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Multiscale Wavelet Transformation and Amplitude Zone Time Epoch Coding for ECG Data Extraction and Compression

S. Velmurugan[*] *and A. Mahabub Basha*

Department of Electronics and Communication Engineering, K.S.R College of Engineering, Tiruchengode, Tamilnadu, India.

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Abstract: Tele-health monitoring plays a vital role in healthcare applications. Electrocardiogram (ECG) signals are an essential part in diagnosis and analysis of cardiac diseases. It consumes large amount of time and space during transmission and data storage. To reduce the time and space complexity, an Integrated Multiscale Gabor Wavelet Transformation (IMAGWT) and Amplitude Zone Time Epoch Coding (IMGWT–AZTEC) mechanism is introduced. Multiscale Approximated Gabor Wavelet Transformation (MAGWT) is used in IMAGWT–AZTEC mechanism to decompose the ECG signals into many sub-bands and to extract the P, T waves and QRS complex. After extraction of signals, AZTEC and decoding techniques are introduced for data compression and decompression. This in turn helps to improve the data extraction and data compression performance in IMGWT–AZTEC mechanism.

Keywords: Electrocardiogram, heart diseases, noise artifacts, data extraction, compression ratio.

1 Introduction

An electrocardiogram is a graph where the electrical movement of heart over time is recorded. The ECG signal P, QRS and T are constructed by measuring electrical potentials between various points of the body. Wavelet transform is used for signal decomposition into basis functions termed as wavelets. The functions are attained from single prototype wavelet through dilations, reductions and moves. De-noising the non-stationary signals like ECG can be achieved by Discrete Wavelet transform (DWT). Wavelet transform (WT) is used for the analysis of non-stationary signals because it presents an alternative to Gabor transform.

Symlets sym5 was chosen in [1] to decompose the ECG signals for noise extraction. Soft-thresholding method was employed for feature detection. For ECG feature identification, R peak of heart beat was recognized as well as onset and offset of the QRS complex was identified. But, feature extraction consumed large amount of time using discrete wavelet transform. Singular Value Decomposition (SVD) and Adaptive Scan Wavelet Difference Reduction (ASWDR) technique were introduced in [2] with low-rank matrix for initial compression on two-dimensional (2D) ECG image. In addition, WDR/ASWDR is used for final compression. But, the compression ratio was not improved using SVD-ASWDR technique. An accurate patient-specific electrocardiogram (ECG) classification and monitoring system were designed. An adaptive implementation of 1-D convolutional neural networks (CNNs) was joined in [3] with ECG classification. The patient-specific feature extraction improved the classification results. An Optimum Sparsity Order Selection (OSOS) method [4] computed the sparsity order by reducing the reconstruction error. The basis matrix was structured depending on Cosine kernel with improved efficiency over Gaussian basis matrices. But, the time complexity was not reduced. A cross wavelet transform (XWT) was carried out in [5] for analysis and classification of electrocardiogram (ECG) signals. The cross-correlation of two time-domain signals determined the similarity between two waveforms. A new electrocardiogram (ECG) processing technique was portrayed in [6] for joint data compression and QRS detection. The designed algorithm reduced the complexity through sharing the load between signal processing tasks. However, the compression ratio was not at the required level. Mobile processors were

[*] Corresponding author e-mail: s.velmuruganksrce@yahoo.com

utilized and there is no need for the computers to serve. The initial preprocessing like baseline noise extraction, Gaussian noise, peak detection and heart rate were carried out and then ECG signal was compressed in [7]. In compression stage, 3 steps of wavelet transform, thresholding methods were employed. But, this type of compression caused information loss. A parallel general regression neural network (GRNN) was introduced in [8] to classify the heartbeat with better accuracy consistent with the Association for Advancement of Medical Instrumentation (AAMI). An online learning program was constructed for patient-personalized classification model. A cubic Hermitian vector-based technique was presented in [9] for online compression of asynchronously sampled ECG signals. The designed method was efficient for data compression. The algorithm has complexity $O(n)$ suited for asynchronous ADCs. The designed algorithm failed to need data buffering, maintaining energy of asynchronous ADCs. A sample entropy (SampEn)-based complexity sorting pre-processing technique was designed in [10] for 2D ECG data compression. But the compression ratio was not improved using SampEn technique.

