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RESEARCH ARTICLE

Wireless ECG Signal Acquisition using Bio Radio and Compression through SVD on PYNQ-Z2

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Abstract

Background/Objectives: The primary purpose of this research is to investigate the feasibility and effectiveness of Singular Value Decomposition for compressing wirelessly collected ECG signals using a Bio Radio device and to show its implementation on a PYNQ-Z2 platform. **Methods** This study includes 20000, 80000, and 270000 ECG samples from different people having different ages. The Bio Radio device with an ECG lead-1 and lead-2 configuration was used to collect ECG data from various persons aged of 22,23,24,35,37,49. Singular Value Decomposition has been used to compress all ECG data on the PYNQ-Z2 FPGA, which offers a Python programming environment. Here, To analyze the result of compression various parameters like compression ratio, percent root mean square difference, and percent root mean square residual energy were calculated. **Findings**: In the matrix-based SVD technique, the signal is divided into many fundamental patterns and scaling factors. The most intriguing aspect of SVD is that only a small number of unique values may effectively preserve the majority of the signal's information. Here, we used a Bio Radio device to capture ECG signals at a sampling rate of 1 K S/s. After applying SVD to these data, we were able to reconstruct signals with sample sizes of 20000, 80000, and 270000. The highest compression ratio we were able to obtain was 35.6506, while the lowest PRD (%) was 0.00812, the same as the PRRE (%) for 20000 samples. For 80000 samples, we were able to reach a maximum compression ratio of 108.108 with a minimum PRD (%) of 0.0012, the same as the PRRE (%) of 1.3077. For 270000 samples, we achieved a maximum compression ratio of 228.8136 with a minimum PRD (%) of 0.0437, the same as PRRE (%). The highest value of QS is 1076.42 for lead 1 and 1721.76 for lead 2 for singular values q=70 and the sample size is of 80000. **Novelty:** Bio Radio utilizes Bluetooth for capturing biomedical signals that make user easy for doing any activity wirelessly in proximity to it. Pynq-Z2 provides Python programming which is quite an innovative platform for algorithm deployment on hardware.

Keywords: Bio Radio; SCA; PynqZ2; PS; PL; CR; PRD; PRRE; QS

1 Introduction

The leading cause of abnormal human mortality today is cardiovascular disease, and the number of people dying from it each year has been rising alarmingly. The amount of ECG data produced is significant because of several cycles and high-resolution collecting, which has a detrimental impact on the data's portability and transmission effectiveness. ECG signal compression is required in this situation.

We must examine a vast quantity of data for long-term ECG monitoring or in an ambulatory monitoring system to have sufficient knowledge about the individual under-diagnosis. This made it possible to successfully compress the ECG signals for a variety of applications, including ambulatory ECG recorders, transmission across communication networks, and data storage. Even a real-time ECG monitoring system has to transmit and compress data in real-time, which calls for wired or wireless connection resources. The following categories of data compression techniques exist direct data compression techniques (DPCM, AZTEC, SAPA)[1][2], parameter extraction approaches (average beat subtraction, cycle pool-based subtraction), and transform methods[1] (KL transform, Wavelet transform) It is categorized as both lossless and lossy compression. Data compression reduces storage and memory bandwidth for various types of data[3]. Syed Salman Kabir et al.[4] used SVD for ECG compression using data extraction and TSVD for ECG signal compression. The amplitude difference was measured, and it was compared with thresholds of 0.001 and 0005, then SVD. Ting Yu Li et al.[4] used SVD to encrypt and compress ECG data, and by applying key matrix Q to the ECG data of the Y matrix, they were able to get the resulting matrix C. They had recorded 10 min of ECG data from the MIT-BIH database at a sampling rate of 360 Hz and a resolution of 11 bits per sample. When using non-encrypted data, they were able to get CR=40.90 for single value Q=5, and CR=39.8 for singular value Q=38.9. The Q=13 method produced a CR=50.34 when compared to the other 12 compression techniques. Waltengus Dargie et al[4] employed a 5-lead ECG, a 3-D accelerometer, a 3-D gyroscope, and a 3-D magnetometer while removing motion artifacts from the measurement of wireless ECG. They discovered that SVD was more accurate for detecting P and T waves during regular movements and was more effective and consistent at detecting QRS complex in all motions. The Jacobi technique provides superior accuracy for singular values than the QR algorithm for parallel implementation, according to the authors Anlikumar et al.[4] who studied SVD computation with the Jacobi Method, QR Algorithm, and one-sided Hestenes Jacobi method. BLV suggested an array architecture for that Jacobi technique that can compute the SVD of an nxn real matrix. The Hestenes Jacobi technique is implemented with the following hardware: ROM of (mxn) matrix, two-port RAM, Control unit, Jacobi rotation block for orthogonalizing rows and removing off-diagonal components, Square root block for computing singular values. Singular value decomposition was implemented on an FPGA by Aidin Sihri et al.[5], who also modified the hardware by employing the Jacobi technique to calculate SVD matrices. The tremendous parallel processing capabilities of the Jacobi algorithm were the primary factor in its adoption. To calculate fundamental trigonometric functions using the CORDIC algorithm, they created a novel way that improved the hardware and computation performance. The approach in[6] can completely eliminate the computational load associated with compressing ECG data on wearable devices.

