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The effect of Photoplethysmography signal denoising on compression quality

Mohammadreza Alizadeh Aliabadi*, Mohsen Karimi **(C.A.) , Zahra Karimi** and Mehrdad soheili Fard**

Abstract: Photoplethysmography (PPG) signals provide a non-invasive means of monitoring cardiovascular status during physical exercise; however, they are prone to noise, especially motion artifacts (MA). For specific telemedicine applications, compression is necessary for tasks such as PPG signal generation and secure data transmission. In this study, the investigation focused on determining whether it is better to perform compression before or after noise removal by applying a noise removal method and various compression methods. To achieve the aim, the study explored a subspace-based denoising method called "Maximum Uncorrelated PPG Denoising." Additionally, signal compression methods were examined in nine distinct steps. Compression quality is evaluated using various criteria, such as compression rate (CR) and Percentage Root Mean Square Difference (PRD). The results showed that regardless of the type of compression method, it is better not to remove noise before the compression process because doing so reduces CR and increases PRD.

Keywords: Photoplethysmography (PPG), signal denoising, compression ratio (CR), Percentage Root Mean Square Difference (PRD).

1 Introduction

Purpose of PPG data compression, a low-cost and straightforward optical technique, is to detect blood volume using microvascular tissue. Generally, PPG signal compression and denoising are divided into two categories: data reduction for storage and transmission efficiency, achievable with a sensor. PPG records a large amount of data using pulse signals over time with a high sampling rate and accurate waveform. The second category involves effectively reducing noise and improving signal quality by smoothing fluctuations. However, if compression is too aggressive, significant signal details and information of signal may be lost, including those affected by noise and artifacts [1]. This can decrease signal quality and clinical utility, as it's crucial to preserve the integrity of the natural physiological signal. One of the efficient methods for signal denoising is compressive sensing (CS). CS offers a modern framework for managing sparse signals, allowing sampling below the Nyquist rate and reducing the required number of measurements, particularly in nearly sparse signals [2]. An incorrect choice of scattering order may introduce significant noise into the estimated signal. The CS technique determines the optimal number of basis vectors (scattering order) for signal compression by minimizing the reconstruction error. Typically, conventional methods rely on thresholds or empirical data to select these parameters [3]. There are various research on PPG signal denoising.

Banerjee et al. proposed a compression and encoding of PPG signals, crucial for secure biomedical data transmission and storage. High compression ratio (CR) and minimizing data distortion are key characteristics. They have developed a reversible reconstruction algorithm that fully reconstructs the compressed data, and also discusses the importance of correct PPG sensor placement and the broader context of developing secure networks and data encryption for multimedia applications [4].

Mukhopadhyay et al. present an algorithm for compressing steganographic PPG signals with high reconstruction quality. This algorithm is tested on four

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* The author is with the Department of electrical engineering, Institute Mehr Astan University, Guilan, Iran.
E-mail: mohammadrezaalizadeh@stu.mehrastan.ac.ir
** The authors are with the Department of Biomedical Engineering, Isfahan University of Medical Sciences, Isfahan, Iran.
E-mails: mohsenkarimi@amt.mui.ac.ir
Corresponding Author: Mohsen Karimi.
Zahra Karimi :z.karimi286@gmail.com

diverse databases, achieving high CRs and low error rates. They have concluded that their algorithm, in addition to its efficiency, provides a high level of security for compressing PPG signals containing sensitive patient information. This reassures the safety of patient data in clinical settings [5].

Abdulkader et al. present a summary of signal compression techniques for the PPG signal, offering a comparative analysis to aid in selecting appropriate PPG compression techniques. The goal is to remove irrelevant data while preserving important information for specific clinical applications. It highlights the importance of PPG compression in continuous and real-time monitoring, such as telemedicine, which is necessary to minimize storage and efficiently manage data in embedded processors. These processors handle tasks such as signal compression, noise removal, clinical data extraction, and data encryption. The paper also mentions the importance of careful compression of PPG signals to avoid significant distortion, as this may significantly affect the clinical usefulness of the reconstructed signal. This study emphasizes the need for PPG compression techniques that strike a balance between minimal signal distortion and meet performance requirements for storage and communication. Selecting a PPG compression technique is challenging due to factors such as storage requirements and algorithm computational requirements [6].

Reddy et al. describe a new technique for reducing motion artifacts in PPG signals through cycle-by-cycle Fourier series analysis (CFSA), allowing the extraction of clean PPG data from motion-corrupted signals typically encountered when using pulse oximeters. This process reduces artifacts and compresses the data by representing each PPG cycle with fewer Fourier series coefficients. In CFSA representation, once the Fourier coefficients for one PPG cycle are calculated and stored, subsequent PPG cycles are similarly analyzed and stored, resulting in a reconstructed PPG signal. Successful reconstruction of PPG signals, especially the dicrotic notch, indicates the fidelity of the compressed signal to the original. The paper suggests an adequate PPG signal representation can be achieved by accurately capturing the dichroic gap and preserving the first seven significant Fourier coefficients [7].

Zhou et al. present a centralized method for compressing PPG signals using an extreme learning machine (ELM). This method is particularly beneficial due to the large data volume of PPG signals. It involves dividing the PPG signal into segments, processing them as input and output data, and then compressing and reconstructing the signal one band at a time until completion. The technique employs random generation of parameters for the ELM hidden layer during the training process, which enhances its efficiency and effectiveness [8].

Sivaranjini et al. proposed a method for estimating the pulse rate (PR) is discussed using compression measurement techniques CS with PPG photoplethysmograph signals. Different measurement matrices (for example, random Gaussian, Bernoulli, sparse binary, and deterministic binary block diameter (DBBD)) are used to obtain CS measurements, and the DBBD matrix is effective in PR estimation. CS measurements are utilized for pulse rate estimation and pulse rate variability analysis owing to their convenient structure [9].

Rezaii et al. proposed a lossless compression algorithm designed for ECG and PPG signals, with a practical application in real-time data collection from an AD8232 ECG module and a Raspberry Pi (R-Pi). The algorithm, which uses delta encoding techniques and run-length encoding, demonstrates superior performance in terms of signal-to-noise ratio, density ratio, and root mean square error compared to existing methods. This makes it a viable option for remote monitoring programs. The method also highlights the use of R-Pi 4 for data acquisition, processing, and transmission, showing an improvement in efficient cardiac signal compression [10].

Raj et al. discuss an efficient PPG signal compression technique using modified adaptive Fourier decomposition (AFD). They propose a superior compression method with a lower error rate and higher signal quality than traditional methods such as Fourier transform and wavelet. Their approach is based on the Takenaka-Malmquist system and Nevanlinna factorization. Their findings demonstrate that their approach can apply to real-time e-health applications due to its high fidelity in signal compression [11].

Alam et al. proposed a compression method for PPG signals in wearable devices that utilize the energy of Discrete Cosine Transform (DCT) coefficients. This approach includes creating a simple and effective compression and denoising scheme for PPG raw data, adjusting DCT coefficient energy levels to evaluate compression effects, analyzing PPG signals from different databases to verify the significance of the framework, and using adjustable compression parameters, such as energy thresholds proportional to the signal noise frequency. The adaptability of these parameters reassures that the method can be fine-tuned to suit various noise and artifact scenarios. As a result, this approach aims to effectively manage the power and storage of wristband PPG devices without compromising signal integrity. It can handle different types of noise and artifacts [12].

Reddy et al proposed a research study focused on improving the accuracy of PPG signals used to measure arterial blood oxygen saturation by addressing the issue of artificial movements that occur when the patient moves. They used Fourier series analysis to process PPG signals on a cycle-by-cycle basis, reducing motion artifacts, increasing PPG data quality, and enabling compression [13].

