

# **A STUDY ON ELECTROCARDIOGRAM SIGNALS DENOISING USING S-TRANSFORM & MODIFIED S-TRANSFORM**

*A thesis submitted in partial fulfillment of the  
Requirement for the award of degree of*

**Master of Engineering  
In  
Wireless Communication**



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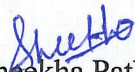
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## ***DECLARATION***

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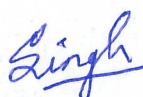
I, Sheekha Pathania, hereby declare that the work presented in this thesis entitled “A study on Electrocardiogram signals denoising using S-transform & Modified S-transform” in fulfillment of the requirement for the award of degree of **Master of Engineering in Wireless Communication** submitted at Electronics and Communication department, Thapar University, Patiala is an authentic record of work carried out under supervision of **Dr. Ashutosh Kumar Singh**, Assistant Professor, **Department of Electronics and Communication Engineering, Thapar University, Patiala, Punjab**. The matter presented in this thesis has not been submitted either in part or full to any other university or institute for the award of any other degree.

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I certify that the above statement made by the student is correct to the best of my knowledge and belief.

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## ***ABSTRACT***

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Electrocardiogram (ECG), a non-invasive technique is used as a primary diagnostic tool for cardiovascular diseases. It plays an important role in monitoring of patient and diagnosis attributable to its ease of use and non-invasive nature.

Today, ECG signal processing is one of the challenging computational processes as different noises get embedded with it such as channel noise, electrode motion, muscle artifacts and baseline wander during the acquisition and transmission of signals. A cleaned ECG signal provides required information about the electrophysiology of the heart diseases and ischemic changes that may happen thereby giving valuable information about the functional details of the heart.

The aim of this thesis is to remove the noise components from the ECG signal based on time-frequency domain representation using a denoising technique called S-transform. S-transform has a time-frequency resolution which is far from ideal. In this work, S-transform represents the noisy ECG signal in the time-frequency domain. Next, masking and thresholding technique is applied to remove the unwanted noise components from time-frequency domain. But, a noisy time series, with both signal and noise varying in frequency and in time, presents special challenges for improving the signal to noise ratio.

This thesis proposes a modified S-transform, which offers better time frequency resolution compared to the original S-transform. This is achieved through the introduction of a new scaling parameter for the Gaussian window used in S-transform. This method gives good performance with high SNR value for different noises as compared to S-transform.

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## *LIST OF ABBREVIATIONS*

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ECG	Electrocardiogram
MIT/BIH	Massachusetts Institute of Technology - Beth Israel Hospital
ST	Stockwell Transform (S-transform)
MST	Modified S-transform
STFT	Short time Fourier transform
WT	Wavelet Transform
EKF	Extended Kalman Filter
ICA	Independent Component Analysis
TFR	Time-frequency representation
SNR	Signal to noise ratio
MA	Muscle Artifacts
EM	Electrode Motion
BW	Baseline Wander
GT	Gabor Transform

# CHAPTER 1

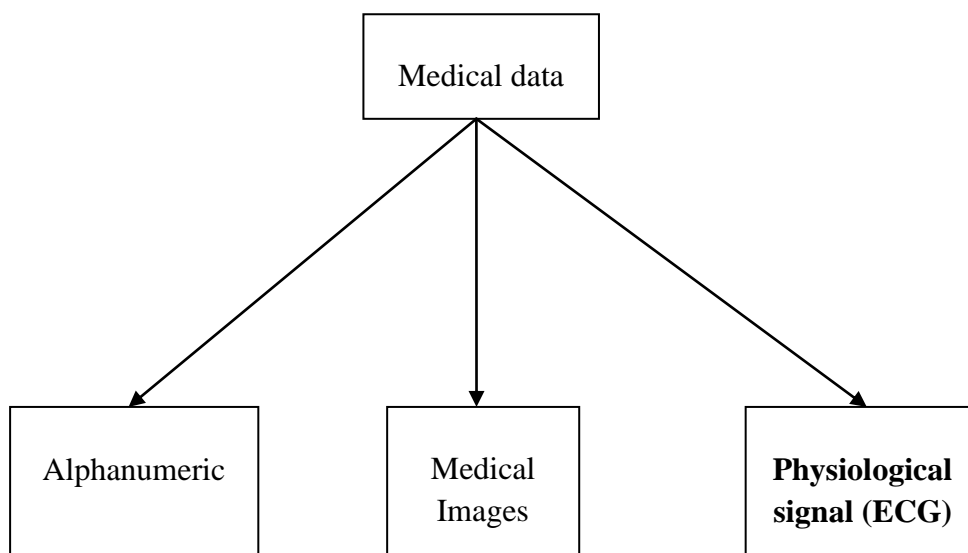
## INTRODUCTION

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**S**IGNAL processing is mainly about the inventive utilizations of signal processing methods in signals which can be of different types through different innovative integrations of the signal processing techniques. And in biomedical signals (Electrocardiogram here), these signal processing techniques are performed in vast majority of systems for ECG analysis and interpretation in order to enable an improved medical diagnosis. Daily clinical practice creates enormous amount of biomedical signals amid the monitoring of patients. As a rule, the ECG is recorded amid wandering or strenuous conditions to such an extent that the signal is adulterated by various sorts of noises, infrequently beginning from other physiological procedure of the body. Hence, denoising represents an important part of ECG signal processing.