In this study, we collected ECG signals from a variety of individuals ranging in age. Their ECGs were recorded using BIO RADIO[7] data devices in Lead 1 and Lead 2 configurations at a 1Khz sample rate. Following the filtering of all ECG signals, all ECG beats were then aligned and peak identification of the QRS complex was carried out using the first derivative approach[8]. After that SVD algorithm on wirelessly collected ECG signals was deployed in PS part of PYNQ-Z2. Compression performance parameters like compression ratio, PRD, PRRE and QS were analyzed for SVD. The experimental research shows significant enhancement in compression ratio and QS as compared to[1] make it feasible to deploy on PS part PYNQ-Z2 which is novelty and make it feasible for edge computing.

2 Methodology

The proposed model consists of the wireless acquisition of ECG of various persons with different ages with Lead 1 and Lead 2 configurations. Here in this research, we have considered 20000, 80000 and 270000 samples of ECG signals. The ECG signals preprocessing, peak detection, and beat matrices are generated using software platform . After that SVD is applied in the PS part of PYNQ-Z2.At the end the parameters for the analysis those are CR,PRD and PRRE, QS were calculated and analyzed.

2.1 Software Platform

2.1.1 MATLAB

It was used for QRS complex and beat alignment for ECG Signal. The procedure used to find the QRS Complex is described below.

2.1.2 First Derivative Method for QRS Detection

The first derivative y(n) is calculated for each point of the ECG signal of x(n) mentioned in [9] as:

$$Y(n) = [X(n+2) - 2X(n-2) + X(n+1) - X(n-1)] \tag{1}$$

Using 0.6*max(Y), the slope threshold (Th) is computed [9]. The first derivative-based array was searched for spots that exceed the slope overload. To create the ECG Beat matrix, which has each column representing a single beat of the ECG, the points that fulfill the requirement are now taken as QRS and their locations are noted.

2.1.3 Jupyter Notebook Python3

Here, we have implemented SVD using the python libraries listed below.

1. Pandas: It loads the ECG signal
2. Matplotlib: Used to plot the Reconstructed ECG Beat Matrix and ECG Beat Matrix
3. Heartpy: For ECG signal preprocessing
4. SciPy is used to implement the SVD function

2.1.4 Singular Value Decomposition

Let's consider an Electrocardiogram Signal with p periods and q length. Each period is an R-R interval. This signal can be arranged in a two-dimensional matrix having pxq dimensionality. Each row of the matrix shows each period of the ECG signal shown in equation 2.

$$M = \{m_i(t) | i = 1,2,3,\ldots.p, t = 1,2,3,\ldots..q\} \tag{2}$$

$$\begin{pmatrix} m(1) & m(2) & m(q) \\ m(q+1) & m(q+2) & m(2q) \\ \vdots & \vdots & \vdots \\ m(p-1)q+1 & m(p-1)q+2 & m(pq) \end{pmatrix}$$

where m_i(t) is ith period of m(t).SVD of a given matrix having a dimension of pxq can be found by [4] as shown in equation 3 given below.

$$M = U \sum V^T \tag{3}$$

Where $U \in R^{p\times p}$, $V \in R^{q\times q}$are left and right singular vectors. $\sum$ is $p \times q$ matrix where $x_1, x_2, x_3, \cdots x_n$ are singular values.

The singular Value Decomposition theorem says M can be decomposed into scaling factors uixi and v vector where i is ranging from 1 to R. If matrix M is having rank one then except x_1, other singular values will be zero. To reconstruct that matrix again, only principal components v_1 and u_1x_1 are required.