It's important to consider that the process of removing noise and artifacts from PPG signals before compression could significantly increase compression efficiency. This could result in a clean signal, free from noise and artifacts, that the compression algorithm can efficiently compress. The algorithm's ability to identify the redundancy of the signal is a key factor in its effectiveness for clinical use, as it ensures the signal's integrity is maintained. Surprisingly, even compression methods like lossy compression, which can enhance noise and artifacts in the signal, can be effective. The compression algorithm's interpretation of noise fluctuations as part of the signal and its efforts to preserve them highlight the potential of lossy compression in this context.

Additionally, reducing computational complexity can accelerate the compression process and simplify its display. When the signal is compressed, artifacts and noise become part of it. When the signal is decompressed, these unwanted components are also decompressed, making it very difficult to remove them. Cleaning PPG data before compression helps ensure that the resulting compressed data are of the highest quality and suitable for their intended purpose, whether clinical diagnosis, monitoring, or research.

This research aims to investigate whether denoising is better before or after compression, a topic not explored in previous studies on the PPG signal. Our research aims to enhance the quality of PPG signals using advanced signal processing and compression techniques. Specifically, we aim to analyze PPG signals with greater accuracy by removing noise and motion artifacts and reducing data volume through optimized compression methods without significantly compromising signal quality. Our research introduces several novel and unique aspects. In brief, the contribution of the proposed method is

- Firstly, we combine PPG sensors and accelerometers to effectively separate motion artifacts, allowing for more precise isolation of PPG signals from motion-induced noise.
- Secondly, we explore new compression techniques employing wavelet transforms and principal component analysis, which offer significant advantages over older methods in preserving signal quality and reducing data volume.
- Thirdly, the proposed method has the potential to substantially impact fields related to biosensing and signal processing. By improving PPG signal quality and reducing data volume, these techniques can be applied to real-time health monitoring and more accurate clinical analysis. Ultimately, they will provide better tools for clinicians and researchers to assess and monitor patient health, enhancing treatment outcomes and diagnostic accuracy.
- Finally, the paper is organized as follows: In the second section, the proposed method is discussed. In the third section, results and discussion are presented, and in the fourth section, the conclusion is discussed.

2 Method

In this research, the PPG signal is used from [1]. This dataset focuses on the signals obtained from individuals during physical exercises, which are associated with movement artifacts. The database includes twelve tracks from male subjects aged 18 to 35 years recorded while running and ten tracks from eight other subjects (seven men and one woman) affected by cardiovascular disease, aged nineteen to fifty-eight years, recorded during rehabilitation and boxing training. Generally, each test lasts about 300 seconds, and each trace produces between 4000 and 35000 samples. Additionally, all participants are male and in perfect health [1].

These PPG signals are captured using a pulse oximeter with a green LED, which has a wavelength of 515 nm and is positioned 2 cm from center to center. They are sampled at 125 Hz and transmitted via Bluetooth to a computer. Furthermore, the PPG sensors are equipped with three-axis accelerometer sensors that are attached separately. This auxiliary sensor enables noise removal and elimination of various waveform components using signal processing techniques. Noise removal includes the removal of motion artifacts (MA), which can be achieved by analyzing the signal based on the underlying space or using an adaptive filter.

In the initial step, the accelerometer signals are fed into a time-varying filter with recursive adjustment coefficients. The output of this filter provides an estimate of the signal components related to movement artifacts, which are then removed from the PPG signal [1].

2.1 How to remove signal noise

PPG denoising refers to the denoising PPG signals used to measure heart rate and other physiological parameters. Alessandra Galli et al [1]. Discuss a new method for subspace-based denoising called "maximum uncorrelated PPG denoising." This approach aims to maximize the correlation between the genuine and spurious components of the PPG signal and is described as robust. It is achieved through subspace decomposition, which separates the signal into different components based on frequency content. The components most associated with noise are removed, leaving a purified signal.

Singular value decomposition (SVD) decomposes matrices into singular vectors and singular values. The subspace approach aims to find an index subset that preserves valuable information from the PPG sensor output while minimizing interference effects from the artificial component of motion artifacts (MA). The criterion for selecting the main component of the signal is based on the degree of non-correlation with the accelerometer signals. The principal components of the PPG signals are determined based on their minimum prediction along the acceleration principal components. The selected subsets of indicators provide the possibility of reconstructing the deleted versions of the two outputs of the PPG sensor [1].

The paper used a threshold value of 0.6 to select the principal components of the PPG signals. The authors chose the threshold value of 0.6 to analyze the main elements of the PPG signals for specific reasons. This threshold value is mainly used to select the main components of signals and remove unnecessary components or noise [1]. Choosing this threshold has preserved signal quality, minimized noise, and involved a careful trade-off between compression and quality. It should be noted that this value was obtained by conducting several tests, informing our decision-making process. This refined criterion improves upon previous methods and allows the effective removal of PPG signals. In this analysis, each signal was examined using an observation window with a length of time window (TW) TW=8 seconds, resulting in it being sampled to create a segment of N=1000. Consecutive windows overlap by 75% (i.e., 6 seconds), for example, in a way that every TR=2 seconds. The algorithm has advanced to provide a new heart rate with a sampling rate of 0.5 Hz.

For each data, $s1(nT_S)$ or $s2(nT_S)$ with the length of N is obtained from the two PPG sensors. For each three-axis accelerometer output of the data sensor, $a_x(nT_S)$, , $a_y(nT_S)$, and $a_z(nT_S)$ are achieved from the corresponding path matrices: D_{s_1} , D_{s_2}, and D_{a_x}, D_{a_y}, and D_{a_z} . For the output of the PPG sensor $s(nT_S)$,the vectors s(j) are expressed as follows: $\underline{\boldsymbol{s}}(j) = [s(jT_s)\ s((j+1)T_s \ldots\ldots s((j+L-1)T_s))]$ with L<N, where the subscript "T" indicates displacement and transposition of s(j). L is the overlapped samples in the signal, *i* and *j* are the number of samples, and the average of the signal is as follows equation

$$\mu_s(j) = \frac{1}{L}\sum_{i=1}^{L} S[(j+i)T_s] \tag{1}$$

The above equation $\mu_s(j)$ is the average of signal s*(j), and* from each element of s(j). The vectors related to $ds(j)$ are obtained by subtracting the average. The path matrix *Ds* is then displayed as follows [1].

$$Ds = [ds(1)ds(2) \ldots . ds(J)] \tag{2}$$

With this formula 1 ≤ j ≤ J = N - L + 1, it can be noted that the matrix product: (1/(L-1)) DT s Ds is an estimate of the autocovariance $s1(nT_S)$. Similarly, Da is formed by the output samples of the accelerometer arranged in the vectors a(j). SVD is obtained for each path matrix [18].

$$D = UVT \tag{3}$$

The matrix U = [u(1)u(2) . . . u(J)] contains the left singular vectors of D, while the matrix V is formed by the appropriate singular vectors, and Σ is the diagonal matrix of singular values in decreasing order. The subspace approach applied to $s(nT_S)$aims to find the index subset of JPPG ⊂ {1, . . . J} so that all valuable information from the PPG sensor output is retained in the matrix [1].

$$D_{PPG=\sum j\in JPPG \underline{u}_s(j).\sum s(j,j).\underline{v}_s(j)^T} \tag{4}$$

In this way, the interference caused by the MA component is minimized. The choice of composition in principal component analysis (PCA) is based on the classification of signal vectors or the thresholding of PPG values. The criterion proposed for selecting the main component of the signal is based on the degree of non-correlation with the accelerometer signals. Therefore, the consideration includes the left eigenvector matrices Us and Ua, whose columns represent the direction vectors of the principal components $s(nT_S)$ and a(nTs), respectively. The PPG-related components of $s(nT_S)$are those whose representation along the main acceleration components is minimal. Consequently, for every axis of the accelerometer, the index is related to the first principal component $s1(nT_S)$ [1].

$$C_{s.a}(i) = \max_{1\le j\le J} \underline{u}_S^T(j)\underline{u}_a(j) \tag{5}$$

In equation (4) T is a transposition of u , Then, the selection process involves choosing the main components $s1(nT_S)$, which is the sum of the indices (5) calculated on the three axes of the accelerometer. This is done below a certain threshold τpr to form the JPPG [1].

$$JPPG = \{i : Cs,ax(i) + Cs,ay(i) + Cs,az(i) < \tau pr\}. \tag{6}$$

In equation (5), τpr = 0.6 is set. This process is conducted in PPG channels and selects index subsets JPPG1 and JPPG2, enabling the reconstruction of the deleted versions from the two PPG sensor outputs.