### 1.1 CHARACTERSTICS OF MEDICAL DATA

Fig. 1.1 demonstrates the three essential sorts of information that must be gained, controlled and filed in the doctor's facility. Alphanumeric data contain the name of patient and address, identification number, lab test results, and notes of physician. Medical Images indicate X-beams and scopes from PC tomography, attractive reverberation imaging, and ultrasound. Here, the physiological banner gone for is the 'electrocardiogram'.



**Figure 1.1: Sorts of Medical information [30]**

## 1.2 ECG

Electrocardiography (ECG) is a non-invasive technique which is utilized to demonstrate the underlying condition of heart by showing its electrical activity [10, 31]. This technique is attained by setting electrodes on the skin surface at certain focuses on the body. Since the electrical action of heart is straightforwardly correlated to its functioning, ECG signal is utilized to diagnose the disorders and heart rhythm's rate. As a result, any adjustment in the rhythm of heart induced via cardiac arrhythmias will reflect in the individual's ECG as well [17, 32]. Abnormality in the shape of ECG is called arrhythmia.

Generally, ECG signal gives the below information [33]

- Position of the heart and the extent of the chambers
- Heart rhythm and rate of heart
- Origin of impulse and its propagation
- Variations in electrolyte concentrations

Hence, ECG is broadly utilized as an essential apparatus by the doctors all through the world to analyze the state of heart as it gives significant data about the useful parts of the cardiovascular framework.

Early recognition of heart illness can extend the duration of life as well as lift the nature of living through accurate treatment. In recent years, numbers of researchers have focussed on the processing of signals. Mostly, they utilize either time or frequency domain filtering of ECG signals. Overview of ECG signal is given in this chapter and the commonly noticed artifacts during its acquisition and transmission of signals [34].

## 1.3 HEART ANATOMY

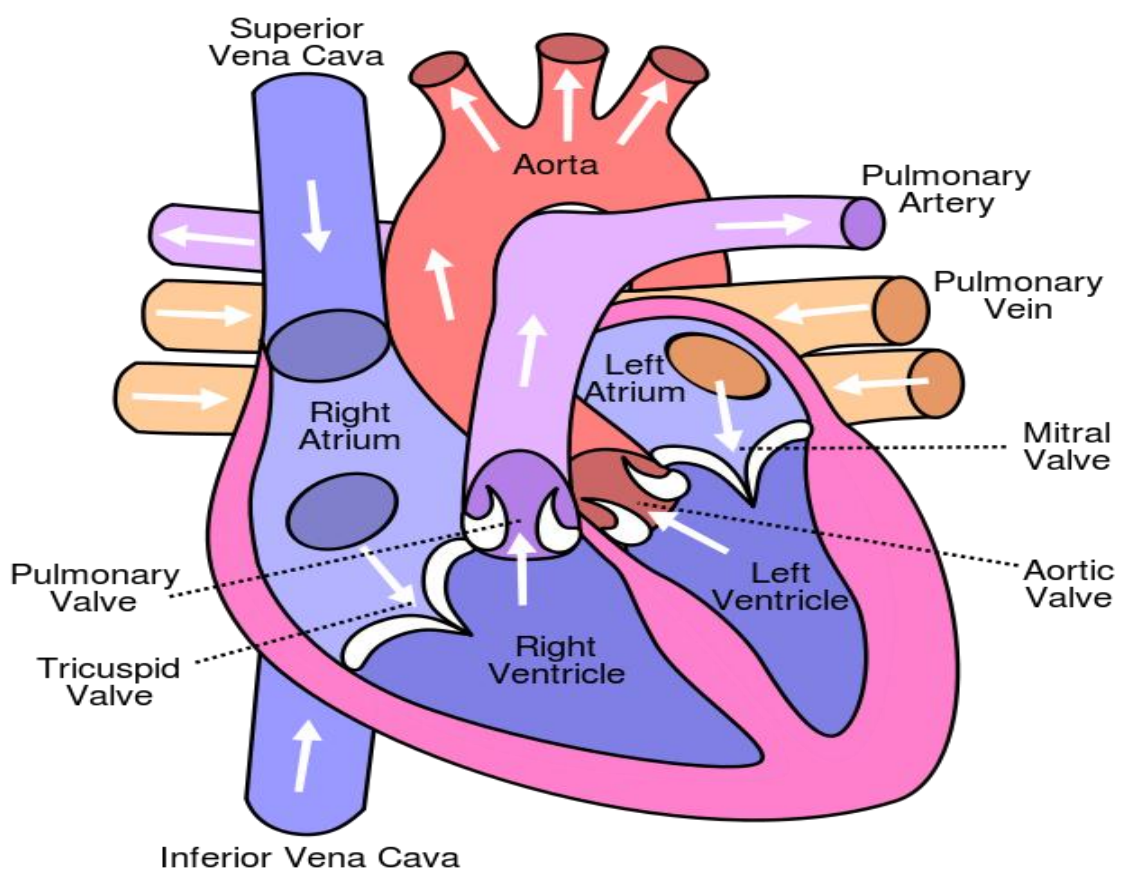
In the human body, the heart is the central part of the cardiovascular system [31]. Human heart's cross section is shown in Fig. 1.2. The arteries are in charge of conveying the blood from the heart to all the different parts of the body and the veins are capable to convey the blood from all body parts back to the heart. Heart comprises of four chambers:

- Upper two chambers are called atria
- Lower two chambers are called ventricles

These two chambers are separated by A-V valves.

The right atria and right ventricle are responsible for circulating blood between the heart as well as lungs. From the veins, oxygen poor blood streams to the right atria by the superior and inferior venacava. During the contraction of right atria, this blood streams to the right ventricle by the tricuspid A-V valve. At that time, the right ventricle draws the blood from the heart to the lungs along the left pulmonary artery. In the lungs, the blood gets oxygenated [36].

The left atria and the left ventricle are responsible for circulating the blood rich in oxygen between the heart and the other parts of the body. Through the left pulmonary veins, the oxygenated blood flows from the lungs to the left atria. During the contraction of left atria, the pumping of blood to the left ventricle is done by the mitral valve. At that time, the left ventricle draws this blood to the all others parts of the body through the aorta [36].



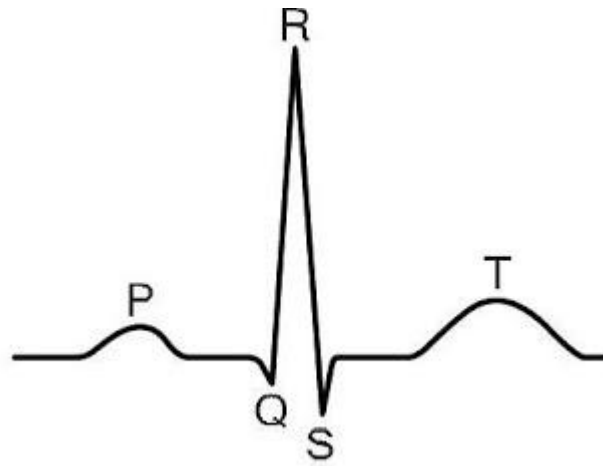
**Figure 1.2: Heart Anatomy [35]**

Generally, muscles of the heart have a polarity which is negative and when this charge winds up plainly zero, there is depolarization [32] of heart muscles. In a cardiac cycle, there is occurrence of depolarized wave which brings about the contraction of atria and ventricles

which represent a beat of heart. ECG signal identifies these minute changes in the electric charges and is shown on a screen or ingrained on a chart paper [34].

#### 1.4 WAVE PATTERN OF ECG SIGNAL

Electrocardiography represents the recording of the electrical manifestation of the contractile heart's activity [37]. The heart's rhythm is evaluated easily as beats per minute (bpm). The typical ECG signal is shown in Fig. 1.3. Generally, ECG signal comprises of a P wave, a QRS complex, a T wave and U wave which is obvious on and off. These contain the useful details about the disease's nature affecting the human heart.



**Figure 1.3: The typical ECG wave pattern [36]**

P-wave happens because of the depolarization of atria when the circulations systems from atria to ventricles. The fragment of PQ creates spreading time of fervor from atria to ventricles while depolarization of ventricles shows the era of QRS complex. The blood is directed out from right ventricle to blood vessel pulmonalis and by the left ventricle to aorta. Amid repolarization of atria, it is covered by QRS complex which is imperceptible by on the record. Then again, the T-wave happens amid the repolarization of ventricles. Once in a while, the U wave is seen after the T-wave which is created amid the late repolarization of Purkynje filaments in ventricles and which is likewise imperceptible [7]. The length and interims of various waves is appeared in Fig. 1.3.

#### 1.5 NOISES IN ECG

Many types of noises are responsible for affecting the ECG signal amid its securing and transmission [22]. Such noises may contaminate the ECG and may change its characteristics thereby making its analysis very difficult. These noises affecting the ECG signal are divided into two parts based on its transmission and securing. These are as follows:

- Channel noises
- Real Noises within the frequency band of ECG.