Hence, from [4] reconstruction can be implemented by equation 4 given below.

$$M' = u_1 x_1 v_1^T \tag{4}$$

Now, ECG is a periodic signal with characteristics as compared to the sinusoidal signal in that it is containing periodic as well as aperiodic signals, and with that M can be the full rank matrix.

The information energy can be shown in terms of [4] given below in equation 5.

$$Q_M = x_1^2 + x_2^2 + \ldots\ldots\ldots\ldots\ldots + x_R^2 \tag{5}$$

and main information we can still recover from very few singular values if [1] ratio is given in equation 6.

$$\frac{x_1^2}{x_i^2} \gg 1 \tag{6}$$

whrere i=1,2,3,4,.........N

From the above N singular values, if only r values are greater than the remaining values then we can remove those nonrequired values from $\sum$ and matrix m can be reconstructed by [1] with the equation given 7 given below.

$$M' = u' \Sigma' v^{T'} \tag{7}$$

Where $U' \in R^{p\times p}$,$\sum \in R^{r\times r}$, $V' \in R^{q\times q}$ and U' and $V'$are having orthonormal columns.

2.2 Hardware Platform

2.2.1 Bio Radio Signal Acquisition Device

Bio Radio is essentially a data acquisition system. It has wireless signal acquisition capabilities and is very accurate and precisely customizable. It is lightweight and versatile enough to be carried wirelessly for a variety of biomedical applications, including data gathering, signal processing, signal analysis, and other applications. The researcher may move around more freely away from the computer where the signal is presented in the Bio Capture program with the adoption of wireless connectivity technologies, particularly Bluetooth, and the device's downsizing. Additionally, Bio Radio's inbuilt memory may be used to capture signals for later study. After the signal has been amplified, sampling and digitalization may be applied. Additionally, Bluetooth allows for wireless transmission to the PC.

For a wide range of measures, Bio Radio is compatible with many different types of sensors. It features a Bluetooth band with a 2.484 GHz frequency that allows for signal transmission up to 100 meters. Several sensors may be configured with BioRadio to collect a range of signals. Bluetooth's 2.4-2.484 GHz band and a range of around 100 feet are used for wireless streaming and recording. For post-analysis, data can be concurrently recorded to onboard memory

It offers a Transmission Range of 100 feet line of sight, an RF Band of 2.4-2.484 GHz ISM Band, an Input Range of 2V, 12-24 bit resolution, 0.30 V RMS (250 Hz sample rate, and a gain of 24) noise, a sampling rate of 250 Hz-16 kHz, -CMRR of -100 dB, and an 8-hour battery life. it has 500 MΩ input impedance. It has a 6μV resolution for ECG recording with a gain of 24 and a resolution of 16 bits.

2.2.2 PYNQ Z2 development board

PYNQ is an open-source platform made available by Xilinx for the development of simple-to-use embedded systems. It supports Python programming and several libraries. Before the development of the Zynq architecture, combining a microprocessor and field programmable gate array was challenging. The Zynq architecture, the newest member of Xilinx's SOC family, combines an FPGA with a dual-core ARM Cortex-A9 processor. So it consists of the Processing System (PS) and Programmable Logic. Figure 1 below displays the PYNQ-Z2 board.

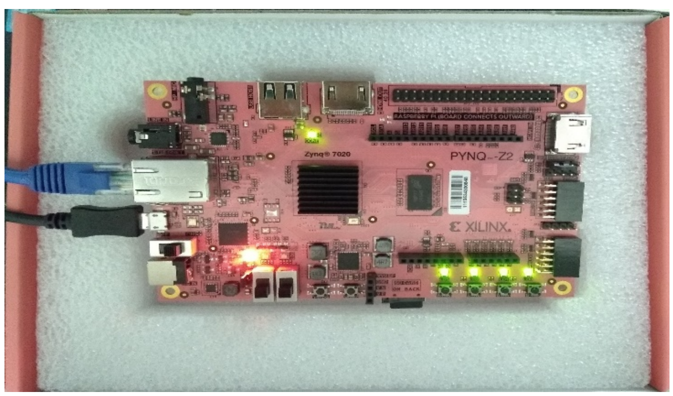

Fig 1. PYNQ Z2 Board [9]

The application Processing Unit of the PYNQ-Z2 is made up of two ARM cortex-A9 processors, each of which has the following components. The neon unit gives an ARM CPU Single Instruction Multiple Data, which speeds up DSP and Media algorithms. The floating point unit (FPU) accelerates floating point operations. Every processor has a separate data and instruction cache for storing these elements. Using MMU, virtual memory locations are converted to physical memory addresses. The snoop control unit facilitates communication between processors, L1 caches, and L2 caches. The L2 cache, which is shared by the two processors and allows for the most recent updates to variables.