A multiscale principal component analysis (MSPCA) was introduced in [11] for multichannel electrocardiogram (MECG) data compression. Principal Component Analysis (PCA) of multiscale multivariate matrices of multichannel signals minimized the dimension and removed the redundant information in signals. But, the feature extraction was not improved using MSPCA. A weak ECG signal denoising method was designed in [12] depending on fuzzy thresholding and wavelet packet analysis. The weak ECG signal is decomposed into different levels through wavelet packet transform. After that, the threshold value is identified by fuzzy s-function. Though the denoising method was designed, the compression ratio was not increased. A variable step size LMS adaptive filter was introduced [13] to remove the noise from ECG signal. The extraction of R peak ECG was carried out with discrete wavelet transform-based QRS detection algorithm. But, the space complexity was not reduced. Extracted features were employed [14] to minimize the information loss in signal. The features reduced the resource need for describing the large data. It minimized the execution complexity and information processing cost to compress the information. However, data extraction rate was not improved. A compressed sensing (CS) framework of data reduction was introduced in [15] for multi-channel electrocardiogram (MECG) signals in eigenspace. The sparsity of dimension-reduced eigenspace MECG signals was developed to transmit CS. Principal Component Analysis (PCA) was employed over MECG data to maintain the ECG features in principal eigenspace signals depending on maximum variance. But, the error rate was not minimized using CS framework. A new method was designed in [16] for nonlinear feature extraction of ECG signals through joining Wavelet Packet Decomposition (WPD) and approximate entropy (ApEn). But, the data extraction rate was not improved. An efficient electrocardiogram (ECG) data compression algorithm was designed [17] to telemonitor cardiac patients by two encoding techniques, namely discrete cosine transform with higher compression ratio. But, compression time was not minimized by ECG data compression algorithm. A method was introduced [18] using PCA, where the selected principal components and eigenvectors were compressed with delta and Huffman encoder. But, time complexity was not addressed by quality aware compression method. A variation mode decomposition (VMD) was introduced [19] to classify the arrhythmia electrocardiogram (ECG) beats. But, the feature extraction rate is not enhanced using VMD. A new method was introduced [20] for nonlinear feature extraction of ECG signals through combining PCA and Kernel Independent Component Analysis (KICA). The technique used PCA to reduce the ECG signal training set dimensions for extracting the nonlinear features. But, the feature extraction accuracy was not at required level.

The certain issues are identified from the existing techniques, namely lower data extraction rate, lower compression ratio, higher memory space consumption, higher execution time and so on. In order to overcome such kind of issues, IMGWT–AZTC mechanism is introduced.

The major contribution of the work is:

– Gaussian filter preprocessing technique is introduced in IMGWT–AZTEC mechanism to remove the noise from input signal through convolution with Gaussian function.
– MAGWT is carried out to decompose data into many sub-bands and removes the redundant data for minimizing the space complexity. In addition, the transformation is used to extract and classify the P wave, T wave and QRS wave based on the time period.
– AZTEC technique is introduced in IMGWT–AZTEC mechanism for minimizing the space and time complexity without any information loss. AZTEC converts extracted data into horizontal lines and slopes. AZTEC reduces the extracted data size of ECG signal. After that, Amplitude zone time epoch decoder is used to obtain the reconstructed data after further processing.

The organization of the work is followed in different subsections. Section 2 describes IMGWT and AZTEC with architecture diagrams. Section 3 and Section 4 describe the experimental settings and result analysis of different parameters. Section 5 concludes the paper.

2 Integrated Multiscale Gabor Wavelet Transformation and Amplitude Zone Time Epoch Coding Mechanism

Electrocardiogram (ECG) is a tool for assessing the electrical and muscular functions of the heart. The electrocardiogram is employed to identify the abnormal heart rhythms for studying the cause of chest pains. A complete cardiac cycle in ECG signal comprises of *P*, QRS complex and *T* waves. The most essential information in ECG is originated in time intervals and amplitudes described by peaks and time durations. But, the existing techniques fail to extract and compress the information from ECG signal. In order to improve the data extraction rate and compression ratio, IMGWT–AZTEC mechanism is introduced for ECG data extraction and data compression without any information loss.

