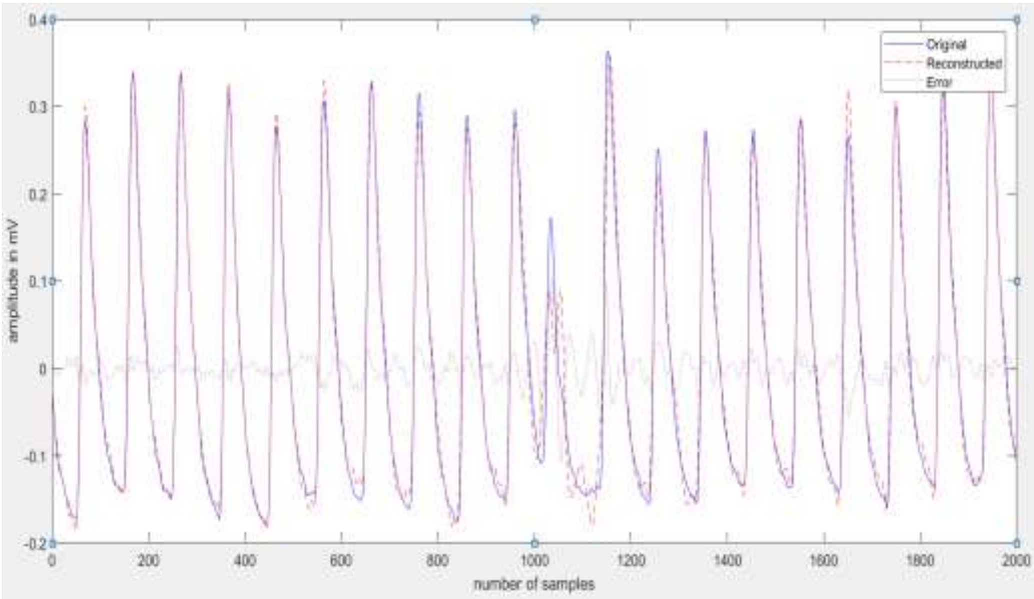

Figure 34. FFT Compression-Original Signal, Reconstructed Signal and error

Table 12. Performance of FFT Compression

Id	CR	PRD	CC
s01182	97.93	59.29	0.9823
s01241	95.23	31.19	0.9958
s01795	96.22	28.42	0.9961
s03386	97.27	28.14	0.9963
s03386	97.98	24.56	0.9968
s03386	96.75	27.56	0.9965
s08452	96.92	23.71	0.9968
s08936	93.27	29.98	0.9960
s09483	97.86	37.01	0.9921
s11342	97.29	62.58	0.9828
s17497	95.34	37.65	0.9948
s17735	97.17	37.23	0.9928
s22348	95.78	30.39	0.9962
s24455	96.31	31.22	0.9956
s25323	95.78	22.09	0.9969
s29093	91.62	12.61	0.9996
s29125	93.23	39.52	0.9948
s29622	89.64	7.80	0.9998
s31400	97.31	29.45	0.9959

5.4 SVD-IEGLC technique (Fusion of IEGLC with the SVD Compression)

The thesis also proposes a more efficient lossy compression technique that is based on a combination of Singular Value Decomposition and IEGLC based quality guaranteed PPG compression (SVD-IEGLC). The lossless compression is done using iterative extensive grouping techniques.

The algorithm of SVD-IEGLC technique consists of six steps.

1. Preprocessing
2. Singular Value Decomposition of the preprocessed signal
3. Truncation of Singular Values

4. Estimating the optimal number of Singular Values
5. Lossless Compression of the truncated Left Singular Matrix
6. Lossless Compression of the truncated Right Singular Matrix

Figure 35 demonstrate the schematic of the proposed SVD-IEGLC technique.