Its adjustable logic blocks have two slices, and it has a programmable logic structure. Each one has a switch matrix, block RAM, eight flip-flops, four look-up tables, and DSP slices. Resources are available for both combinational and sequential circuit implementation in each slice. In LUT, the ROM, RAM, or shift registers can be used to build logic functions with up to six inputs.FF to construct a sequential 1-bit reset element in a register. The switch matrix links various components both inside and between CLB and other PL sections.

PYNQ-Z2 features include a twin 650 MHz ARM Cortex A9 CPU, 13,300 logic slices with each having 6 input LUTs and 8 flip-flops, 630 KB of block RAM, and 220 DSP slices with ADC. JTAG, MicroSD, and Quad-SPI Flash programming. 512

MB DDR3 memory and storage with a 16-bit bus that can support 1050 Mbps and 16 MB Quad-SPI Flash. microSD port For programming and other uses, it supports USB and Ethernet.

2.3 Block Diagram and Flow of Model

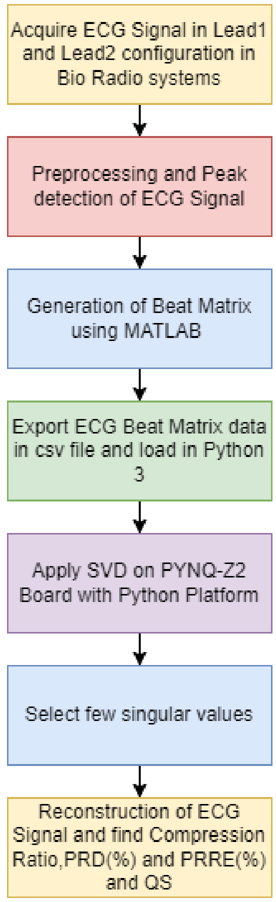

Fig 2. Block Diagram and Flow of Our Model

Fig 3. ECG acquisition of person in Lead I configuration using Bio Radio

The block diagram and workflow are displayed in Figure 2 . In this, we used the ECG signals of more than 10 individuals of various ages. Their ECGs were captured using BIORADIO equipment with the lead 1 and lead 2 configurations seen in Figure 3 . The baseline drift was then eliminated once the filter was applied. After that peak detection, indicated in 2.1.2, was applied to the ECG Data. First, we created an ECG Beat Matrix using 20000 ECG data. This ECG Beat matrix data was put into the Python environment PYNQ-Z2, which makes use of the Zynq architecture's PS component. The signal was subjected to SVD analysis. A decreased number of singular values were used in the reconstruction of the ECG, and compression ratios and QS were computed. For the research analysis was carried out for 20000, 80000, and 270000 samples of ECG in lead 1 and lead 2 configurations.

3 Results and Discussion

3.1 Compression Ratio

$$CR = \frac{b_0 \sum_{i=1}^{p} Ti}{(M+N+1)\times q \times b_s + Pxb_p + \left(b_\alpha + b_\beta + b_\gamma\right)\times 2} \tag{8}$$

Here, the quantization level bit/sample b0 is multiplied by the total of all ECG period lengths in the numerator. P is the overall ECG segment count, and Ti is the i-th ECG cycle. M in the denominator denotes the identical number of elements as P of the left singular vector (ui). The right singular vector (vi), for which q is a truncated index, has N elements. The quantization level of singular triplets is denoted by the symbol bs. The second word, which stands for bits for segment storage, is used to store related beat information. The final terms are made up of several parameters, such as bα,bβ, and bγ which indicate the number of bits needed to record the initial singular value, the number of beats, and the lengths of the shortest and longest periods.

3.2 Percent root mean square difference

$$PRD\,(\%) = \sqrt{\frac{\sum_{i=1}^{L}\left[(x_0(i) - x_r\,(i)\right]^2}{\sum_{i=1}^{L} x_0^2\,(i)}} \times 100 \tag{9}$$

The parameter that demonstrates the error between the original data and the reconstructed data is the percent root mean square difference.