2.2 Compression method

In this article, several compression methods have been employed, which are responsible for both compression and signal reconstruction and utilized for compressing images and signals. The compression method comprises 9 steps, each performed separately.

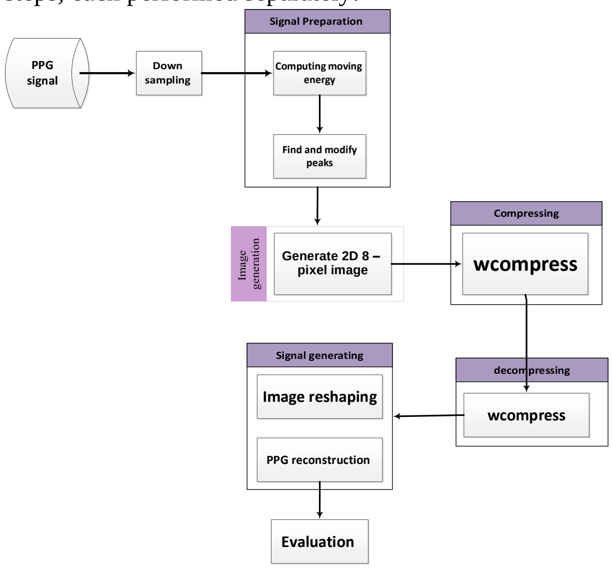


Fig. 1 proposed compression method.

In the first step, the signals consist of two noise-free signals and two noisy signals. These signals are processed using a cell array called a wavelet. Then, the desired PPG signal is isolated by dividing each element by the maximum absolute value in the array and normalizing the result to a range of 8-bit integers (from -127 to 127) by multiplying by 127. The output is rounded to the nearest integer, resulting in a normalized form.

In Step 2, the total energy of the original PPG signal is calculated by squaring its values and adding them. Consequently, by adjusting the threshold to retain 98% of the energy of the original signal in the sampled signal, the most significant part of the signal is preserved. In contrast, the least important parts are removed. Thus, the compressed signal represents the version signal. The original signal is processed to ensure that no more than 2% of the signal information is removed.

In Step 3, the signal's motion energy is calculated, which can be used to detect peaks, heartbeats, or other features in the down-sampled PPG signal. This calculation serves as a local measure of the energy moving with the signal and can highlight periods of higher variance or activity in the signal. The plot visualizes this kinetic energy for further analysis.

In Step 4, the objective is to analyze the signal for specific features, such as peaks, and to quantify the characteristics of these features, such as the regularity of their intervals, aiming to identify the high points and their exact specifications. This data can be utilized to examine the features and patterns present in the signal. These analyses are performed using entropy and standard deviation.

In Step 5, the sampled PPG signal is divided into segments based on provided locations, and an array of signals is calculated along with the length of each segment. Subsequently, the signal is resampled to create an "8-bit 2D image in grayscale", presenting the signal data as an image for analysis or visualization purposes.

In Step 6, the image is compressed using various wavelet-based methods that normalize the pixel values within the standard range of 0-255 for an 8-bit grayscale image. This normalization process involves subtracting the minimum pixel value from the entire image and scaling it based on the maximum value. The compression is achieved using the "compress" function, which includes compression methods such as 'ezw', 'spihtz', 'stw', 'wdr', 'aswdr', 'lvl_mmc', 'gbl_mmc_f', and 'gbl_mmc_h'. This records each compression operation's CR and bits per pixel (bpp).

In Step 7, the "wcompress" function is employed to compress the image, and the peak signal-to-noise ratio (PSNR) is calculated to compare the original and uncompressed images. The PSNR array contains the PSNR values for each decompression method, enabling the evaluation of which compression method preserved the most quality relative to the original image. PSNR serves as a standard measure for assessing the reconstruction quality of lossy compression algorithms, with higher PSNR values generally indicating better quality.

In Step 8, the image is divided into eight components (channels and layers) in the pastureland of image processing. The image grayscale value is normalized between [0 1] as the following equation.

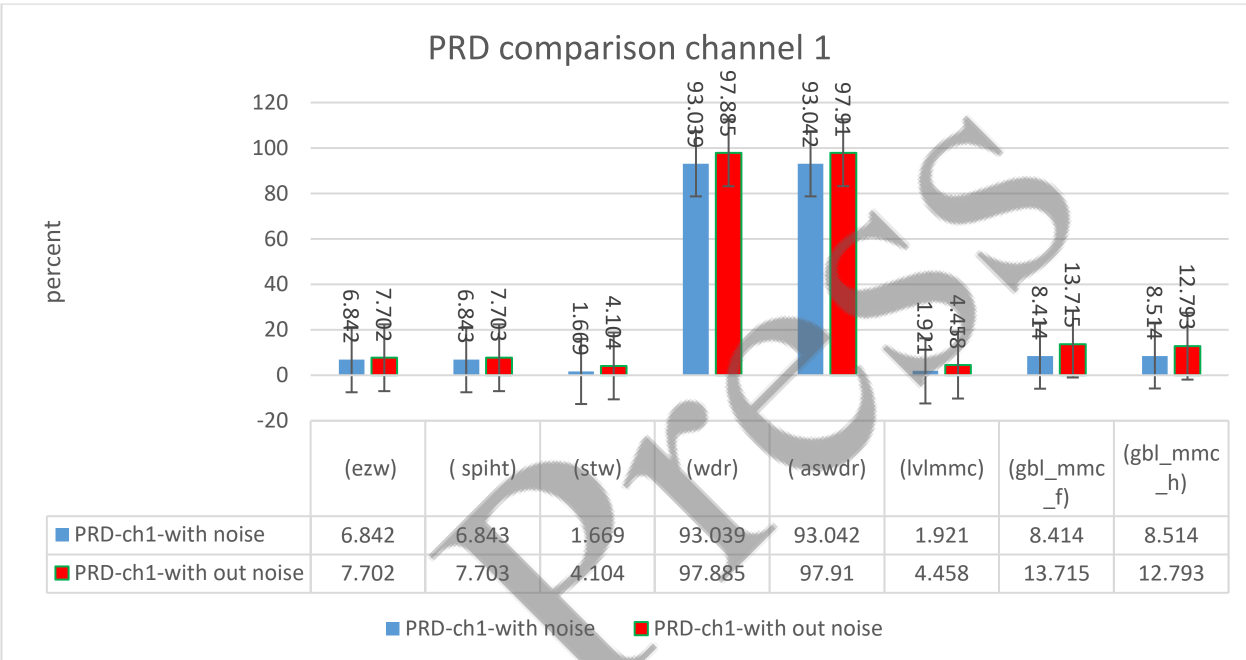
$$y_i = y_{min} + (y_{max} - y_{min}).\frac{(x_i - x_{min})}{x_{max} - x_{min}} \qquad (7)$$

In the above equation x_{max} is a grayscale maximum value, y_i is normalized value, y_{max} is equal to 1, y_{min} is equal to 0, x_{min} is the lowest grayscale value of the image. This process aims to standardize the range of pixel values for consistency and reliability in downstream processing or to restore the original pixel range after modification [14,15].