The first four steps of SVD-IEGLC technique is same as that of SVD-LAC. After SVD compression, the optimal number of singular values, γ_{opt} is found. Based on γ_{opt}, the singular value matrix (S), the left singular matrix(U) and the right singular matrix (V) are truncated. The U matrix is subjected to IEGLC for reducing the number of coefficients. The V matrix undergo 16-bit quantization and is then subjected to IEGLC for reducing the number of coefficients. Finally, the actual lengths of all the PPG beats, the optimally truncated singular values, the compressed U matrix, and the compressed V matrix constitutes the compressed data file. Besides the bit wise compression ratio, the file size compression ratio was also calculated for this technique

The reconstruction algorithm consists of the following parts.

1. Decoding the U matrix coefficients
2. Decoding the V matrix coefficients
3. Regenerating the signal using the beat lengths, S, U and V matrices.

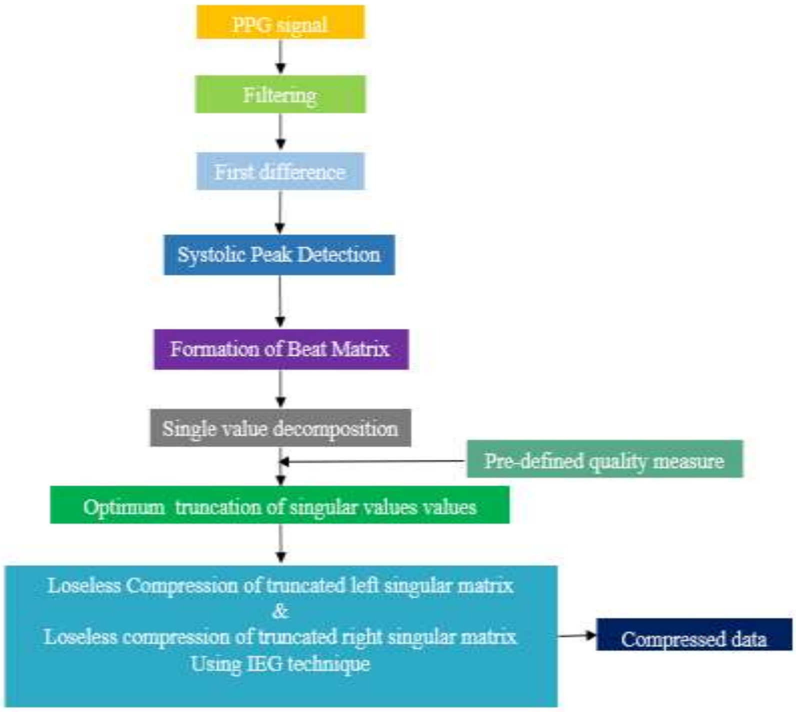

Figure 35. Schematic of the proposed SVD-IEGLC algorithm

Table 13 and

Table 14 shows the performance of the proposed SVD-IEGLC technique on Database 'A' and Database 'B' for UDPRD values of 9.

Abbreviations used in Table 13 and

Table 14

PRDr -Actual PRD value upon PPG signal reconstruction

PRDe -Estimated PRD based on a user defined quality measure (UDPRD)

Table 13. Performance of the SVD-IEGLC technique on Database 'A' for UDPRD=9%

Id	OSV	File CR	CR	PRDr	PRDe	CC	RMSE	QS
s01182	6	91.03	22.79	10.81	8.72	0.9941	0.014	2.11
s01241	6	85.61	21.43	10.15	8.14	0.9948	0.022	2.11
s01795	4	143.58	35.97	10.40	8.54	0.9946	0.021	3.46
s03386	2	227.38	57.03	9.40	8.46	0.9956	0.021	6.07
s03386	2	197.53	49.53	10.02	7.61	0.9959	0.023	4.94
s03386	2	165.52	41.48	12.02	8.26	0.9931	0.030	3.45
s03386	3	177.84	44.58	9.01	7.48	0.9959	0.019	4.95
s08452	4	102.89	25.76	10.09	7.70	0.9949	0.024	2.55
s08936	6	94.56	23.67	10.15	8.40	0.9948	0.025	2.33
s09483	4	122.45	30.67	10.25	8.20	0.9947	0.016	2.99
s11342	7	88.38	22.12	10.49	8.66	0.9945	0.014	2.11
s17497	5	109.74	27.48	9.94	8.67	0.9951	0.022	2.77
s17735	7	89.17	22.32	10.15	8.43	0.9948	0.016	2.20
s22348	3	172.97	43.35	10.46	8.88	0.9945	0.026	4.15
s24455	5	103.38	25.88	10.96	9.00	0.9940	0.031	2.36
s25323	6	102.72	25.72	10.06	8.32	0.9949	0.026	2.56
s29093	2	227.70	57.12	9.06	8.39	0.9960	0.022	6.30
s29125	5	103.00	25.79	10.32	8.22	0.9947	0.022	2.50
s29622	7	106.81	26.74	10.07	8.71	0.9949	0.026	2.65
s31400	3	151.18	37.88	9.29	7.18	0.9958	0.023	4.08