The architecture diagram of IMGWT–AZTEC mechanism is explained in Fig. 1. Initially, ECG signals from MIT-BIH arrhythmia database get preprocessed in order to remove the noise artifacts. Wavelet Transformation decomposes the data into many sub-bands and removes the redundant data for minimizing the space complexity. In addition, the useful information is extracted from ECG signal for data compression. After that, Data compression encodes the data into horizontal lines to reduce the memory space with higher compression ratio. Then, data decompression decodes the compressed data to obtain the reconstructed data with lower time complexity. The brief explanation of Gaussian filter preprocessing, MAGWT, and AZTEC techniques are described in following sub sections.

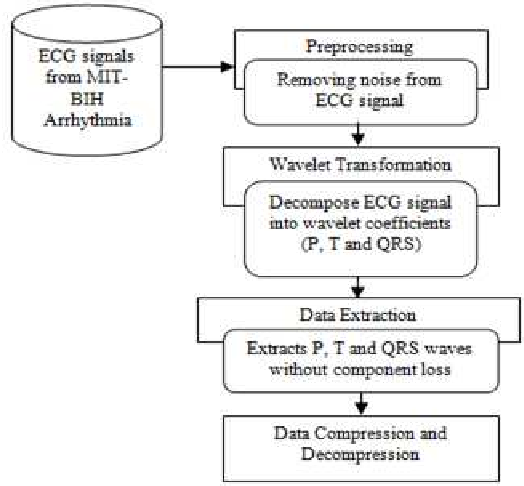

Fig. 1: IMGWT–AZTEC mechanism

2.1 Gaussian Filter Preprocessing

ECG is an important element for primary diagnosis of heart abnormalities like myocardial infarction, conduction defects, and arrhythmia. But, the extracted ECG signal is contaminated with various noises. For removing the noise from extracted ECG signals, Gaussian filter preprocessing technique is employed in IMGWT–AZTEC mechanism. Gaussian filter removes the noise from input signal through convolution with Gaussian function. The filtering process in gaussian distribution is carried out by,

$$g(x,y) = \frac{1}{2\pi\delta^2} \cdot e^{-\frac{x^2+y^2}{2\delta^2}} \tag{1}$$

In (1), x denotes the distance of the ECG signal from the horizontal axis, y denotes the distance of the signal from the vertical axis. δ denotes standard deviation of the Gaussian distribution. The algorithmic description of Gaussian filter-based preprocessing algorithm is given by Algorithm 1.

Algorithm 1 explains Gaussian filter preprocessing process in IMGWT–AZTEC mechanism. For each ECG signal from dataset, the noise artifacts are removed through preprocessing. In this mechanism, Gaussian filter is exploited for preprocessing. For efficient transmission, the data needs to be extracted from ECG signal. The data extraction process is briefly explained in next subsection.

Algorithm 1: Gaussian filter preprocessing algorithm

Input: ECG signals from MIT-BIH Arrhythmia Database
Output: Preprocessed ECG signal
Step 1 begin
Step 2 For each ECG signal *S*
Step 3 Preprocessing is carried out using Gaussian filter using (1)
Step 4 end for
Step 5 end

2.2 Multiscale Approximated Gabor Wavelet Transformation for Data Extraction

After preprocessing, the data has to be extracted from ECG signal and compressed for reducing the space and time complexity with higher compression ratio. Data extraction is used for the dimensionality reduction process. The process of transforming input signal into set of data is termed as data extraction. When the data are extracted, it is predictable that relevant information from input ECG signal is enough rather than full size input for further processing. In order to perform the data extraction and classification, MAGWT is carried out in IMGWT–AZTEC mechanism.

