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# Compression of Time series signal using Wavelet Decomposition, Wavelet Packet and Decimated Discrete Wavelet compression Transforms Techniques and their Comparison

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**Abstract**: Time series is a collection of observations in well-defined data items obtained through repeated measurements over a uniform time interval. Time series analysis comprises methods for analyzing time series data in order to obtain meaningful statistics and other characteristics of the data transmission time. Compression is the method of reduction in size of data in order to save space or transmission time. Wavelet compression is a form of data compression well defined for image compression. This paper analyzes Wavelet Decomposition, Wavelet Packet and Decimated Discrete Wavelet compression. From the results it is observed that Decimated discrete wavelet compression gives better performance in compression compared with other methods. The wavelet packet method is a generalization of wavelet decomposition that offers a richer wavelet analysis.

**Keywords**: Time Series Signal, Compression, Wavelet Decomposition, Wavelet Packet, Decimated Discrete Wavelet compression Transforms

## I. INTRODUCTION

The data generated in time series signals like EEG, ECG or stock market need to be stored every second, every minute and every hour in the database. As the data generated is enormous, the importance of time series compression is well justified from the necessity of reducing the storage space, time and the quantity of information. Biological signals especially ECG, EEG has an important role in diagnosis of human health. As more and more hospitals around the world are implanting the use of the electronic patient record (EPR), reducing storage requirements for clinical examinations (like ECG,EEG) is essential to include the results of these examinations within the EPR without the saturation of the storage system. The key concept is to preserve the diagnostic quality of the original time series signal. The main goal of any compression technique is to achieve maximum data reduction while preserving the original morphology reconstruction.

Data compression methods can be classified into two main types lossless and lossy methods. The method of the lossless types can obtain an exact reconstruction of the original signal, but they do not achieve low data rates. On the other hand, lossy type do not obtain an exact reconstruction, but higher compression ratios can be obtained .The commonly Time Series Compression techniques are lossy in nature. These mainly fall into two methods (i) Direct methods, in which actual signal samples are analyzed (time domain). Direct compression such as Amplitude-Zone-Time Epoch Coding (AZTEC) method, the coordinate reduction time coding system (CORTES) (ii) Transformational methods, in which first apply a transform to the signal and perform spectral and energy distribution and analysis of signals. Some of the transformations used in transformational compression methods are Fourier transform, Walsh Transform, Karhunen-Loeve Transform (KLT), Discrete cosine transform(DCT), Wavelet Transform (WT).

In most of the cases, direct methods are superior than transform based methods with respect to its system simplicity and error. The transform methods usually achieve higher compression ratio compared to direct method. Compressor using wavelet packet (WP) based techniques are efficient than discrete wavelet transform (DWT) based method for Time Series compression.

## II. DATA DESCRIPTION

Table 1 shows the description of own data which is taken as data set 1 here. It is an Electrocardiogram (ecg) signal and ecg (L) generates a piecewise linear ecg signal of length L. The ecg signal must be filtered or smoothed with an N-point smoother, Savitzky-Golay FIR filter. Savitzky-Golay Filtering sgolayfilt (K,F,X) smoothes the

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signal X using a Savitzky-Golay smoothing filter. The polynomial of order K must be less than the frame size, F, and F must be odd. The length of the input X must be greater than or equal to F. If X is a matrix then filtering is done on the columns of X. F=3,5,9 and L=500.Table 2 shows the data description of the data set extracted from "Dictionary-Based Compression for Long Time-Series Similarity", IEEE paper 2010. The said data is taken as data set 2 here. Both data are time series *i.e.* collection of observations of well-defined data items obtained through repeated measurements over a uniform time interval.

TABLE 1
DATA SET 1 DESCRIPTION

| x | Amplitude | | | | | | |
|---|---|---|---|---|---|---|---|
| Frequency | 2 | 5 | 8 | 2 | 11 | 3 | 6 |

TABLE 2
DATA SET 2 DESCRIPTION

| Data | Value | min | Max |
|---|---|---|---|
| x | <121×3181 double> | 0 | 29010……. |
| y | <1×121 double> | -1 | 1 |

## III. METHODOLOGY

The compression of time series is implemented in these steps

Step 1) The time series signal like ECG, EEG generated and stored in the Database.