In Step 9, the images are resized from the compressed state to measure the actual signal. Various PPG signal reconstruction techniques are then evaluated after compression, assessing their fidelity using PRD and CR diagrams and numerical criteria.

3 Results and Discussion

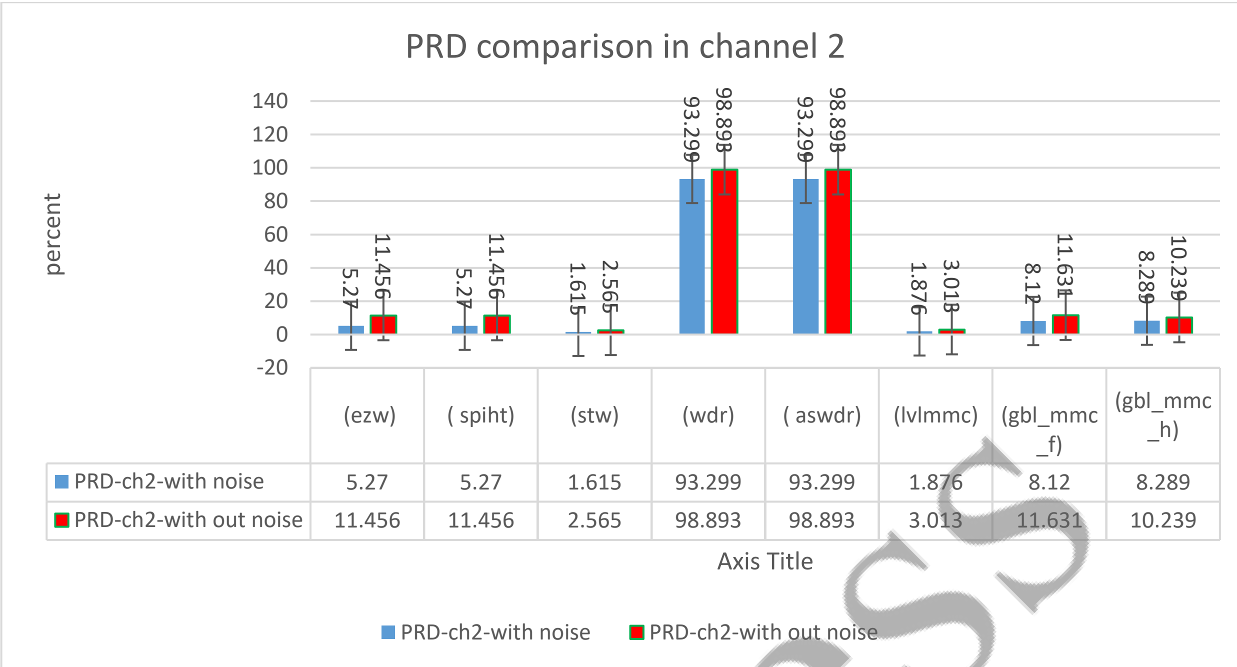
For evaluation, the proposed compression method PRD and CR is used. PRD in channel 1 was measured across different compression methods, Figure 2 shows this measurement. As Figure 2 shows, signals without noise exhibit higher PRD than signals with noise across all compression methods. Additionally, in the Wavelet Difference Reduction (WDR) and Adaptively Scanned Wavelet Difference Reduct (ASWDR) methods, higher PRD values are observed compared to other compression methods, suggesting that while potentially offering other benefits, these methods do not compress effectively in terms of maintaining signal quality, whether in the presence or absence of noise. Furthermore, in the Spatial Orientation Tree Wavelet (STW), IVI, and Multi-Resolution Morphological Compression (MMC) methods, lower PRD values are noted. This indicates that these methods are better at preserving the quality of the original signal during compression, resulting in less distortion and lower PRD.



	(ezw)	(spiht)	(stw)	(wdr)	(aswdr)	(lvlmmc)	(gbl_mmc_f)	(gbl_mmc_h)
PRD-ch1-with noise	6.842	6.843	1.669	93.039	93.042	1.921	8.414	8.514
PRD-ch1-with out noise	7.702	7.703	4.104	97.885	97.91	4.458	13.715	12.793

Fig. 2 PRD values in different compression methods with and without noise channel 1

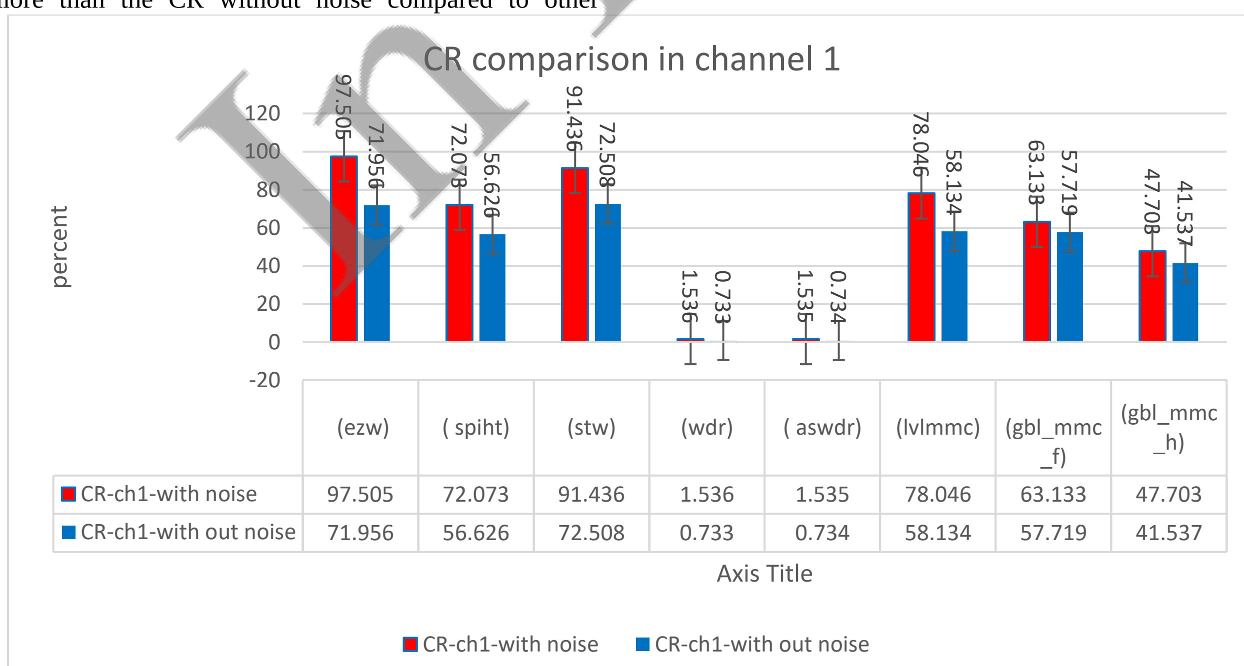
In channel 2 in Figure 3, the vector pattern of channel 2 resembles that of channel 1, with slight variations in the methods compared to each other. The ratio of PRD without noise to PRD with noise has increased in the EZW and SPIHT methods compared to channel 1. Conversely, in the Global Multi-Resolution Morphological Compression-Full Mode (GBL_MMC_F) and Global Multi-Resolution Morphological Compression-Half Mode (GBL_MMC_H) methods, a decrease can be observed compared to channel 1. It is noteworthy that the PRD ratio in channels 1 and 2 has decreased in the MMC method in the STW and IVI methods. Moreover, in the WDR and ASWDR methods in channels 1 and 2, a slight increase in their ratio is observed relative to each other. Furthermore, in channels 1 and 2, the WDR and ASWDR methods have shown a more pronounced increase than other compression methods. The vector pattern of channel 2 mirrors that of channel 1, indicating that the general behavior of compression algorithms exhibits a consistent trend or response in both channels. Additionally, for the GBL_MMC_F and GBL_MMC_H methods, PRD reduction in channel two compared to channel one suggests that these methods may offer more flexibility in noise than EZW and SPIHT.



