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# Electrocardiogram data compression using DCT based discrete orthogonal Stockwell transform

Chandan Kumar Jha*, Maheshkumar H. Kolekar

*Department of Electrical Engineering, Indian Institute of Technology Patna, 801103, India*

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ABSTRACT

This paper reports a novel electrocardiogram (ECG) data compression algorithm which employs DCT based discrete orthogonal Stockwell transform. Dead-zone quantization is utilized to apply quantization as well as a threshold condition to transform coefficients. Further, integer conversion of coefficients is performed. It improves compression at the cost of very less reconstruction error. All integer coefficients are encoded using run-length coding. It exploits the repetition of data instances. Run-length coding helps to achieve higher compression without any relevant information loss. Performance of the proposed compression algorithm is evaluated using 48 single channel ECG records which are taken from the MIT-BIH arrhythmia database. A competitive compression performance is observed in comparison with other ECG compression methods.



## 1. Introduction

Electrocardiogram (ECG) is a graphical recording of tiny electrical impulses generated by heart muscles. It is used extensively in cardiology. Cardiologists use the ECG signal as a non-invasive medical tool to detect abnormalities in the human heart. In the long-term monitoring of heart-patients, recorded ECG data acquire a large volume of memory space for storage. It also consumes large bandwidth of communication channels in case of transmission of data for remote monitoring of patients or telemedicine. In this regard, application of ECG compression techniques resolves the problems of a healthcare system used for remote monitoring, Holter monitoring, patient-history review or telemedicine.

In past, many ECG compression techniques have been proposed which are broadly classified into three types [1]: direct, parameter extraction and transform domain methods. Direct methods remove redundancy of ECG signal directly in time-domain. This class includes turning point (TP), amplitude zone time epoch coding (AZTECH) [2], improved AZTEC coding [3], entropy coding [4] and ASCII character encoding [5]. The parameter extraction methods are based on the extraction of important features of ECG signal such as P-wave section, QRS-complex, and T-wave section. Extracted features utilize beat codebook matching and long-term prediction [6] to achieve compression. Other typical examples of this method include artificial neural network [7], peak picking and vector quantization [8]. In transform domain methods, first ECG signal is decomposed by means of a linear orthogonal transformation, after which the transform coefficients are appropriately encoded. Discrete Fourier transform (DFT) [9], discrete cosine transform (DCT) [10], Walsh transform [11], discrete wavelet transform (DWT) [12–16] are commonly used transform methods for ECG data compression. Numerous researchers have proposed ECG compression techniques based on two-dimensional transform methods such as 2D-DCT [17], 2D-DWT [18,19] and singular value decomposition (SVD) [20]. Empirical mode decomposition [21,22] and accuracy driven sparse model [23] were recently introduced for ECG data compression.

In the field of ECG data compression, transform-based techniques have gained a significant growth in the past few decades. Among transform based ECG compression approaches, Fourier transforms (FTs) and wavelet transform are used widely. Since FTs are not able to provide information regarding the time occurrence of frequency components of the signal. Therefore, it is not suitable for the analysis of non-stationary signals. Limitations of FTs can be overcome by introducing a constant window in short-time Fourier transform (STFT) but selection of window size is a problem. Wavelet transform fixed this problem by selecting a variable window size. Larger window is used at low frequency and shorter window at high frequency of the signal. In wavelet transform, proper selection of sampling frequency and mother wavelet plays a major role in frequency component extraction, failing which may produce misleading information. The drawback of wavelet trans-

* Corresponding author.
*E-mail addresses:* ckjha.pee15@iitp.ac.in, ckjha.bit@gmail.com (C.K. Jha).

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form is overcome by Stockwell transform (S-transform) [24] which combines the frequency-dependent resolution of time-frequency space and local phase information uniquely. The phase information is absolutely referenced. Till now, S-transform has been used in many research areas such as atmospheric studies, cardiovascular studies, magnetic resonance image analysis, characterization of seismic signals etc. In this paper, S-transform is employed as a compression tool for ECG signal which is a novel aspect in the area of ECG signal compression.

Organization of this paper is as follows: Section 2 introduces the discrete orthogonal Stockwell transform. Methodology of the proposed technique is elaborated in Section 3. Section 4 describes the performance metrics. Experimental results and discussion are detailed in Section 5. Section 6 presents the concluding remarks of this paper.

## 2. Discrete orthogonal Stockwell transform (DOST)

S-transform bridges the gap between FT and wavelet transform. It uniquely combines the time-frequency resolution with absolutely referenced phase (the phase referenced to time $t=0$) information. As described in [24], continuous S-transform of an input function $h(t)$ can be defined as the product of FT of $h(t)$ and a Gaussian window.

$$S(\tau, f) = \frac{|f|}{\sqrt{2\pi}} \int_{-\infty}^{+\infty} h(t) e^{-(\tau-t)^2 f^2/2} e^{-i2\pi f t} dt \qquad (1)$$

$S(\tau,f)$ is a one-dimensional function of time for a constant frequency $f$. It shows how the amplitude and phase change over time for the frequency $f$. If $h[kT]$, $k=0, 1, 2, \ldots, N-1$ is the discrete form of $h(t)$ and $H[n/NT]$ is the discrete Fourier transform (DFT) of $h[kT]$ then discrete S-transform of $h[kT]$ can be represented as

$$S\left[jT, \frac{n}{NT}\right] = \sum_{m=0}^{N-1} H\left[\frac{m+n}{NT}\right] e^{-2\pi^2 m^2/n^2} e^{i2\pi mj/N} \qquad (2)$$

where $T$ is the sampling time interval, $n=1, 2, 3, \ldots, N-1$ and $j=m=0, 1, 2, \ldots, N-1$. In the discrete case, S-transform is suffered from the high redundancy of data instances. It represents a signal of length N by $N^2$ data instances. DOST is developed to remove the redundancies of discrete S-transform which has an orthonormal basis and multiple scales. An orthonormal transformation shows an N-point time-frequency representation of an N-point time series, thus maximum representation efficiency can be achieved by using it.