Step 2) In order to compress the stored time series signal, performed the three compression methods.

i) Wavelet Decomposition
ii) Wavelet Packet Compression
iii) Decimated Discrete Wavelet Transform

Steps for data compression:

A) Decompose
Choose a wavelet, choose a level N. Compute the wavelet decomposition of the signal S at level N.

B) Threshold detail co-efficient
For each level from 1 to N, a threshold is selected and applied thresholding to the detail.

C) Reconstruct
Compute wavelet reconstruction using the original approximation coefficient of level N and modified detail coefficient of level from 1 to N.

Step 3) Depending on the compression methods, different number of coefficients is rounded to zero in different positions, hence the reconstructed signal is more or less similar to the original one. Generally, there exists measures that show how much reconstructed signal is similar to the original one, and the most used is Percentage Root mean square difference.

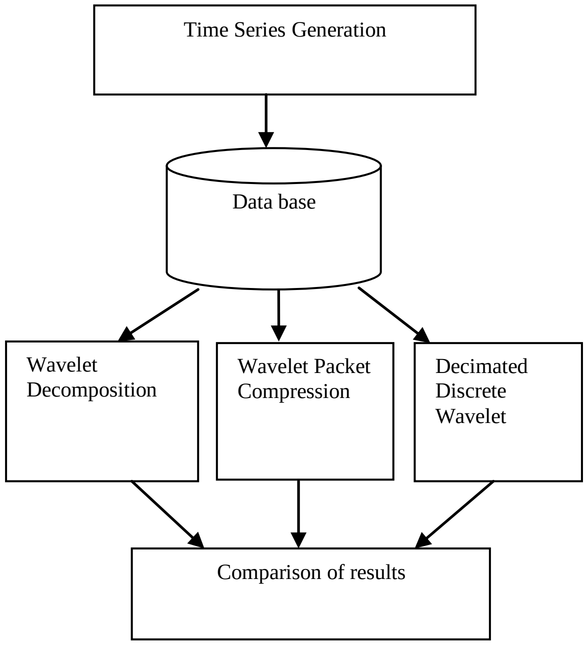


Fig.1 Block diagram of the Time series compression and its comparison.

## IV. WAVELET DECOMPOSITION

Wavelet decomposition can be defined as projection of the signal on the set of wavelet basis vectors. Each wavelet coefficient can be computed as the dot product of the signal with the corresponding vector basis. The signal can be fully recovered from the wavelet decomposition that is it is lossless compression. B-term decomposition uses only a small number of coefficients that carry the highest energy. The signal reconstructed using the B-term coefficients and the corresponding vector is known as the Best B-term approximation. Most signals that occur in nature can be well approximated by collecting only a small number of coefficients (5-10).

Wavelets are the signals which are local in time and scale and generally have an irregular shape. Wavelet is a waveform of effectively limited duration that has an average value of zero. The term 'wavelet' comes from the fact that they integrate to zero and their wave is up and down across the axis. Many wavelets also display a property ideal for all compact signal representation that is orthogonality. This property ensures that data is not all over represented.

A signal can be decomposed into many shifted and is scaled representations of the original mother wavelet. A wavelet transform can be used to decompose a signal into many component wavelets. Once this is done the coefficients of the wavelets can be decimated to remove some of the detail signal. Wavelets have the greatest advantage of being able to separate the fine details in a signal. A very small wavelets can be used to isolate very fine details in a signal, while very large wavelets can identify coarse details. In addition, there are many different wavelets to choose from various types of wavelets, they are Morlet, Daubechies, etc.