	(ezw)	(spiht)	(stw)	(wdr)	(aswdr)	(lvlmmc)	(gbl_mmc_f)	(gbl_mmc_h)
PRD-ch2-with noise	5.27	5.27	1.615	93.299	93.299	1.876	8.12	8.289
PRD-ch2-with out noise	11.456	11.456	2.565	98.893	98.893	3.013	11.631	10.239

Fig. 3 PRD values in different compression methods with and without noise channel 2

As depicted in Figure 3, the CR is higher with noise than CR without noise, and the CR of the WDR and ASWDR methods is significantly lower than that of other methods. Moreover, in the EZW, SPIHT, STW, and IVImmc methods, there is a more noticeable increase in CR compared to other methods. Specifically, in the EZW method, the CR with noise has increased more than the CR without noise compared to other methods. The EZW, SPIHT, STW, and IVImmc methods substantially increase CR compared to other methods, suggesting that they are more efficient or aggressive in data compression. Importantly, this may reassure you of their suitability for the type of data or the presence of noise in the data.



	(ezw)	(spiht)	(stw)	(wdr)	(aswdr)	(lvlmmc)	(gbl_mmc_f)	(gbl_mmc_h)
CR-ch1-with noise	97.505	72.073	91.436	1.536	1.535	78.046	63.133	47.703
CR-ch1-with out noise	71.956	56.626	72.508	0.733	0.734	58.134	57.719	41.537

Fig. 4 CR values in different compression methods with and without noise channel 1

Figures 4 and 5 show that CR values are almost similar to each other, with the difference that in the method with noise, the CR of EZW for channel two is higher than the CR of channel 1, and also, WDR and ASWDR methods are nearly identical to each other in both channels, with a slight decrease in channel 2 for each method. Additionally, the CR of the EZW method without noise has a higher value in each channel than the other methods. Importantly, it can be observed that CR with noise and without noise has significantly increased in all methods in channel two compared to channel 1, underscoring the importance of this trend. As evident from Figures 2 to 5 present a compelling trend: the WDR and ASWDR methods consistently exhibit low CR values in both channels, coupled with high PRD values. In contrast, other methods consistently demonstrate high CR values and low PRD. This trend highlights the underperformance of the WDR and ASWDR methods, a finding further supported by Figure 8. The same pattern is evident in Figure 9, underscoring the implications of these findings for our understanding of data analysis methods. WDR and ASWDR in these methods have a higher PRD, which indicates a reduction in the reconstructed signal quality compared to the original signal. This is due to the failure of these methods to preserve the details of the signal in the compression process.

EZW, SPIHT, STW, IVI, and MMC of these methods have higher CR, which indicates that these methods can compress the signal more effectively without much information loss. In other words, these methods have compressed a more significant amount of signal information in a smaller size. EZW and SPIHT methods in noisy signals show higher CR in these conditions, which means they can compress data more effectively even in noisy situations. Meanwhile, WDR and ASWDR methods have lower CR, which indicates less efficiency in data compression in the presence of noise.

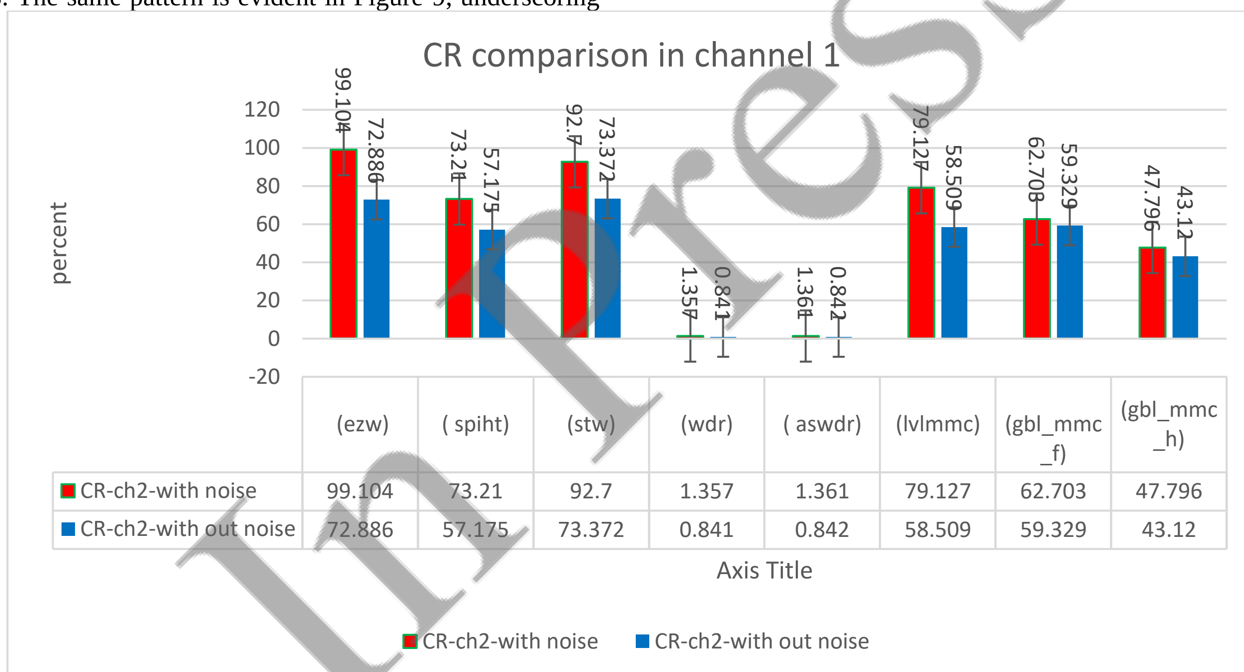


Fig. 5 CR values in different compression methods with and without noise in channel 2

The results presented in Figures 2-5 illustrate the performance of different compression methods in terms of PRD and CR with and without noise. It is evident that the WDR and ASWDR methods consistently yield higher PRD values than other compression methods, indicating their ineffectiveness in preserving signal quality regardless of noise presence. Conversely, the STW, IVIMMC, GBL_MMC_F, and GBL_MMC_H methods demonstrate lower PRD values, suggesting their effectiveness in maintaining original signal quality during compression, thereby reducing distortion. Comparing PRD and CR values between channels 1 and 2 reveals some interesting trends. The pattern observed in channel 2 mirrors that of channel 1, indicating a consistent behavior of compression algorithms across both channels. Additionally, specific compression methods exhibit differences in behavior between channel 2 and channel 1, such as the relative reduction of PRD for the GBL_MMC_F and GBL_MMC_H methods in channel 2.

After noise removal, CR values decrease, with the EZW, SPIHT, STW, and IVImmc methods showing a more significant increase in CR than other methods. This trend suggests that these methods are more efficient in data compression and may be better suited for the data type or noise presence in the data.