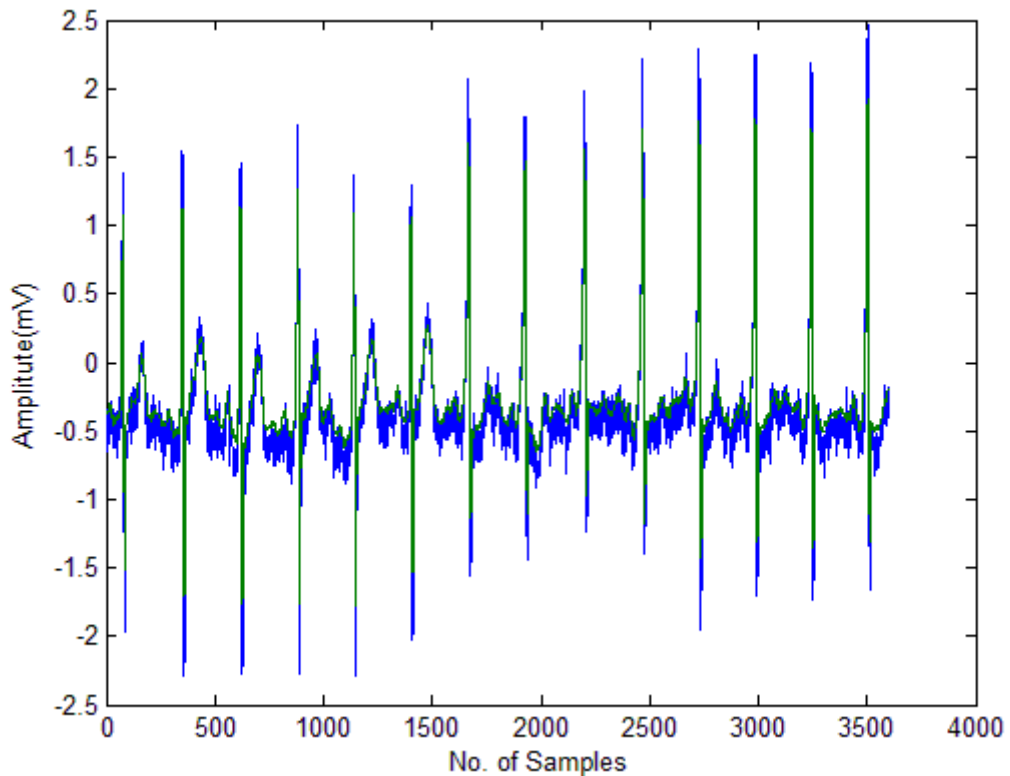
### 1.5.1 Channel noises

Wireless electrocardiogram checking includes the estimation of ECG signals and their timely transmission over wireless systems to remote medicinal services experts. Be that as it may, fluctuations in remote channel conditions posture nature of-administration difficulties for real-time ECG observing services in a portable situation.

#### 1.5.1.1 Additive white Gaussian Noise

The poor conditions of channel can likewise initiate noise to ECG when it is transmitted. Normally, it is modelled utilizing additive white Gaussian noise which comprises the entire frequency component [22]. The expression for generating awgn in Matlab is:

$$y = \text{awgn}(\text{ECGsignal}, \text{SNR});$$



**Figure 1.4: ECG signal corrupted with additive white Gaussian Noise at an SNR of 5 dB.**

The AWGN adjusts the variance of the noise so a particular SNR is accomplished for a given signal. Obviously it can be done with ‘randn’ too, but it needs to be figured out precisely how to implement it so there will be different values every time during its performance. Though,

'awgn' does it itself. ECG signal corrupted with awgn at an SNR of 5 dB is shown in Fig. 1.4.

### 1.5.1.2 Rayleigh Fading

Over substantial separations, signal quality corrupts even without the nearness of huge amounts of AWGN. This debasement is known as fading, and channels that display these properties are known as fading channels. ECG signal corrupted with Rayleigh Noise at an SNR of 5 dB in shown in Fig. 1.5. The expression for generating Rayleigh fading in Matlab is:

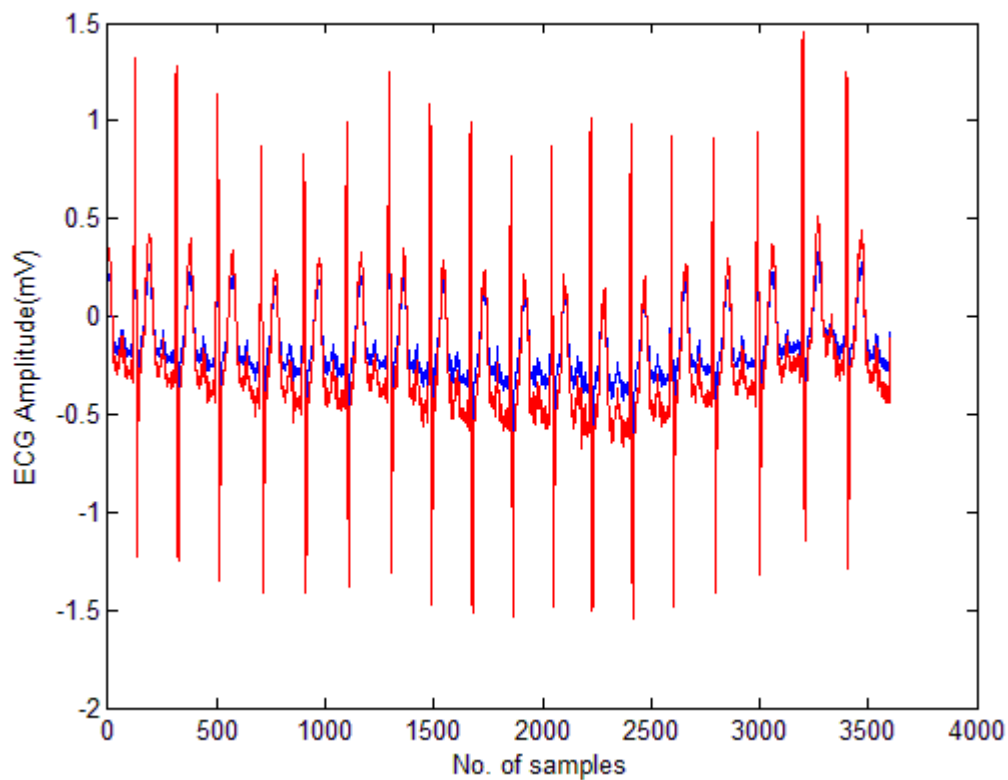
```
Variance = 1/(L*(10^(SNR /10)));
```

```
p = randn(size(ECGsignal,1),1);
```

```
q = randn(size(ECGsignal,1),1);
```

```
w = sqrt(variance*(p.^2 +q.^2));
```

```
y = ECGsignal + w;
```



**Figure 1.5: ECG signal corrupted with Rayleigh fading at an SNR of 5 dB.**

Just including the two Gaussian Random factors and taking the square root (envelope) gives a Rayleigh fading process. Here, two Gaussian random arrays are created utilizing randn work in Matlab. Rayleigh fading also influences the final signal-to-noise ratio when it comes to the real and imaginary part of the signal.

### 1.5.2 Real noises in ECG

The heart's electrical activity is detected by checking electrodes put on the surface of skin. The range of electrical signal is small (regularly 0.0001 to 0.003 volt) and are inside the frequency scope of 0.05 to 100 Hertz or cycles every second. Tragically, other artifactual signals of comparable frequency and often bigger amplitude achieve the skin surface and blend with the ECG signals. In electrocardiography, an ECG artifact is utilized to show something that is not heart-made. These real noises are explained as follows-

#### 1.5.2.1 Muscle Artifact (MA) Noise

Muscle artifacts are otherwise called as Electromyography (EMG) noise. Such noises arise because of the movement of muscles amid the ECG obtaining for the most part amid an anxiety test [22]. The signals contracting from muscle withdrawal are thought to be transient blasts of zero mean band-restricted Gaussian noise. The duration of burst can be up to 50ms with maximum frequency of 10 KHz [28].