Gabor wavelet is a discrete wavelet transform with continuous or discrete input signal. Gabor functions present the optimal resolution in time and frequency domains. In IMGWT–AZTEC mechanism, Multiscale Approximated Gabor Wavelet Transformation (MAGWT)

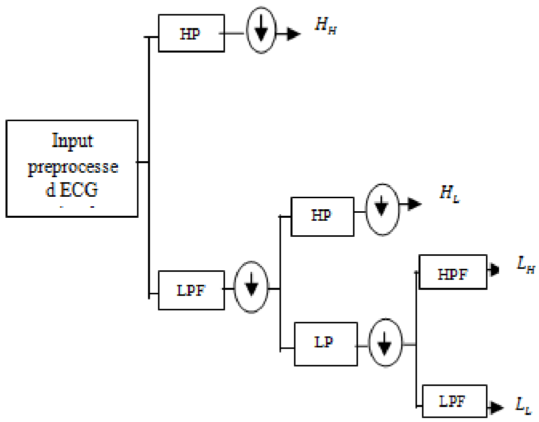

Fig. 2: Three-level decomposition of ECG signal

decomposes the signal into data in many sub-bands to extract the local data. The equivalent definition of MAGWT is given by,

$$\Phi(\vec{z}) = \frac{1}{2\pi} \frac{\| \vec{k} \|^2 \cdot \| \vec{z} \|^2}{2\sigma^2} \exp(j\, \vec{k} \cdot \vec{z}) \tag{2}$$

From (2), $\vec{k}\ 2\pi f \exp(j\theta)$ and scaling functions for two elliptical axes are similar to σ. A family of $P \times Q$ Gabor wavelets performs multiscale and multi-orientation analysis for data extraction from ECG signal. The multiscale approximation is given by,

$$x\left\{\Phi_{discrete(f_p\theta_q\gamma,\eta)}(a,b)\right\} \tag{3}$$

where

$$\begin{gathered} f_p = \frac{f_{\max}}{\sqrt{2}^p}; \quad \theta_q = \frac{p}{P}\pi; \\ p = 0,1,\ldots,p-1; \quad q = 0,1,\ldots,q-1; \end{gathered} \tag{4}$$

From (3) and (4), f_p and θ_q describe orientation and scale of Gabor wavelets. $f_{\max}$ explains maximum central frequency. $\sqrt{2}$ denotes spacing factor between central frequencies. γ represents self-defined constant. MAGWT decomposes the input preprocessed ECG signal into four wavelet coefficients namely L_L, L_H, H_L and H_H called three level of wavelet decomposition for QRS complex, P waves and T wave extraction. Third level of wavelet decomposition is illustrated in Fig. 2.

As shown in Fig. 2, the input preprocessed ECG signal is decomposed with four wavelet coefficient in IMGWT–AZTEC mechanism. The decomposition includes low-frequency and high-frequency wavelet coefficients for improving the extracted data quality. At every decomposition level in IMGWT–AZTEC Mechanism, half-band filter forms the signals spanning half-frequency band. It doubles the frequency resolution as the uncertainty in frequency is decremented by half. Using Nyquist rule where the unique signal has higher frequency of ω with sampling frequency of 2ω, the decomposed signal has maximal frequency of $\omega/2$ radians. The frequency of ω radians are sampled through removing the half samples without loss. Then it decrements by two half time resolutions as entire signal is denoted by half number of samples. By this way, the ECG signal gets decomposed.

In IMGWT–AZTEC mechanism, MAGWT classifies the extracted date into P wave, T wave and QRS wave based on the time period. It combines the amplitude and time period of extracted data from ECG data to characterize into two or more classes of waves. When the time period of extracted data is equal to 200 ms, then it is called QRS wave data. When the time period of extracted data is equal to 600 ms, then it is called as T wave data. When the time period does not matches 200 ms and 600 ms, then it is called as P wave data. By this way, the extracted data are classified and given for the data compression.