3.3 Percent root mean square residual energy

$$PRRE\,(\%) = \sqrt{\frac{\sum_{i=1}^{L}\left(x_0^2(i) - x_r^2(i)\right]}{\sum_{i=1}^{L} x_0^2\,(i)}} \times 100 \tag{10}$$

The energy information of the reconstructed signal is represented by the percent root mean square residual energy, which is used to evaluate the reconstructed error. Since x0(i) is extremely near to xr(i).

3.4 Quality Score (QS)

The CR/PRD ratio assesses the overall performance of the compression method.

$$QS = \frac{CR}{PRD} \tag{11}$$

The simulation results that we achieved are shown in Tables 1, 2, 3, 4, 5 and 6 for various samples of ECG containing 20000, 80000, and 270000 samples from various persons having aged of 49 and 35 with lead 1 and lead 2 configurations. Results show that the maximum value of CR is 35.6506, PRD=1.2192, PRRE=1.2192 that is for Punit Lead 1 with 20000 samples. The maximum value of CR is 106.2417, PRD=1.4926, PRRE=1.4926 that is for Mayur Lead 1 with 80000 samples. The maximum value of CR is 229.7872, PRD=0.9592, PRRE=0.9592 that is for Punit Lead 2 with 2700000 samples.

This matrix has undergone the SVD process to keep just a small number of singular values and eliminate redundancy. By analyzing various parameters like CR, PRD, and PRRE for 20000 samples and singular values 2 we achieved CR=22.9621, PRD=0.6769, PRRE=0.6769 for Lead 1 configuration likewise CR=22.805, PRD=0.7752, PRRE=0.7752 for Lead 2 configuration. For 80000 samples and singular values 2 we achieved CR=63.745, PRD=0.5986, PRRE=0.5986 for Lead 1 configuration likewise CR=22.805, PRD=0.7752, PRRE=0.7752 for Lead 2 configuration. For 270000 samples and singular values 2 we achieved CR=128.028, PRD=1.6924, PRRE=1.6924 for Lead 1 configuration likewise CR=128.6327, PRD=0.4716, PRRE=0.4716 for Lead 2 configuration. Results show more enhancement in CR on singular value 2 as compared to [4]. The authors in [4] used

Table 1. Singular Values, PRD, PRRE, and CR, QS of Punit for Lead1 for 20000 samples

Punit lead1				
Singular Values	**PRD**	**PRRE**	**CR**	**QS**
20	0.0812	0.0812	3.1003	38.18
15	0.1269	0.1269	4.0808	32.15
10	0.1897	0.1897	5.9684	31.46
5	0.3076	0.3076	11.1049	36.10
3	0.4839	0.4839	16.9348	34.99
2	0.6769	0.6769	22.9621	33.92
1	1.2192	1.2192	35.6506	29.24

Table 2. Singular Values, PRD, PRRE, and CR, QS of Punit for Lead2 for 20000 samples

Punit lead2				
Singular Values	**PRD**	**PRRE**	**CR**	**QS**
20	0.0997	0.0997	3.0717	30.80
15	0.1562	0.1562	4.0437	25.88
10	0.2407	0.2407	5.9154	24.57
5	0.3864	0.3874	11.0132	28.42
3	0.5359	0.5359	16.8067	31.36
2	0.7752	0.7752	22.805	29.41
1	1.1374	1.1374	35.461	31.17

Table 3. Singular Values, PRD, PRRE, and CR, QS of Mayur for Lead 1 80000 samples

Mayur lead1				
Singular Values	**PRD**	**PRRE**	**CR**	QS
70	0.0021	0.0021	2.2605	1076.42
60	0.0042	0.0042	2.6341	627.16
50	0.0092	0.0092	3.1557	343.01
40	0.0217	0.0217	3.9349	181.33
30	0.0528	0.0528	5.225	98.95
20	0.1227	0.1227	7.7738	63.35
15	0.1771	0.1771	10.2815	58.05
10	0.2543	0.2543	15.1774	59.68
5	0.3586	0.3586	28.975	80.80
3	0.4137	0.4237	45.5322	107.46
2	0.5986	0.5986	63.745	106.49
1	1.4926	1.4926	106.2417	71.17