Table 14. Performance of the SVD-IEGLC technique on Database ‘B’ for UDPRD=9%

Id	OSV	File CR	CR	PRDr	PRDe	CC	RMSE	QS
0018	3	218.51	54.70	14.29	6.55	0.9897	0.053	3.83
0023	3	275.80	69.06	13.90	7.89	0.9908	0.063	4.97
0029	6	251.42	62.95	12.86	8.80	0.9917	0.048	4.90
0030	6	530.14	132.96	12.02	8.76	0.9931	0.052	11.06
0031	6	251.42	62.95	12.86	8.80	0.9917	0.048	4.90
0035	5	286.07	71.64	11.53	8.20	0.9933	0.034	6.21
0103	3	292.09	73.15	14.84	8.28	0.9890	0.063	4.93
0104	3	294.48	73.75	14.01	8.66	0.9914	0.065	5.26
0122	3	402.23	100.81	13.06	7.80	0.9928	0.054	7.72
0125	4	328.95	82.40	13.65	8.66	0.9908	0.051	6.04
0128	5	303.72	76.07	13.76	8.60	0.9907	0.045	5.53
0133	4	352.94	88.42	13.03	8.61	0.9915	0.050	6.79
0134	4	324.69	81.33	12.79	8.57	0.9918	0.052	6.36
0148	6	225.18	56.37	12.64	8.35	0.9920	0.049	4.46

Id	OSV	File CR	CR	PRDr	PRDe	CC	RMSE	QS
0311	2	571.43	143.35	12.67	8.31	0.9923	0.059	11.32
0312	5	379.45	95.08	11.14	8.62	0.9938	0.020	8.54
0322	2	566.65	142.15	11.86	8.42	0.9942	0.054	11.98
0325	1	807.29	202.82	12.59	8.95	0.9926	0.052	16.12
0331	4	377.83	94.67	11.71	7.93	0.9932	0.038	8.08
0332	2	530.14	132.96	12.02	8.76	0.9931	0.052	11.06

5.4.1 Advantages of SVD-IEGLC over SVD-LAC

The SVD-IEGLC provides better CR than the SVD-LAC as the truncated V matrix also undergoes lossless compression. Although the SVD-LAC method achieved good compression performance, it can process PPG signals of higher amplitude range. The proposed SVD-IEGLC method overcomes the amplitude range limitation faced in [37] and [42]. The original PPG signal is regenerated with minimum distortion, thereby preserving the clinical characteristics of the original signal. Table 15 illustrates the comparison of compression performance of SVD IEGLC & SVD-LAC techniques.The comparison is done taking the mean values of the CR, PRD, CC, RMSE and QS of all the 20 recordings in the dataset.

Abbreviations used in Table 15

CT-Compression time in seconds, DT-Decompression time in seconds

Table 15. Comparison of performance of SVD IEGLC & SVD-LAC techniques

Technique	Database	CR	PRD	CC	RMSE	QS	CT	DT
SVD IEGLC	A	33.37	10.16	0.9949	0.022	3.33	1.55	0.30

Technique	Database	CR	PRD	CC	RMSE	QS	CT	DT
SVD LAC	A	17.35	8.40	0.9965	0.018	1.99	1.41	0.29
SVD IEGLC	B	100.76	12.85	0.9920	0.051	7.97	1.27	0.30
SVD LAC	B	60.33	12.14	0.9923	0.050	4.73	0.97	0.25

The above results reveal that both the techniques have superior compression performances than most of the existing PPG Compression techniques. The compression performance of the SVD-IEGLC technique is much advanced than the SVD-LAC technique.