2.3 Amplitude Zone Time Epoch Coding Technique for Data Compression

After extracting and classifying the data from ECG signal using Gabor multi-linear discriminant analysis, AZTEC technique is employed in IMGWT–AZTEC mechanism for minimizing the space and time complexity without any information loss. Data compression is used for minimizing the size in bytes without affecting the ECG signal quality. Data compression stores large amount of data in given memory space with minimal time consumption. AZTEC process performs encoding and decoding process without any data loss. AZTEC encoder converts the extracted data into horizontal lines and slopes. AZTEC encoder is used to reduce the extracted data size of ECG signal. The encoder uses maximum and minimum threshold value (i.e., amplitude and slope) for each extracted data where n denotes the number of extracted data taken. When data is less than threshold, then it is taken as minimum value. Otherwise, it is taken as maximum value. In this way, the data gets compressed with minimum time. Subsequently in IMGWT–AZTEC mechanism, data decompression is performed to obtain the reconstructed data after receiving for further processing by using AZTEC decoder. The algorithmic process of IMGWT–AZTC is given in Algorithm 2.

IMGWT and amplitude zone time coding algorithm comprise three steps, namely data extraction compression and decompression. Initially, the preprocessed signal is decomposed and extracted the P, QRS complex and T waves. Then the extracted data from ECG signals are compressed using Amplitude Zone Time Epoch Encoder, to reduce the space and time complexity. Finally, the compressed data are decompressed using AZTEC decoder with minimal time consumption. By means of above algorithmic process, space complexity and time complexity is reduced in an efficient way.

Algorithm 2: IMGWT–AZTC algorithm

Input: Preprocessed ECG signal
Output: Reduce space complexity and time complexity
Step 1 begin
Step 2 For each preprocessed ECG signal
Step 3 Multiscale Approximated Gabor Wavelet Transform is carried out using (2) to decompose the signal into wavelet coefficients namely LL, LH, HL, and HH
Step 4 Extracts P, QRS and T waves based on time period
Step 5 Compress the extracted data through encoding using Amplitude Zone Time Epoch Encoder
Step 6 Decompress the encoded data into the original data using Amplitude Zone Time Epoch Decoder
Step 7 Apply Inverse Multiscale Approximated Gabor Wavelet Transformation to obtain the Reconstructed signal
Step 8: End For
Step 9: End

3 Experimental settings

The proposed IMGWT–AZTC mechanism is implemented in MATLAB simulator using MIT-BIH arrhythmia database from Physionet. The efficiency of IMGW-AZTC mechanism is compared against with the existing two techniques namely Symlets sym5 wavelet function [1] and the SVD and ASWDR (SVD-ASWDR) technique [2]. MIT-BIH arrhythmia database has 48 half-hour extracts of ambulatory ECG recordings. The recordings are digitized at 360 samples per second in one channel with 11-bit resolution over 10 mV range. Two or more cardiologists are explained for every record.

4 Results and Discussions

IMGWT–AZTEC mechanism is designed to increase the data extraction and compression performance compared with existing Symlets sym5 wavelet function [1] and SVD-ASWDR technique [2]. The experimental evaluation of IMGW-AZTEC mechanism is carried out with the different parameters such as data extraction rate, compression time, space complexity and time complexity.

4.1 Impact of Data Extraction Rate (DER)

Data extraction rate is the ratio of number of data correctly extracted from input ECG signal to the total number of data extracted from ECG signal. Data extraction rate is measured in terms of percentage (%). The data extraction rate is mathematically formulated as,

$$DER = \frac{\text{Number of data correctly extracted from signal}}{\text{Total number of data extracted from ECG signal}} \times 100 \quad (5)$$

Table 1: Tabulation for data extraction rate

Number of ECG signals	Data Extraction Rate (%)		
	Existing Symlets sym5 wavelet function	Existing SVD-ASWDR	Proposed IMGWT–AZTEC
5	40	60	80
10	70	80	90
15	73	67	87
20	75	75	85
25	72	76	88
30	77	83	90
35	77	83	91
40	78	85	93
45	80	84	96
50	82	86	96