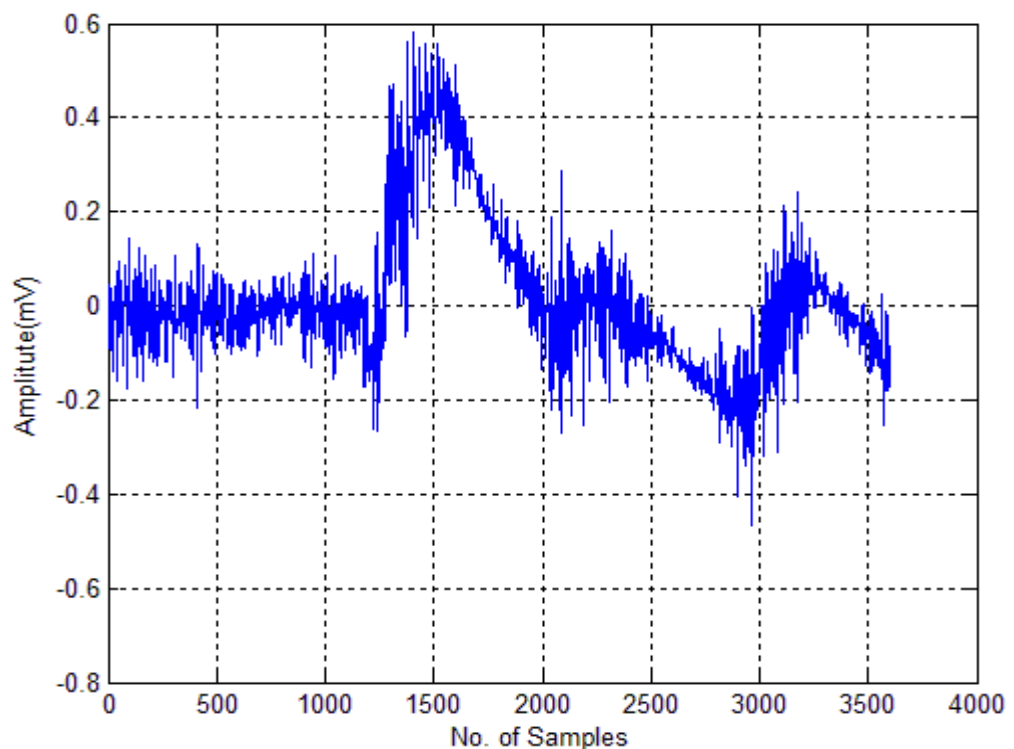
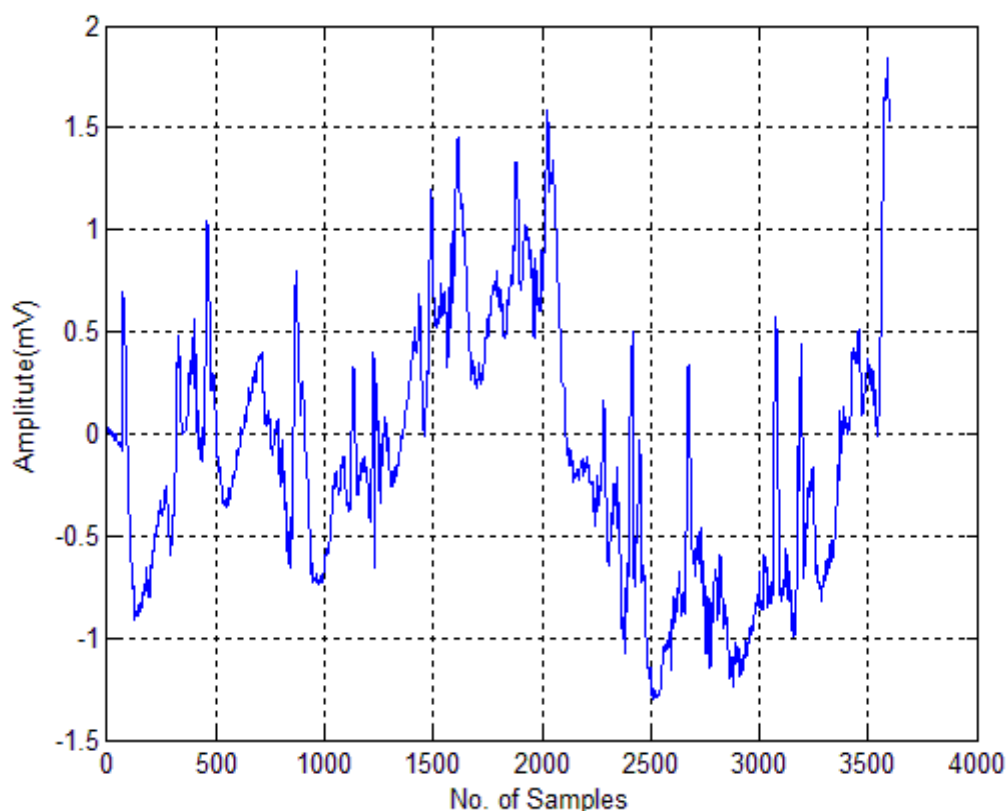


Figure 1.6: Muscle Artifacts (MA) Noise

The heart is by all record is not the only organ in the body that produces quantifiable power. Right when the skeletal muscles encounter tremors, ECG is besieged with evidently self-assertive movement. The term noises do not imply sound but rather to obstruction which is electrical. The low amplitude of muscle tremor noise can impersonate the pattern observed in atrial fibrillation. ECG signal gets corrupted with MA noise, which is in shown in Fig. 1.6.

### 1.5.2.2 Electrode Motion (EM) Noise

In real-time condition, when the ECG signal is obtained, the EM noise is often found with ECG motion because of the transient change in baseline between electrode impedance of skin and electrode movement [22]. The loss of contact can be changeless, irregular, as would be the circumstance when a loose electrode is acquired and out of contact with the skin along these lines of developments and vibration. The movement of electrodes can present a higher amplitude motion in the ECG signal.