The efficient representation of DOST can be defined as the inner product of time series $h[kT]$ and the basis functions defined in terms of the function of [kT]. Parameters of the basis functions are $\nu$, $\beta$, and $\tau$. $\nu$ is a frequency variable which indicates the centre of the frequency band. $\beta$ indicates the width of the frequency band and $\tau$ is a time-variable which denotes the time localization.

$$S\{h[kT]\} = S\left(\tau T, \frac{\tau}{NT}\right) = \sum_{k=0}^{N-1} h[kT] S_{[\nu,\beta,\tau]}[kT] \qquad (3)$$

In general case, basis functions $S_{[\nu,\beta,\tau]}[kT]$ are defined as

$$S_{[\nu,\beta,\tau]}[kT] = \frac{ie^{-i\pi\tau}}{\sqrt{\beta}} \frac{e^{-i2\pi(k/N-\tau/\beta)(\nu-\beta/2-1/2)} - e^{-i2\pi(k/N-\tau/\beta)(\nu+\beta/2-1/2)}}{2\sin[k/N-\tau/\beta]} \qquad (4)$$

At this point, orthogonality is ensured by applying some rules to the sampling of time-frequency space. These rules are as follows:

1.) Rule 1: $\tau = 0, 1, 2, \ldots, \beta - 1$
2.) Rule 2: $\nu$ and $\beta$ have to be chosen suitably such that each Fourier frequency sample is used once.

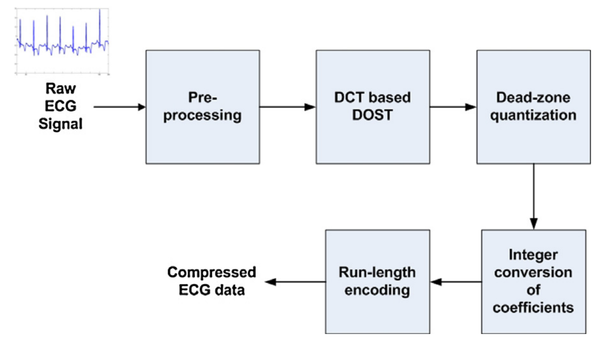


**Fig. 1.** Block diagram of compression procedures.

For each frequency band ($\beta$), there are one or more local time samples ($\tau$). It should be equal to $\beta$ (by Rule 1). Thus, wider frequency resolution (large $\beta$) results in more samples in time (large $\tau$). Values of $\nu$ and $\beta$ are determined by imposing some specific rules on the basis function. Octave sampling [24] is used for the strict definition of $\nu$ and $\beta$. Operation of DOST can be summarized as:

**Algorithm 1.** Operation of DOST

**INPUT**: discrete time series $h[kT]$
**OUTPUT**: DOST of $h[kT]$
**Step 1**: Perform DOST by the inner product of $h[kT]$ and $S_{[\nu,\beta,\tau]}[kT]$
**Step 2**: To ensure orthogonality, apply the two aforementioned rules to $\tau$, $\nu$ and $\beta$. For this employ octave sampling to time-frequency space.

## 3. Proposed methodology

Methodology of the proposed compression algorithm is shown in Fig. 1 using a block diagram. It involves following steps i.e., pre-processing of raw ECG signal, DOST implementation, dead-zone quantization of DOST coefficients, integer conversion of coefficients and run-length encoding.

### 3.1. Pre-processing

At first, raw ECG signals are acquired from the MIT-BIH arrhythmia database [25]. Base and gain of raw ECG signals are 1024 and 200 respectively. Original ECG signal is achieved from the raw ECG signal by subtracting base and dividing the resulting data by gain. Much high frequency (HF) noises are present in the original ECG signal due to artifacts such as muscle contraction, power-line interference, and electrode movement. These HF noises are removed by employing Savitzky–Golay filter (SGF). SGF is also known as polynomial smoothing filter which rejects HF noises efficiently without losing key information of the signal. Polynomial order 3 and window dimension 17 are chosen for SGF.

### 3.2. DCT based DOST

After filtering, DOST is applied to the ECG data. Instead of DFT, discrete cosine transform (DCT) is utilized in the kernel of the DOST. DCT is a real-valued transform which shows energy compaction property. It is widely used in the field of data compression. The DCT based DOST produces only positive (increasing) frequencies [26] and carries no symmetry in the coefficients. Consequently, higher frequencies are required in frequency space. There is also a need of adjustment in the partitioning of frequency space. However, it is achieved by continuing dyadic partition as is used in the case of DOST.