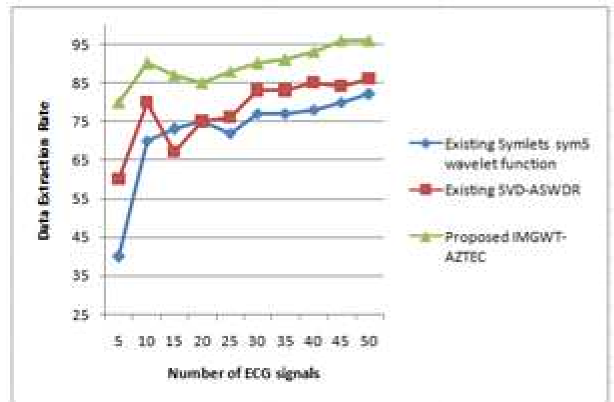

Fig. 3: Measurement of data extraction rate

When the data extraction rate is higher, then the method is said to be efficient.

Table 1 describes the data extraction rate with respect to10 different ECG signal. For medical scenario, the number of ECG signal in the range of 5 to 50 is considered for conducting experimental purpose This table denotes the data extraction rate of three different methods such as IMGWT–AZTEC mechanism, Symlets sym5 wavelet function [1] and SVD-ASWDR technique [2]. In healthcare environment for transmitting the ECG signals of the patients, it consumes large amount of resources like energy, time, space, etc. For reducing the resource utilization, the required data are extracted from ECG data and transmitted to the doctor. In our method, we have taken MGWT for extracting the significant data from ECG signals without any information loss. By using MGWT, the proposed IMGWT–AZTEC mechanism achieved higher data extraction rate than existing work. The diagrammatic representation of data extraction rate is explained in Fig. 3.

Fig. 3 describes the data extraction rate based on the different ECG signal size. As a result the data extraction rate is increased based on MGWT by 15% and 19%. The data extraction rate of the proposed IMGWT–AZTEC mechanism is higher than Symlets sym5 wavelet

Table 2: Tabulation for compression ratio

ECG Signal Name	Data Size (kB)	Compression Ratio		
		Symlets sym5 wavelet function	SVD-ASWDR Technique	IMGWT–AZTEC mechanism
Signal 1	28.5	7	8	11
Signal 2	29.2	8	9	12
Signal 3	30.7	9	10	13
Signal 4	31.5	10	11	14
Signal 5	32.1	12	13	16
Signal 6	33.2	13	14	17
Signal 7	34.4	15	16	19
Signal 8	35.3	16	17	20
Signal 9	36.1	17	18	21
Signal 10	37.4	18	19	22

function [1] and SVD-ASWDR technique [2]. This shows that the proposed IMGWT–AZTEC mechanism increases the data extraction rate by using MGWT. MGWT decomposes the input preprocessed signal into wavelet coefficients in order to extract the necessary data without any information loss. In addition, MGWT categorizes the extracted data as *P* wave, QRS complex and *T* wave based on the time period. This in turn helps to improve the data extraction rate. The data extraction rate of proposed IMGWT–AZTEC mechanism is increased when compared with existing Symlets sym5 wavelet function [1] and SVD-ASWDR technique [2] respectively.

4.2 Impact of Compression Ratio

Compression Ratio is given by the ratio of uncompressed data size to the compressed data size. The compression ratio is formulated as,

$$\text{Compression ratio} = \frac{\text{Uncompressed data size}}{\text{Compressed data size}} \qquad (6)$$

From (4), compression ratio of different data size is obtained. While the compression ratio is higher, the technique is said to be more efficient.

Table 2 explains the compression ratio with respect to 10 different ECG signal size ranging from 28–35 kB. This table represents the compression ratio of three different methods such as IMGWT–AZTEC mechanism, Symlets sym5 wavelet function [1] and SVD-ASWDR technique [2]. Let us consider the healthcare environment. In healthcare environment, patients take ECG test in order to find the abnormality in heart. After taking the test, the ECG signals are sent to the doctor in order to identify the defects in heart. When the ECG signals are sent directly, it consumes huge amount of time and memory space. In order to reduce the transmission time and memory utilization, ECG signal has to be compressed. In our proposed mechanism, Amplitude zone time data compression is used to compress the extracted data with higher compression ratio to reduce the memory utilization and time consumption. By using amplitude zone time data compression, proposed IMGWT–AZTEC mechanism has higher compression ratio than existing work. The diagrammatic representation of compression ratio is explained in Fig. 4.