On analyzing the time complexities of the proposed techniques, it was found that the time required for compression is low i.e. in the range from 0.25 seconds to 1.45 seconds whereas that required for decompression is less than half a second.

Table 16 shows the comparison of the time complexities of the three proposed tehcniques,SVDLAC,IEGLC and SVDIEGLC.

Table 16. Time complexities of SVDLAC, SVDIEGLC and IEGLC techniques

Technique	Database	Number of samples	Compression time	Decompression time
SVD IEGLC	A	60000	1.43	0.30
SVD LAC	A	60000	1.41	0.29
SVD IEGLC	B	144000	1.12	0.28
SVD LAC	B	144000	0.97	0.25
IEGLC	A	60000	0.30	0.16
IEGLC	B	144000	0.26	0.09

5.5 Comparison of the three proposed techniques with the existing techniques

The three proposed techniques exhibit excellent performance when compared to the existing PPG compression techniques. Both the lossy methods provide very high file CR, CR and CC with acceptable PRD and low RMSE. The lossless IEGLC technique provides good CR and high CC with very low PRD. All the three techniques are quality guaranteed and can regenerate the signal with minimum distortion thereby preserving the clinical characteristics of the signal. All the three methods exhibit superior performance when compared to the state-of-the-art methods. Table 17 shows the comparison of the overall performance of the three proposed techniques with the existing PPG compression techniques.

Table 17. Performance comparison of the three proposed PPG compression techniques with the existing techniques

Algorithms	SF(Hz)	FileCR	CR	PRD (%)	QS	CC	RMSE
Gupta et al [8]	125		2.223	0.127	17.5	-	
Alam et al [40]	125		3.84	5.82	0.7	-	
CFSA [21]	200		12	1.67	-	-	
Delta modulation [26]	1 K		16	0.000392	40816	-	
Dhar et al. [37]	500	122.24		0.02	7228.41	0.9988	
Mukhopadhyay	125	60.78		2.34	24.21	0.9966	0.03
et al. [38]	250	114.92		0.05	1159.58	0.9970	0.02
	500	471.02		1.94	100.92	0.9973	0.006
Mukhopadhyay	125	28.77		2.34	24.21	0.9966	0.03
et al. [42]	250	30.52		0.05	1159.58	0.9970	0.02
	500	30.852		1.94	100.92	0.9973	0.006
Sadhukhan, D, Pal, S. and, Mitra, M [41]	125		35.95	3.88			
Proposed SVD-	125	60.66	17.35	8.40	1.99	0.9965	0.018
LAC Technique	300	230.24	60.33	12.14	4.73	0.9923	0.050

Algorithms	SF(Hz)	FileCR	CR	PRD (%)	QS	CC	RMSE
Proposed IEGLC	125	11.43	2.86	0.56	6.13	0.9997	0.0029
Technique	300	29.25	7.31	7.36	1.03	0.9969	0.2713
Proposed SVD	125	133.17	33.37	10.16	3.33	0.9949	0.022
IEGLC technique	300	401.86	100.76	12.85	7.97	0.9920	0.051

CHAPTER 6: CONCLUSION ANF FUTURE WORK

The chapter concludes the thesis and presents some ideas for future work that can be done based on this work.

6.1 Conclusion

The thesis started with a survey on the significance of PPG signal compression in e-health and remote health monitoring. The contribution of wearable health devices in wireless medical field was also surveyed. A detailed study was done on the basic compression techniques that can be employed for biomedical signal compression. A thorough review was done on the implementation of the existing PPG compression techniques available in published literature.