the MIT-BIH database for experimental analysis while we used a Bio Radio device to capture real-time ECG signals wirelessly. The authors in[4] used various methods to deploy the algorithm of SVD on FPGA while we used the PS part of PYNQ-Z2 which utilizes zynq architecture with python programming. Apart from this, we achieved noticeable compression performance with high QS=36.10 for lead 1 and QS=28.42 for 20000 samples with singular value q=5. Likewise, QS=80.80 for lead 1 and QS=131.90 were achieved for 80000 samples with singular value q=5. Furthermore, QS=59.45 for lead 1 and QS=249.46 were achieved for 270000 samples which shows significant enhancement of our compression method performance as compared to[1] and outperforms the compression methods analyzed in[2]. The highest value of QS is 1076.42 for lead 1 and 1721.76 for lead 2 for singular values q=70 and the sample size is of 80000.

Table 4. Singular Values, PRD, PRRE, and CR, QS of Mayur for Lead2 Configuration with sample values of 80000

Mayur lead2				
Singular Values	**PRD**	**PRRE**	**CR**	**QS**
70	0.0013	0.0013	2.2383	1721.76
60	0.0029	0.0029	2.6083	899.41
50	0.0071	0.0071	3.1249	440.12
40	0.0157	0.0157	3.8965	248.18
30	0.0347	0.0347	5.1743	149.11
20	0.0775	0.0775	7.699	99.34
15	0.1157	0.1157	10.1833	88.01
10	0.1635	0.1635	15.0348	91.95
5	0.2177	0.2177	28.715	131.90
3	0.2932	0.2932	45.1467	153.97
2	0.2543	0.2543	63.2411	248.68
1	0.3341	0.3341	105.5409	315.89

Table 5. Singular Values, PRD, PRRE, and CR, QS of Punit for Lead 1 270000 samples

Punit Lead1				
Singular Values	**PRD**	**PRRE**	**CR**	**QS**
30	0.1938	0.1938	9.6014	49.56
20	0.3961	0.3961	14.3381	36.19
15	0.5498	0.5498	19.0328	34.61
10	0.7308	0.7308	28.2989	38.72
5	0.9275	0.9275	55.1471	59.45
3	1.0327	1.0327	88.8743	86.06
2	1.6924	1.6924	128.0228	75.64
1	3.3564	3.3564	228.8136	68.17

Table 6. Singular Values, PRD, PRRE, and CR of Punit for lead 2 270000 samples

Punit lead2				
Singular Values	**PRD**	**PRRE**	**CR**	**QS**
30	0.0437	0.0437	9.6529	220.89
20	0.0998	0.0998	14.4146	144.43
15	0.1379	0.1379	19.134	138.75
10	0.1771	0.1771	28.448	160.63
5	0.2222	0.2222	55.4301	249.46
3	0.3207	0.3207	89.3152	278.50
2	0.4716	0.4716	128.6327	272.76
1	0.9592	0.9592	229.7872	239.56

4 Conclusion

In this study, we used BioRadio equipment to capture 4.5-minute-long ECG signals for lead-1 and lead-2 configurations for a wide range of individuals. As part of this research study, the wireless ECG signals of 25 persons were taken. We can reconstruct ECG signals with extremely few singular values after applying SVD to all ECG signals on the PYNQ-Z2 platform (PS). Since PYNQ offers a versatile environment for Python development, it was convenient to apply SVD to the ECG Beat Matrix. Results from experiments indicate that dimensionality reduction was successful because for 20000 ECG samples, the maximum compression ratio was 35.6506 and the minimum PRD (%) was the same as the PRRE (%) of 0.00812. For 80000 ECG samples, the maximum compression ratio was 106.2417 and the minimum PRD (%) was the same as the PRRE (%) of 0.0013. Similarly, For 270000 ECG samples, the maximum compression ratio was 228.8136 and the minimum PRD (%) was the same as the PRRE

(%) of 0.0437. The highest value of QS is 1076.42 for lead 1 and 1721.76 for lead 2 for singular values q=70 and the sample size is of 80000. Additionally, it has been found that when the number of singular values rises, the values of CR, PRD, and PRRE drop.

In this study the SVD is applied on wirelessly captured ECG Signals with 20000, 80000 and 270000 samples with lead 1 and lead 2 configurations. In future , longer durations of ECG of various persons with different age and different leads can be taken to analyze the performance of SVD on that. Even after applying SVD and reconstruction of ECG signals, the % accuracy of various machine learning models can be analysed.

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