The findings across all figures consistently indicate that the WDR and ASWDR methods exhibit low CR values and high PRD values, implying poor performance. Conversely, other methods generally demonstrate higher CR values and lower PRD values. In summary, this study underscores the varying performance of different compression methods in preserving signal quality and achieving compression efficiency, both in the presence and absence of noise. The results offer valuable insights into understanding the strengths and limitations of each method, and comparisons across channels provide further nuances in their performance. However, it is essential to consider the specific nature of the data and the context in which these methods are employed. Further research could explore the trade-offs between compression efficiency and signal quality under different noise conditions and for specific data types. For more evaluation and statistical tests, an error bar is used. Error bars refer to graphical representations of data variability and are used on graphs to indicate the error or uncertainty in a reported measurement. They give a general idea of how precise a measurement is or how far the actual (error-free) value might be from the reported value. The error bar in the results in Figure 3-5 shows the correctness of the statistical test. A small error bar shows the validated results.

The T-test results in Figure 6 illustrate that the mean values of cardiac signal reconstruction differ significantly between the "with noise" and "without noise" conditions across all four channels. In the PRD-ch1 and PRD-ch2 channels, noise has a negative impact on the reconstruction process, leading to a reduction in the mean values of reconstruction. Specifically, in PRD-ch1, the mean values are 27.54 for the "with noise" condition and 30.78 for the "without noise" condition. Similarly, in PRD-ch2, the mean values are 27.13 and 31.02 for the "with noise" and "without noise" conditions, respectively. A paired t-test performed for these channels confirms that the differences are statistically significant (p-value < 0.05), indicating the detrimental effect of noise on the reconstruction process in these channels.

In contrast, in the CR-ch1 and CR-ch2 channels, the effect of noise is different. Unlike the PRD channels, noise results in an increase in the mean reconstruction values. For CR-ch1, the mean values are 56.62 for the "with noise" condition and 44.99 for the "without noise" condition. Similarly, for CR-ch2, these values are 57.17 and 45.76, respectively. The paired t-test for these channels also shows statistically significant differences (p-value < 0.05), highlighting the positive impact of noise on reconstruction in these channels.

Overall, these results indicate that noise significantly impacts the quality of cardiac signal reconstruction, but the nature of this impact varies across channels. In the PRD channels, noise degrades the reconstruction quality, while in the CR channels, it enhances the reconstruction values. This discrepancy in the effect of noise underscores the need for further analysis to clarify the mechanisms by which noise influences signal.

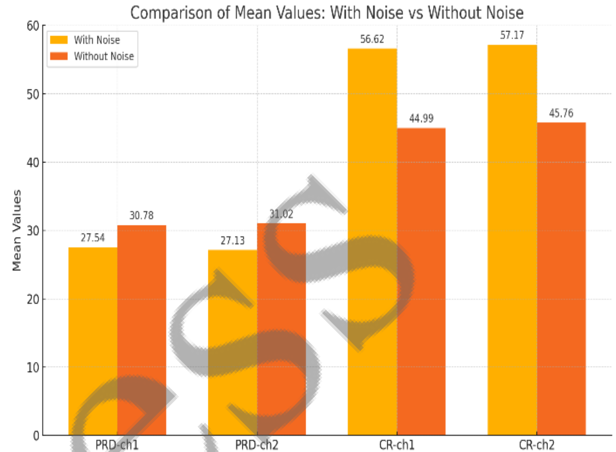


Fig 6. Comparison of paired T-test Results for "With Noise" and "Without Noise" Columns Across Channels

Figure 7 shows the original sample and reconstructed PPG signal with noise for different compression methods. The reconstructed signal is more apparent, and noise is effectively removed. This plot compares the original and reconstructed PPG signals. The blue line represents the noisy raw data, while the red line shows the clearer, noise-reduced signal after applying a compression method. The reconstructed signal maintains critical features, and its improved clarity is essential for accurate real-time health monitoring. Figure 8,9 shows the Original and reconstructed PPG signal with and without noise for different compression methods. As in Figure 8, 9 'WDR' and 'ASWDR' do not produce the best reconstruction results. According to the presented images (Figure 8 9), this method does not perform well in reconstructing PPG signals with noise. However, the final results show that this method cannot maintain the signal quality. While the EZW and SPIHT methods have high CR and good compression ability in noise conditions, the signal reconstruction quality is not high enough. The STW, IVI, and MMC methods have higher reconstruction quality and show good preservation of the original signal features in noise-free conditions. Their high CR indicates high efficiency in compression and reconstruction.

In general, noise-free signals using the STW and IVI MMC methods exhibited the lowest PRD, indicating that these methods effectively preserve the quality of the signal close to the original. These methods are less affected by noise and motion artifacts and are well-suited to maintaining the characteristics of the original signal. Conversely, noisy signals processed with the WDR and ASWDR methods show the highest PRD, suggesting that these methods are less effective in preserving the original signal and suffer significant quality degradation due to noise disturbances. Additionally, noise-free signals using the EZW, SPIHT, STW, and IVI MMC methods demonstrated higher CRs, indicating more effective data compression with minimal loss of information. However, noisy signals processed with EZW and SPIHT methods show a significant increase in CR compared to other methods, highlighting their effectiveness in compressing PPG data in the presence of noise and storing more information in a smaller volume. Furthermore, noise-free signal reconstruction using the STW and IVI MMC methods achieved higher quality and best preserved the original signal features. In contrast, noisy signal reconstructions with WDR and ASWDR methods exhibited the highest noise levels and lowest reconstruction quality, indicating these methods are inadequate for noise removal and signal preservation. Overall, comparisons show that STW and IVI MMC methods offer the best performance in maintaining and reconstructing signal quality for noise-free PPG signals. In contrast, for noisy signals, EZW and SPIHT methods perform better in data compression with higher CR but still require improvement in signal reconstruction, showing higher PRD compared to noise-free signals. Therefore, choosing the appropriate PPG signal compression and reconstruction method is crucial for various applications and specific conditions (such as the presence or absence of noise) to ensure signal quality and effective data compression.