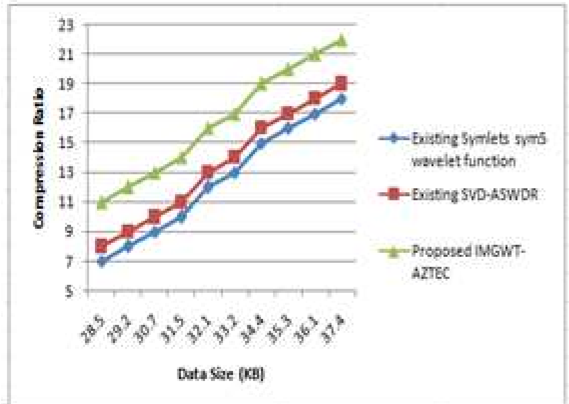

Fig. 4: Measurement of compression ratio

Fig. 4 explains the compression ratio based on the different ECG signal size. From figure, compression ratio of proposed IMGWT–AZTEC mechanism is higher than Symlets sym5 wavelet function [1] and SVD-ASWDR technique [2]. This shows that the proposed IMGWT–AZTEC mechanism increases the compression ratio by using amplitude zone time data compression. Amplitude zone time data compression compresses the extracted data into horizontal lines with higher compression ratio, to reduce the memory space and time consumption. The compression ratio of proposed IMGWT–AZTEC mechanism is increased by 24% and 54% compared to existing Symlets sym5 wavelet function [1] and SVD-ASWDR technique [2] respectively.

4.3 Impact of Space Complexity

Space complexity is defined as the amount of memory space consumed for storing the compressed data after extracting from ECG signal. The space complexity is measured in terms of kilobytes (KB). The mathematical formula is given by,

$$\begin{aligned} SC = {} & \text{No. of ECG signal} \\ & \times \text{Memory (stored data from ECG signal)} \end{aligned} \qquad (7)$$

From (5), the memory space needed for storing the compressed data is measured. When the space complexity is less, the method is said to be more efficient.

Table 3 explains the space complexity with respect to 10 different ECG signal of 5 to 50 with size ranging from 28–35 KB. This table represents the space complexity of three different methods such as IMGWT–AZTEC mechanism, Symlets sym5 wavelet function [1] and SVD-ASWDR technique [2]. In healthcare environment,

Table 3: Tabulation for space complexity

ECG Signal Name	Space Complexity (kB)		
	Existing Symlets sym5 wavelet function	Existing SVD-ASWDR	Proposed IMGWT–AZTEC
5	14	12	8
10	16	14	10
15	17	16	11
20	18	17	12
25	21	20	15
30	22	21	16
35	23	22	17
40	25	24	19
45	26	25	20
50	27	26	21

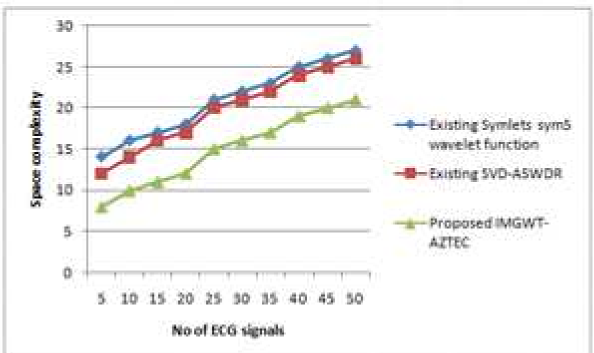

Fig. 5: Measurement of space complexity

patients take ECG test for checking the abnormality in heart. After that, ECG signals are sent to the doctor for identifying the defects in heart. When the ECG signals are sent directly, it consumes large amount of memory space. For reducing the space complexity, ECG signal has to be compressed. In IMGWT–AZTEC mechanism, Amplitude zone time data compression compresses the extracted data to reduce the memory utilization for ECG signal transmission. By using amplitude zone time data compression, proposed IMGWT–AZTEC mechanism reduces the space complexity than existing work. The diagrammatic representation of space complexity is explained in Fig. 5.