## V. WAVELET PACKET COMPRESSION

Wavelet Packet Compression is a wavelet transform where the discrete-time or sample signal is passed through more filters than the discrete wavelet transform (DWT). In the DWT, each level is calculated by passing only the previous wavelet approximation coefficients through discrete-time low and high pass quadrature mirror filters. However in the WPD, both the detail and approximation coefficients are decomposed to create the full binary tree. For n levels of decomposition the WPD produces $2^n$ different sets of coefficients (or nodes) as opposed to (3n + 1) sets for the DWT. However, due to the down sampling process the overall number of coefficients is still the same and there is no redundancy.

From the point of view of compression, the standard wavelet transform may not produce the best result, since it is limited to wavelet bases that increase by a power of two towards the low frequencies. It could be that another combination of base produces a more desirable representation for a particular signal. The best basis algorithm finds a set of bases that provide the most desirable representation of the data relative to a particular cost function. There were relevant studies in signal processing and communications fields to address the selection of sub band trees (orthogonal basis) of various kinds, e.g. regular, dyadic, irregular, with respect to performance metrics of interest including energy compaction e.g. entropy, sub band correlations and others. Discrete wavelets transform theory or continuous in the variable offers an approximation to transform discrete or sampled signals. In contrast, the discrete sub band transform theory provides a perfect representation of discrete signals.

## VI. DECIMATED DISCRETE WAVELET

In Decimated Discrete Wavelet compression, it uses only fixed values for wavelet scales based on powers of two. Wavelet positions are fixed and none overlapping and also form a set of wavelet basis vectors of length N. The Wavelet Series is just a sampled version of CWT and its computation may consume significant amount of time and resources, depending on the resolution that required. The Discrete Wavelet Transform (DWT), which is based on sub-band coding, is found to yield a fast computation of Wavelet Transform. It is easy to implement and reduces the computation time and resources required. Similar work was done in speech signal coding which was named as sub-band coding. In 1983, a technique similar to sub-band coding was developed which was named pyramidal coding. Later many improvements were made to these coding schemes which resulted in efficient multi resolution analysis schemes.

Decimated Discrete Wavelet compression is lossy compression. In lossy compression, the original signal cannot be exactly reconstructed from the compressed data. The reason is that, much of the detail in an image can be discarded without greatly changing the appearance of the image. As an example consider an image of a tree, which occupies several hundred megabytes. In lossy image compression, though very fine details of the images are lost, but image size is drastically reduced. Lossy image compressions are useful in applications such as broadcast television, videoconferencing, and facsimile transmission, in which a certain amount of error is an acceptable trade-off for increased compression performance. Methods for lossy compression include: Fractal compression, Transform coding, Fourier-related transform, DCT (Discrete Cosine Transform) and Wavelet transform.

## VII. COMPARISION OF COMPRESSION METHODS

When the original time series signal is decomposed by time-frequency transformation into groups of coefficients, each group represents signal in appropriate bandwidth. The coefficients which belong to lower frequency bandwidths have higher amplitudes and coefficients which belong to higher frequency bandwidths have lower amplitudes. Thus, if some numbers of coefficient which absolute amplitudes are closed to zero are neglected, the compression is obtained, with no big impact on shape of the signal after reconstruction. The method of setting the value of coefficient to zero if the absolute value of the coefficient is below the threshold preset, is calling 'Thresholding'. It is very important to select appropriate value for threshold as the larger threshold values lead to very good compression but distortion might appear in reconstruction. Smaller threshold values lead to low compression but reconstructed signal is very similar to the original one.

There exist several measures to know the quality of the reconstructed signal after compression. The most popular one is Percentage Root mean square Difference (PRD

$$\mathrm{PRD} = \sqrt{\frac{\sum_{n=1}^{N}(x(n)-\widetilde{x(n)})\hat{}2}{\sum_{n=1}^{N}(x(n)^{2})}}$$

where x (n) and $\widetilde{x(n)}$ are the nth sample of the original and reconstructed time series signal of length N.