The different compression techniques were analyzed to assess the compression performance, the reconstruction fidelity and clinical importance of the reconstructed signal. The computational burden, memory requirement and noise sensitivity of these techniques were also examined.

The thesis proposed three efficient compression techniques for compressing the PPG Signals, two lossy compression techniques and a lossless compression technique. The first lossy technique was based on a combination of Singular Value Decomposition and lossless ASCII compression. The second technique called the IEGLC, is a lossless compression technique based on some iterative extensive grouping techniques. Finally, in the third technique, the proposed IEGLC technique was integrated with the lossy SVD technique to get better compression performance and guaranteed quality. The compression performances of all the three proposed techniques were much superior, when compared to most of the existing techniques in published literature.

6.2 Challenges faced

1. The availability of public PPG Dataset is restricted. Labelled PPG datasets are not freely available.
2. Only limited published literature is available for comparison of compression performances of PPG Signals.

6.3 Future Work

Most of these compression techniques mainly aim to maximize the CR and a few techniques attained good CR. Very few methods talk about the clinical acceptability of the regenerated signals, even though it is mentioned that the error is low. Majority of the techniques had no influence over the required quality of the regenerated signal. More works need to be done in future for instituting quality control in PPG compression techniques, while maintaining high compression ratios.

More effective compression techniques need to be explored using a combination of the proposed grouping technique with other techniques such as SVD, DWT etc.

Another future work that can be proposed is to incorporate a classification module in the SVD-IEGLC compression framework itself, to categorize the sick and the healthy persons by analyzing the compressibility of the PPG signals. The lesser the optimum number of singular values needed for PPG signal reconstruction, the signal will be more structured, and it is more likely that the person is healthier. The accuracy of the technique in classification must be verified using labelled PPG signals. One of the challenges will be the availability of a labelled, public PPG dataset, which is required to verify the correctness of the classification of the sick and the healthy people.

REFERENCES

[1] https://www.who.int/news-room/fact-sheets/detail/cardiovascular-diseases-(cvds)#:.

[2] Shih, E., et al. Continuous medical monitoring using wireless microsensors. in Proceedings of the 2nd international conference on Embedded networked sensor systems. 2004.

[3] https://www.marketsandmarkets.com/Market-Reports/wearable-medical-device-market-81753973.html.

[4] Papa, A., et al., E-health and wellbeing monitoring using smart healthcare devices: An empirical investigation. Technological Forecasting and Social Change, 2020. **153**: p. 119226.

[5] Allen, J., Photoplethysmography and its application in clinical physiological measurement. Physiological measurement, 2007. **28**(3): p. R1.

[6] Hertzman, A.B., Photoelectric plethysmography of the fingers and toes in man. Proceedings of the Society for Experimental Biology and Medicine, 1937. **37**(3): p. 529-534.

[7] Bagha, S. and L. Shaw, A real time analysis of PPG signal for measurement of SpO2 and pulse rate. International journal of computer applications, 2011. **36**(11): p. 45-50.

[8] Gupta, R., Lossless compression technique for real-time photoplethysmographic measurements. IEEE Transactions on Instrumentation and Measurement, 2014. **64**(4): p. 975-983.

[9] Alam, S., R. Gupta, and J. Bera, Quality controlled compression technique for Photoplethysmogram monitoring applications. Measurement, 2018. **130**: p. 236-245.

[10] Mukhopadhyay, S., S. Mitra, and M. Mitra, An ECG signal compression technique using ASCII character encoding. Measurement, 2012. **45**(6): p. 1651-1660.

[11] Chong, K.S., K.B. Gan, and E. Zahedi, Development of a real-time adaptive delta

compression algorithm for photoplethysmography system. IEEJ Transactions on Electrical and Electronic Engineering, 2018. **13**(10): p. 1454-1460.

[12] Craven, D., et al., Compressed sensing for bioelectric signals: A review. IEEE journal of biomedical and health informatics, 2014. **19**(2): p. 529-540.

[13] Elgendi, M., et al., The use of photoplethysmography for assessing hypertension. NPJ digital medicine, 2019. **2**(1): p. 1-11.