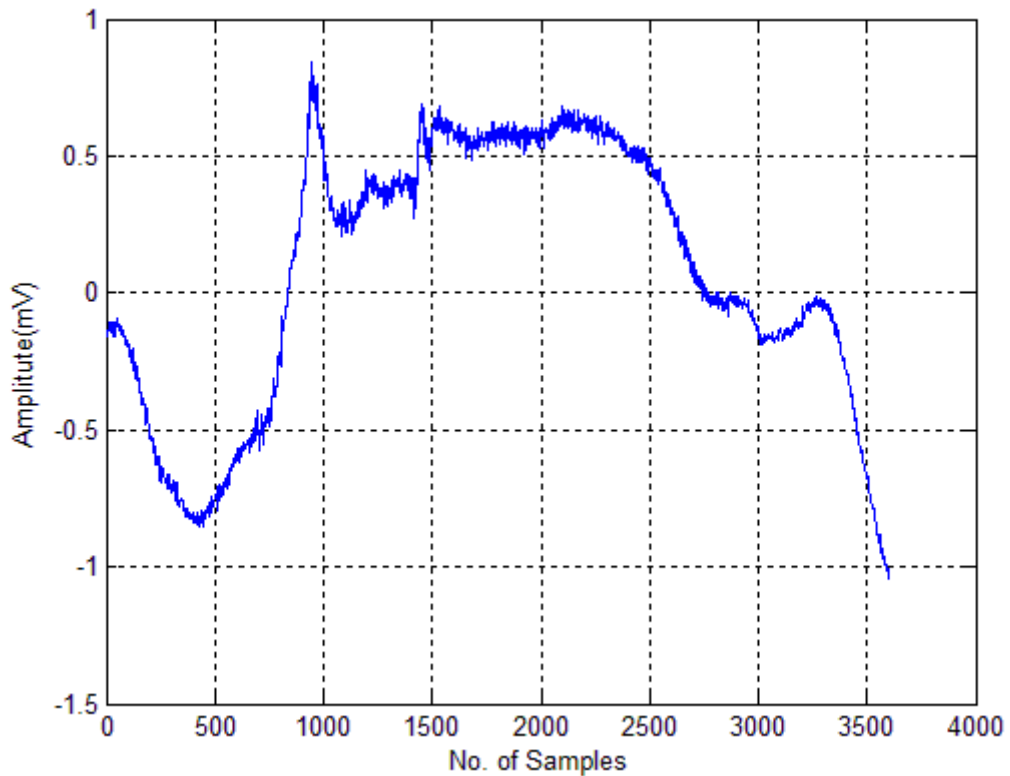


**Figure 1.7: Electrode Motion (EM) Noise**

For the most part, this noise can have a span of 100-500ms [28] and have frequency segments covering with the ECG signal's frequency contents. Fig. 1.7 shows the EM noise, which corrupts the ECG.

### 1.5.2.3. Baseline Wander (BW) Noise

Baseline wander is defined as the variety which occurs in the isoelectric line of the ECG signal. It normally happens because of coughing or respiration which initiates in a huge chest development for a chest-lead ECG as well as development of arm or leg for a limb-lead ECG. Fig. 1.8 shows the BW noise, which corrupts the ECG signal. In a large portion of the ECG recordings, the breath, electrode impedance change because of sweat and expanded body developments are the fundamental causes of baseline wandering.



**Figure 1.8: Baseline Wander (BW) Noise**

The impact of temperature and the varieties of bias on the devices and enhancers may likewise cause deviation in baseline voltage of ECG signal. In general, it is a signal with a low frequency in the range of frequency is 0-0.5 Hz [29].

## 1.6 STOCKWELL TRANSFORM (S-TRANSFORM)

To separate valuable data from the noisy ECG signal, there is a need to process the raw ECG signal. The aim of this thesis is to remove the noise components from the ECG signal based on time and frequency representation of ECG signal [12]. Owing to the non-

stationary nature of ECG, the fundamental digital signal processing technique investigated in this context is S-transform.

The S-transform, derived by Stockwell, is utilized to get the representation of a signal (time series) in time and frequency or which uniquely joins a frequency dependent resolution and simultaneously restricting the real and imaginary spectra. The width of analyzing window scales inversely with frequency in S-transform.

The S-transform has three main characteristics:

- Frequency invariant amplitude response,
- Progressive resolution
- Absolutely referenced phase resolution

It is defined by the following equation:

$$ST(\tau, f) = \int_{-\infty}^{\infty} m(t) \frac{|f|}{\sqrt{2\pi}} e^{-\frac{(\tau-t)^2 f^2}{2}} e^{-i2\pi f t} dt \quad (1.6.1)$$

where:

- $\tau$ : Time
- $f$ : Frequency
- $m(t)$ : Time-varying signal
- $\frac{|f|}{\sqrt{2\pi}} e^{-\frac{(\tau-t)^2 f^2}{2}} e^{-i2\pi f t}$ : Gaussian Window

## 1.7 ECG DATABASE

In order to work or digitally process the real ECG signal (time series), the following two databases were used-

### 1.7.1 MIT-BIH Arrhythmia Database

MIT-BIH Arrhythmia database [26] is organized by Massachusetts Institute of Technology (MIT) as well as Beth Israel Hospital (BIH) in order to direct experimentation on examination of arrhythmia and different flow of heart. The data was made available to more from 1980 and the online accessibly was done in September 1999. Henceforward, these data have been utilized worldwide by scientists for their examination and research.

The database comprises of 48 distinct records each having 30 minutes term. Every one of these records has 360 Hz sampling frequency and has 2 channels consisting of two leads i.e. II and V1. Each tape in these records is correctly commented on by a group of master cardiologists. These records were exported as .mat file and loaded in MATLAB for its processing.

### **1.7.2 MIT-BIH Noise Stress Test Database**

This database comprises 3 noise recordings [27] that typically show up amid the recording of ECG, for example, muscle artefact, electrode motion and baseline wander. The volunteers who are physically fit and standard recorders as well as devices are responsible for the recordings of this database. The terminals are kept on diverse positions on the body where there is no availability of ECG signal.