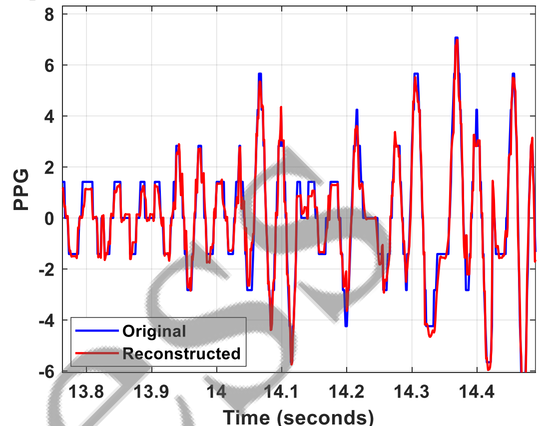
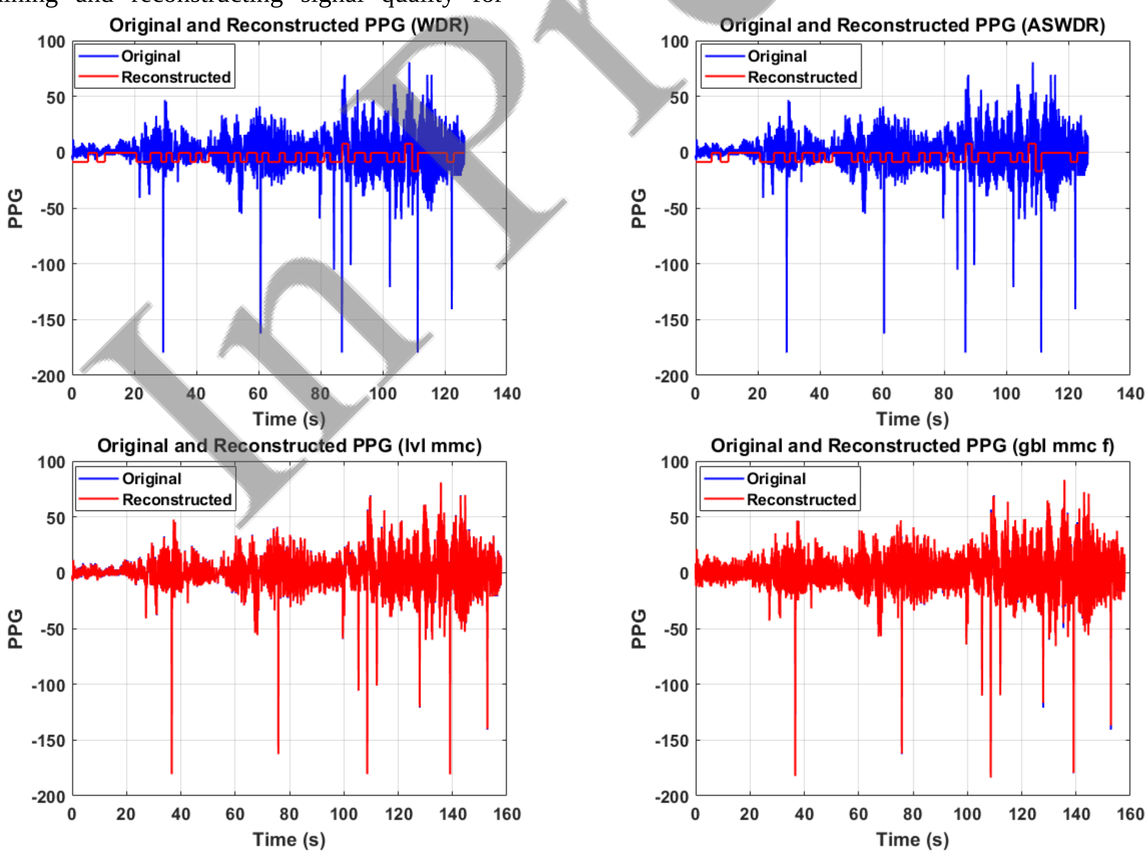


Fig .7 Sample of original and reconstruction PPG signal



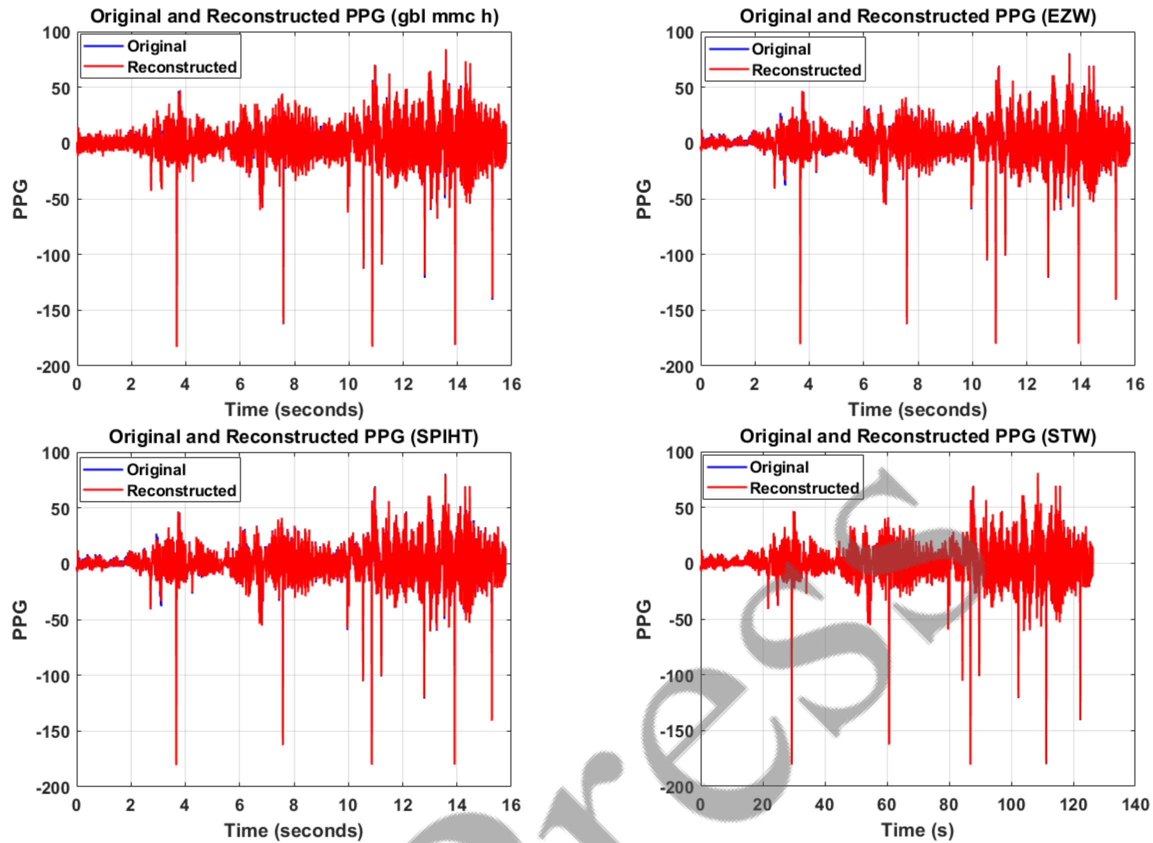
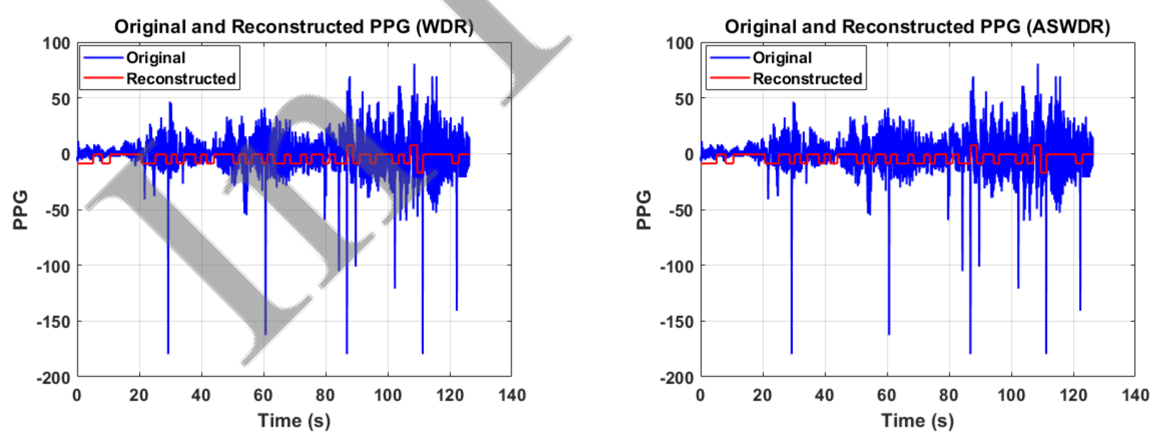


Fig. 8 Original and reconstructed PPG signal with noise for different compression methods.