Fig. 5 describes the space complexity based on the different ECG signal size. From figure, space complexity of the proposed IMGWT–AZTEC mechanism is less than [1] and [2]. This is because that the proposed IMGWT–AZTEC mechanism reduces the space complexity by using amplitude zone time data compression and decompression. It compresses the extracted data into horizontal line in order to reduce the memory space. In addition, it helps to reduce the space complexity. The space complexity of proposed IMGWT–AZTEC mechanism is reduced by 18% and 33% compared to existing [1] and [2] respectively.

5 Conclusion

A new mechanism called Integrated Multiscale Gabor Wavelet Transformation and Amplitude Zone Time Coding (IMGWT–AZTC) mechanism is designed to increase the performance of data extraction and data compression with less space complexity. Initially, IMGWT–AZTEC mechanism accomplishes the preprocessing task by using Gaussian filter to reduce the noise artifacts from ECG signals. Then, MAGWT in IMGWT–AZTEC mechanism decomposes and extracts the P, T waves and QRS complex from ECG signals. Finally, AZTEC technique in IMGWT–AZTEC mechanism compresses and decompresses the data to reduce the space complexity. The performance of IMGWT–AZTEC mechanism is tested with the metrics such as data extraction rate, compression ratio, time complexity and space complexity. The simulation results show that IMGWT–AZTEC mechanism has higher data extraction rate, compression ratio and it also minimizes space complexity than the state-of-the-art works.

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S. Velmurugan is working as a Assistant Professor in the Department of Electronics and Communication Engineering at K.S.R. College of Engineering Namakkal, Tamil Nadu, India. He has completed his Bachelors Degree (Electronics and Instrumentation Engineering), from Mahendra Engineering College, Namakkal, Tamilnadu, India and Masters Degree (VLSI Design) from K.S. Rangasamy College of Technology, Tiruchengode, Tamil Nadu, India. He is currently pursuing his PhD degree from Anna University, Tamilnadu, India. His areas of interest includes, Data Acquisition, Biomedical Instrumentation, Signal processing, Virtual instrumentation and Internet of Things (IoT). He has guided many under graduate and post graduate students and he is a Life member of Indian Society for Technical Education (ISTE), Life member of International Society for Research and Development (ISRD).

A. Mahabub Basha is a Professor and Director of Department of Electronics and Communication Engineering at K.S.R. College of Engineering, Namakkal, Tamil Nadu, India. He has completed his B.E. (Electrical and Electronic Engineering), from Government College of Engineering, Salem, M.Sc. (Engg.) (Power Systems Engineering), from P.S.G. College of Technology, Coimbatore, both are under University of Madras and he has awarded Ph.D. (Microprocessor Applied to Sub Station Protection and Control) at University of Roorkee (Presently IIT, Roorkee). He has over four decades of teaching experience in premier institutions in India and abroad which includes Calicut Regional Engineering College (now National Institute of Technology Calicut), Anjuman Engineering College, Bhatkal, Karnataka, Ibra College of Technology, Ministry of Man Power, Muscat, where he is also involved in research for few decades. He has published more than 100 peer review research articles. He won National award for his outstanding research work in Engineering and Technology from ISTE and also got Best research paper award in Engineering Applications, from System Society of India, IIT, New Delhi and Institutions of Engineers India, West Bengal. His area of interest includes, Modern Power System Relaying and Control, Digital Instrumentation, Electric Drives and Control, Power Quality and Computer Networks. Which his excellent guidance more than 30

Postgraduates are completed and 12 Ph.D., candidates are pursuing their research. He has examined more than 5 Ph.D. Thesis. He is a member of American Biographical Institute, New York Academy of Sciences and also a Life Member of ISTE, System Society of India, Computer Society of India. He is actively involving in Member of Editorial board/reviewers team-IRA publications for International Journal of Advances in Engineering Research, International Journal of Research in Science & Technology and International Journal of Innovations in Scientific Engineering.