Another two measures are commonly used to evaluate the perceptual quality. They are the Mean Square Error (MSE) and the Peak Signal to Noise Ratio (PSNR).MSE represents the mean squared error between the compressed and the original time series signal and is given by

$$\mathrm{MSE}=\frac{1}{mn}\sum_{i=0}^{m=1}\sum_{j=0}^{n=1}[X(i,j)-Xc(i,j)]^2$$

Where X(i,j) and Xc(i,j) are the signal data and its corresponding data compression. The lower the value of MSE, the lower the error of the compressed signal. The Peak Signal to Noise Ratio (PSNR) represents a measure

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of the peak error and is expressed in decibels. It is defined by:

$$PSNR = 10\ \log_{10}\left(\frac{255^2}{MSE}\right).$$

The higher the value of the PSNR, the better the quality of the compressed or reconstructed signal.

## VIII. RESULTS AND COMPARISION

### *A) Time Series Compression by Wavelet Decomposition*

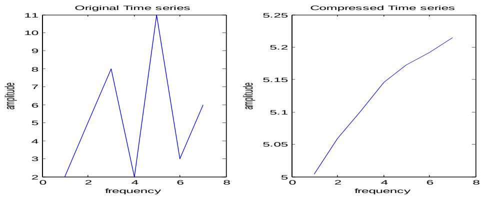


Fig. 2. Data set 1 compression by wavelet decomposition

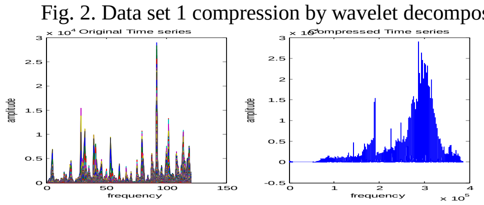


Fig.3 Data set 2 compression by wavelet decomposition

### *B) Time Series Compression by Wavelet Packet Compression*

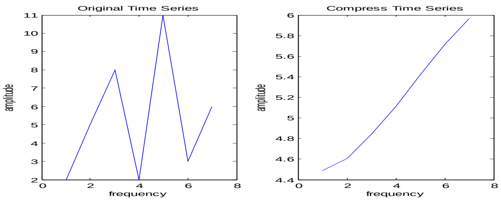


Fig. 4 Data set 1 compression by wavelet Packet

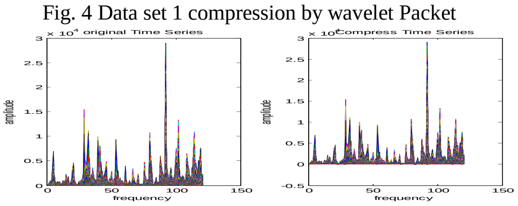


Fig.5 Data set 2 compression by wavelet packet

### *C) Time Series Compression by Decimated Discrete Wavelet Transform*

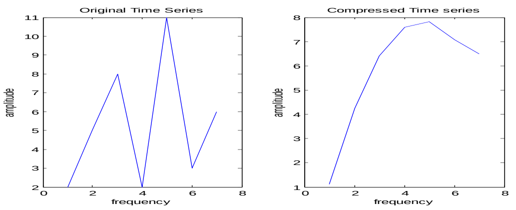


Fig. 6 Data set 1 compression by decimated discrete wavelet

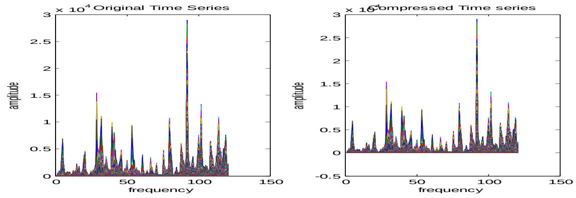


Fig.7 Data set 2 compression by decimated discrete wavelet

TABLE 3.
COMPARISION OF THE DATA SET 1 AND ITS COMPRESSED DATA

| | | | | | | | |
|---|---|---|---|---|---|---|---|
| Input data | 2 | 5 | 8 | 2 | 11 | 3 | 6 |
| Wavelet decomposition | 5.0038 | 5.0589 | 5.1009 | 5.1454 | 5.1725 | 5.1906 | 5.2149 |
| Wavelet packet | 4.4867 | 4.6080 | 4.8408 | 5.1165 | 5.4185 | 5.7172 | 5.9661 |
| Decimated discrete wavelet | 1.1136 | 4.2458 | 6.4088 | 7.6027 | 7.8274 | 7.0829 | 6.4958 |