[14] Castaneda, D., et al., A review on wearable photoplethysmography sensors and their potential future applications in health care. International journal of biosensors & bioelectronics, 2018. **4**(4): p. 195.

[15] Kale, S.B. and D.H. Gawali. Review of ECG compression techniques and implementations. in 2016 International Conference on Global Trends in Signal Processing, Information Computing and Communication (ICGTSPICC). 2016. IEEE.

[16] Iozzia, L., L. Cerina, and L. Mainardi, Relationships between heart-rate variability and pulse-rate variability obtained from video-PPG signal using ZCA. Physiological measurement, 2016. **37**(11): p. 1934.

[17] Park, C. and B. Lee, Energy-Efficient Photoplethysmogram Compression to Estimate Heart and Respiratory Rates Simultaneously. IEEE Access, 2019. **7**: p. 71072-71078.

[18] Moraes, J.L., et al., Advances in photopletysmography signal analysis for biomedical applications. Sensors, 2018. **18**(6): p. 1894.

[19] Li, S., et al., Comparison and noise suppression of the transmitted and reflected photoplethysmography signals. BioMed research international, 2018. **2018**.

[20] Liang, Y., et al., An optimal filter for short photoplethysmogram signals. Scientific data, 2018. **5**: p. 180076.

[21] Reddy, K.A., B. George, and V.J. Kumar, Use of fourier series analysis for motion artifact reduction and data compression of photoplethysmographic signals. IEEE

transactions on instrumentation and measurement, 2008. **58**(5): p. 1706-1711.

[22] Dao, P.T., X.J. Li, and H.N. Do. Lossy compression techniques for EEG signals. in 2015 International Conference on Advanced Technologies for Communications (ATC). 2015. IEEE.

[23] Roy, A.B., et al. Comparison of FFT, DCT, DWT, WHT compression techniques on electrocardiogram and photoplethysmography signals. in IJCA Special Issue on International Conference on Computing, Communication and Sensor Network CCSN. 2012.

[24] Uthayakumar, J., T. Vengattaraman, and P. Dhavachelvan, A survey on data compression techniques: From the perspective of data quality, coding schemes, data type and applications. Journal of King Saud University-Computer and Information Sciences, 2018.

[25] Narasimha, M. and A. Peterson, On the computation of the discrete cosine transform. IEEE Transactions on Communications, 1978. **26**(6): p. 934-936.

[26] Chong, K., et al. Data compression technique for high resolution wireless photoplethysmograph recording system. in 2013 IEEE International Conference on Space Science and Communication (IconSpace). 2013. IEEE.

[27] Francescon, R., et al. Toward lightweight biometric signal processing for wearable devices. in 2015 37th Annual International Conference of the IEEE Engineering in Medicine and Biology Society (EMBC). 2015. IEEE.

[28] Hooshmand, M., et al., Boosting the battery life of wearables for health monitoring through the compression of biosignals. IEEE Internet of Things Journal, 2017. **4**(5): p. 1647-1662.

[29] Del Testa, D. and M. Rossi, Lightweight lossy compression of biometric patterns via denoising autoencoders. IEEE Signal Processing Letters, 2015. **22**(12):

p. 2304-2308.

[30] Ranjeet, K., A. Kumar, and R.K. Pandey. ECG signal compression using different techniques. in International Conference on Advances in Computing, Communication and Control. 2011. Springer.

[31] Ballesteros, D.M., A.E. Gaona, and L.F. Pedraza, Discrete Wavelet Transform in Compression and Filtering of Biomedical Signals. Discrete Wavelet Transforms: Biomedical Applications, 2011: p. 17.

[32] Natarajan, V. and A. Vyas. Power efficient compressive sensing for continuous monitoring of ECG and PPG in a wearable system. in 2016 IEEE 3rd World Forum on Internet of Things (WF-IoT). 2016. IEEE.

[33] Baraniuk, R.G., Compressive sensing [lecture notes]. IEEE signal processing magazine, 2007. **24**(4): p. 118-121.