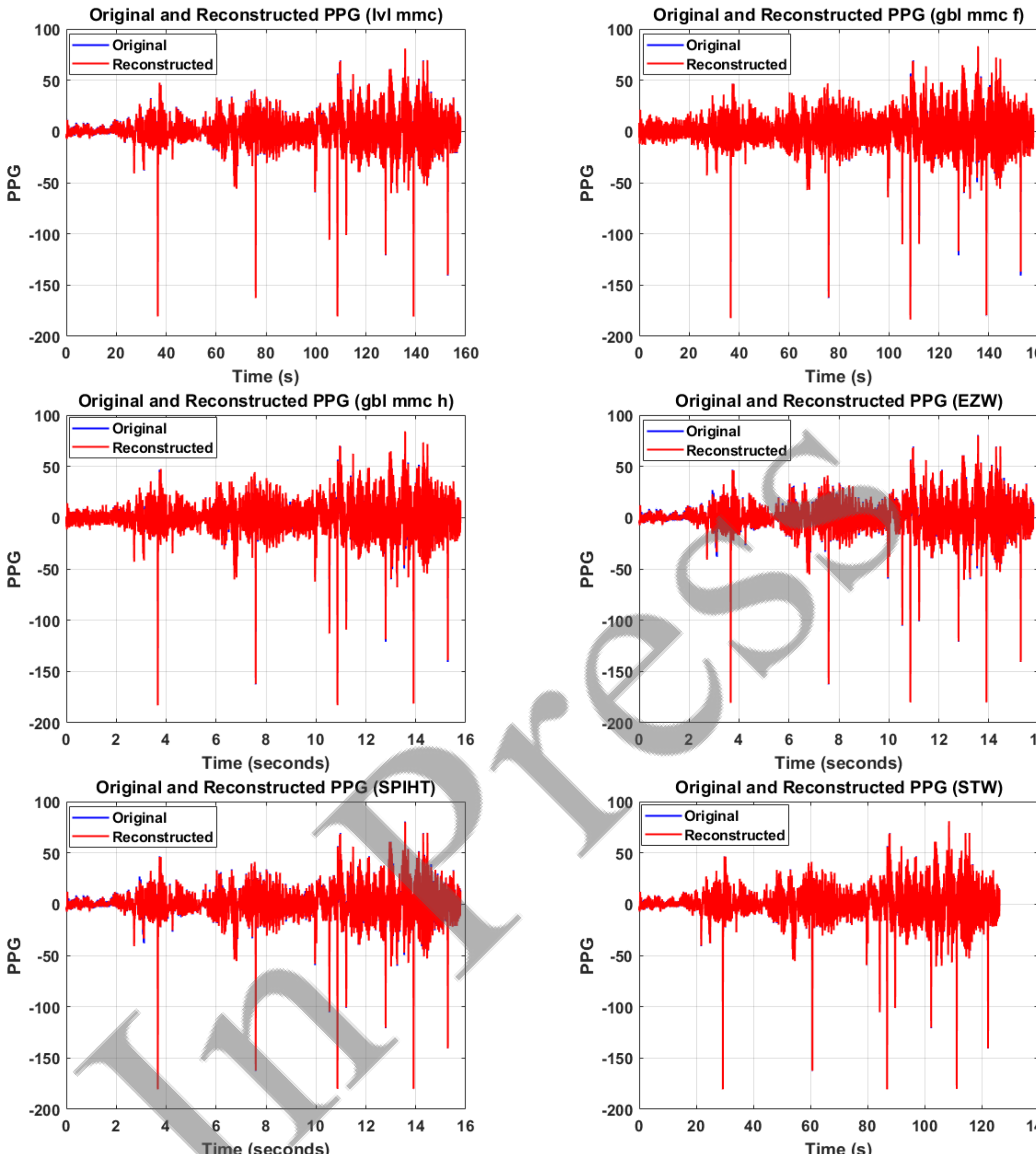


Fig. 9 Original and reconstructed PPG signal without noise for different compression methods

Compared to the previous techniques, the proposed method of this paper is based on image construction and then using wavelet transform in different modes for lossless compression of the PPG signal. In Table 1, the results of these methods are compared. Table 1 shows that the CR value for 12 samples in the database has the average value of 1.851 in PPG signal mode with noise, and the value of 0.917 has been reached in the noise-free state. Meanwhile, the value of PDR in the no-noise state is 1.651, and the value is 4.321 for the signal with noise. In [16], the author used PPG compression based on ASCII character encoding implemented on the database with CR 3.18. This work was not entirely lossless, as a very low PRD (produced by compression) of 1.023 was achieved in their work. [17] proposed a full lossless compression using LP and adaptive GRC, resulting in a CR of 4.073 and the CR value of 2.99.

Table (1) comparison of CR and PRD with other methods

	CR		**PDR**	
mode	noisy	Noise-free	noisy	Noise-free

[16]	3.18	-	1.023	-
[17]	2.99	-	4.073	-
Proposed	**1.851**	**0.917**	**4.321**	**1.651**

For noise-free signals, STW and IVI in MMC methods perform best regarding signal reconstruction quality and information preservation. With high CR and low PRD, these methods show high compression and accurate signal reconstruction ability. While EZW and SPIHT methods perform better in data compression and have higher CR for noisy signals, their reconstruction quality still needs improvement. While WDR and ASWDR show higher PRD and lower CR, meaning these methods cannot maintain signal quality well in noisy conditions.

4 Conclusion

In this study, PPG signals and motion artifacts collected from individuals during physical exercises were examined. The research focused on utilizing accelerometer data to filter out noise and artifacts present in PPG signals. Techniques such as time-varying filters and subspace-based approaches like "Maximum Uncorrelated PPG Noise Removal" were employed. A comprehensive signal compression process was investigated, encompassing several stages, including normalization, energy preservation, peak feature detection, and dimensionality reduction using SVD to retain the most relevant information. This process aims to enhance the accuracy and efficiency of signal analysis without compromising the clinical applicability of PPG signals. This study demonstrates that applying these techniques can significantly improve the quality of PPG signal analysis and increase the accuracy of the results. This study evaluated the performance of various PPG signal compression methods in the presence and absence of noise. The results indicated that the STW, IVIMMC, GBL_MMC_F, and GBL_MMC_H methods successfully preserved the original signal quality and reduced distortion, as evidenced by their lower PRD values. In contrast, the WDR and ASWDR methods performed poorly with lower CR and higher PRD values. The analysis across both channels revealed a consistent pattern in the behavior of compression algorithms; however, specific methods like EZW and SPIHT proved more efficient in data compression and performed better when handling noise. These findings highlight the importance of selecting the appropriate method based on the data type and noise conditions to maintain signal quality and compression efficiency. Overall, the study offers valuable insights into the advantages and limitations of each method and emphasizes the need for further research to explore the balance between compression efficiency and signal quality under varying noise conditions.

Conflict of Interest

The authors declare no conflict of interest.

Author Contributions

Mohammadreza Alizadeh Aliabadi: Simulating and Writing
Mohsen Karimi: Writing and editing
Zahra Karimi: Writing and editing
Mehrdad soheili Fard: Writing and editing

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Mohammadreza Alizadeh Aliabadi was born in Iran. He received his B.S. and M.S. degrees in 2016 and 2018 at Gil and Mehrastan University of Technology, Iran. His research interests are Digital signal processing and Analysis of biological signals at, the Iran University of Science and Technology.

Mohsen Karimi was born in 1983 in Isfahan, Iran. He graduated from the Faculty of Advanced Medical Sciences, Isfahan University of Medical Sciences, Isfahan, Iran in the field of medical engineering. His research areas are medical image and signal processing, deep learning, and machine learning.

Zahra Karimi was born in 1986 in Isfahan, Iran. She is currently a PhD candidate in medical engineering at Isfahan University. Her research areas are medical image and signal processing, deep learning, and machine learning.

Mehrdad soheili Fard was born in Arak, Iran. He is currently studying for a specialized doctorate in BME at Isfahan University of Medical Sciences. His research field is cancer diagnosis, prognosis, and treatment. He is also actively involved in research in Neurology, Neuroscience, and Artificial Intelligence in Medicine.