TABLE.4.
MSE, PRD AND PSNR FOR THE DATA SET 1 BY USING WAVELET DECOMPOSITION, WAVELET PACKET AND DECIMATED DISCRETE WAVELET COMPRESSION

| | Wavelet decomposition | Wavelet packet compression | Decimated discrete wavelet compression |
|---|---|---|---|
| MSE | 9.5294 | 9.2238 | 8.8940 |
| PRD | 3.0870 | 3.0371 | 2.9823 |
| PSNR | 38.3401 | 38.4817 | 38.6398 |

## IX. CONCLUSION

In this paper, wavelet decomposition, wavelet packet and decimated discrete wavelet compression transforms on time series compression is studied. The results are presented on different time series signals of varying characteristics. The results show that Decimated discrete wavelet compression transform gives better performance in compression. On the otherhand wavelet packet compression gives better compression than wavelet decomposition. Compressing time series signal can be fundamental not only for the obvious storage size reduction but also for improving performance. This is because less data needs to be read or written on disk stored in a block device. The work presented here in the paper may be helpful for the design of efficient ECG compressor and EEG compression.

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## Biography

**Suchitra Oinam** presently pursuing M.Tech in Digital Electronics and Communication at AMC Engineering College, Bangalore, India. She was a student of Manipur Institute of Technology (MIT) during her B.E. She got 2nd rank in BE in the stream of Electronics & communication from Manipur University, Canchipur. Her Area of research interest includes Signal processing, Wavelets, Advanced digital image processing, Neural Network and Wireless Communication.

**Hemanth Kumar P**. received the Master's degree in Digital Communication from National Institute of Technology (MANIT) Bhopal, Madhya Pradesh, India in the year 2010. Currently working as Assistant Professor in AMC Engineering College, Bangalore in Department of Electronics & Communication Engineering. I have cleared PhD entrance in the stream of Computer Science Engineering from Visvesvaraya Technological University. My area of interest include Neural Network, Data Mining, Image Processing, Communication etc. I have three years of Teaching Experience and guided four M.Tech projects successfully.

**Dr. S.BASAVARAJ** PATIL is Professor & Head, CSE Deptt., BTL Institute of Technology and he is also Principal Consultant & Founder, Predictive Research. Started career as Faculty Member in Vijayanagar Engineering College, Bellary (1995-1997). Then carried out Ph.D. Research work on Neural Network based Techniques for Pattern Recognition in the area Computer Science & Engineering. Along with that took initiatives to bring several central government projects (AICTE sponsored) and executed successfully. Also consulted many software companies (Aris Global, Manthan Systems, etc.,) in the area of data mining and pattern recognition. Later joined Industry(2003-2004) and worked in diversified domains in the Pharma, Retail and Finance in the predictive analytics space in different capacities such as Technical Architect, Technology Consultant, Manager and Assistant Vice President (2004-2010). The last one was Assistant Vice President, Equity Quantitative Research with HSBC for around five years. He was responsible for building the revenue generating global quantitative research team at HSBC, Bangalore, that spread across different geographical locations such as London, Hongkong and Bangalore from scratch. For smaller stints he also worked at Canary wharf, HSBC Headquarters, London. His areas of research interests are Neural Networks and Genetic Algorithms. He founded Predictive Research in 2011. Now the Company has domestic and international client base and staff strength of 12 people. He is presently mentoring two PhD and one MSc (Engg by Research) Students. He has published around 12 International, 8 National (in referred journals and conferences) and 14 Commercial Research Papers (with HSBC Global Research). His total experience is 19 years in Teaching and Research (10 years in Teaching and 9 years in Industry)