[34] Sharma, R. A data compression application for wireless sensor networks using LTC algorithm. in 2015 IEEE International Conference on Electro/Information Technology (EIT). 2015. IEEE.

[35] Vadori, V., E. Grisan, and M. Rossi. Biomedical signal compression with time-and subject-adaptive dictionary for wearable devices. in 2016 IEEE 26th International Workshop on Machine Learning for Signal Processing (MLSP). 2016. IEEE.

[36] Reddy, G.N.K., M.S. Manikandan, and N.N. Murty. Integrated Data Compression and Pulse Rate Extraction Scheme Using Differential Coding for Wireless PPG Monitoring Devices. in 2018 IEEE 13th International Conference on Industrial and Information Systems (ICIIS). 2018. IEEE.

[37] Dhar, S., et al., An efficient data compression and encryption technique for PPG signal. Measurement, 2018. **116**: p. 533-542.

[38] Mukhopadhyay, S.K., M.O. Ahmad, and M. Swamy, Compression of steganographed

ppg signal with guaranteed reconstruction quality based on optimum truncation of singular values and ascii character encoding. IEEE Transactions on Biomedical Engineering, 2018. **66**(7): p. 2081-2090.

[39] Malgina, O., et al. Methods for ECG signal compression with reconstruction via cubic spline approximation. in 2011 1st Middle East Conference on Biomedical Engineering. 2011. IEEE.

[40] Alam, S. and R. Gupta. Zonal complexity based measure for lossy compression of photoplethysmogram using delta encoding. in 2015 IEEE International Conference on Signal Processing, Informatics, Communication and Energy Systems (SPICES). 2015. IEEE.

[41] Sadhukhan, D., S. Pal, and M. Mitra, Adaptive Band Limit Estimation based PPG data compression for portable home monitors. Measurement, 2019. **134**: p. 153-165.

[42] Mukhopadhyay, S.K., M.O. Ahmad, and M. Swamy, ASCII-character-encoding based PPG compression for tele-monitoring system. Biomedical Signal Processing and Control, 2017. **31**: p. 470-482.

[43] Xiao, J., et al., A Low-Complexity Compressed Sensing Reconstruction Method for Heart Signal Biometric Recognition. Sensors, 2019. **19**(23): p. 5330.

[44] Chong, K., et al., Evaluation of the effect of step size on delta modulation for photoplethysmogram compression. Proc. Technol., 2013. **11**: p. 815-822.

[45] Mukhopadhyay, S.K., M.O. Ahmad, and M. Swamy, SVD and ASCII character encoding-based compression of multiple biosignals for remote healthcare systems. IEEE transactions on biomedical circuits and systems, 2017. **12**(1): p. 137-150.

[46] Banerjee, S. and A. Roy, Linear algebra and matrix analysis for statistics. 2014: Crc Press.

[47] https://physionet.org/content/bidmc/1.0.0/bidmc_data.mat.

[48] Goldberger, A., et al., Components of a new research resource for complex physiologic signals. PhysioBank, PhysioToolkit, and Physionet, 2000.

[49] Pimentel, M.A., et al., Toward a robust estimation of respiratory rate from pulse oximeters. IEEE Transactions on Biomedical Engineering, 2016. **64**(8): p. 1914-1923.

[50] https://www.capnobase.org/index.php?id=857.

[51] Karlen, W., et al., Multiparameter respiratory rate estimation from the photoplethysmogram. IEEE Transactions on Biomedical Engineering, 2013. **60**(7): p. 1946-1953.

[52] Zigel, Y., A. Cohen, and A. Katz, The weighted diagnostic distortion (WDD) measure for ECG signal compression. IEEE transactions on biomedical engineering, 2000. **47**(11): p. 1422-1430.

[53] Thakor, N.V. and Y.-S. Zhu, Applications of adaptive filtering to ECG analysis: noise cancellation and arrhythmia detection. IEEE transactions on biomedical engineering, 1991. **38**(8): p. 785-794.