## **1.8 ORGANIZATION OF THESIS**

This thesis deals with the study of S-transform for the denoising of various noises in the case of ECG signal. The thesis is organized as follows:

**Chapter 1** represents the introduction which includes the objective of the work, the various characteristics of medical data, an introduction of the ECG signal, a review of the operation of heart anatomy, the wave pattern of ECG, the different types of noises that can influence the ECG signal amid its obtaining and diagnosis, the denoising technique used, description of the databases and an outline of the work reported in the thesis.

**Chapter 2** overviews the work done by various researchers in ECG signal denoising from time to time. This section mentions some of the relevant papers that helped in achieving the targeted results.

**Chapter 3** explains the pre-processing steps and ECG signal denoising technique using S-transform. The theoretical background and the methodology for denoising are discussed in this chapter. It is explained step by step and also the denoising of ECG signals using modified S-transform is proposed in this chapter.

**Chapter 4** analyzes the results and the comparison of the affect of various noises has been studied. The comparison between S-transform and the proposed method has been made.

**Chapter 5** sums up the conclusion and gives the future work of this dissertation.

## CHAPTER 2

### LITERATURE SURVEY

---

**T**HIS chapter overviews the work which has been done in the field of ECG signal denoising methods from time to time. The thought process behind studying the existing literature is to pick up inside and out learning identified with the subject and to pick up the inspiration for cutting edge inquire about.

#### 2.1 DIFFERENT TECHNIQUES FOR ECG SIGNAL DENOISING

Various techniques for removing noise parts have been accounted for in the historical backdrop of ECG signal processing. A scheme for denoising of ECG signals utilizing a modified extended Kalman filter (EKF) structure brought about SNR change of 10.16 dB [1] as compared to the previous EKF structure. In this work, a nonlinear Bayesian system assessed its factors by the utilization of state dynamical equations and its observations, noise in phase and noise in ECG signal. This EKF structure could expel the motion artifact noise, while safeguarding the analytical data of the signal.

The concept of adaptive filtering was addressed in the analysis of ECG signal where different adaptive filter structures like baseline wander filter, motion artefact cancellation etc were developed to remove noises that appear from diverse sources during acquisition of ECG signal. Baseline wander reduction was simpler; still the low corner frequencies were high for some applications. This filter was inappropriate when it came to the shape of ST segment which should not be distorted at all. The structures did not offer any significant advantage. However, these filter structures were more suited to rhythm analysis and less suited to the diagnosis of ECG analysis [2].

In the area of blind source separation, another technique was used called independent component analysis (ICA) which dealt with the elimination of various noises from the ECG signal [3]. This method assumed the original signals to be mixed directly, and that these mixed signals are accessible, ICA detects a linear combination of the mixed signals in a blind manner which regains the original source signals, conceivably re-scaled which resulted in fast convergence of output signal, but with a greater error.

The wavelet transform based techniques [4, 5] were also generally utilized in view of its ability to distinguish information of a time domain signal in time-frequency

representation. Be that as it may, the amplitude of wavelet transform change is subject to the frequency. This Transform likewise has different restrictions, [6] for example, having better frequency resolution and poor time resolution for low frequencies as well as the other way around for high frequencies.

In comparison to traditional wavelet transform, fuzzy rules came to limelight which demonstrated the process to select fuzzy principles and to incorporate diverse multiwavelets, pre- and post- filters for denoising of ECG signals at various noise levels. This method achieved 30% improvement as compared to traditional multiwavelet algorithms [4].

## 2.2 STUDY ON STOCKWELL TRANSFORM

In order to have desirable spectral components of the various time series, S-transform was introduced [7]. This transform provided a joint time-frequency dependent resolution and maintained the direct relationship with Fourier spectrum which can be done by several methods.

In [7], it is expressed as the phase correction of the CWT or modified wavelet transform defined by:

$$C(\tau, d) = \int_{-\infty}^{\infty} g(t)c(t - \tau)dt \quad (2.2.1)$$

where,  $c(\tau, d)$  is a scaled replica of the fundamental mother wavelet. ‘Width’ of the wavelet  $c(\tau, d)$  is decided by the dilation  $d$  thus controls the resolution.

Here, CWT with a specific wavelet is given by the function  $g(t)$  that is multiplied with the phase factor so the S-transform is expressed as:

$$S(\tau, f) = e^{i2\pi f\tau}C(\tau, d) \quad (2.2.2)$$

where the mother wavelet is given as

$$c(t, f) = \frac{|f|}{\sqrt{2\pi}} e^{-\frac{(\tau-t)^2}{2}} e^{-i2\pi ft} dt \quad (2.2.3)$$

To write explicitly, the S-transform is

$$S(\tau, f) = \int_{-\infty}^{\infty} g(t) \frac{|f|}{\sqrt{2\pi}} e^{-\frac{(\tau-t)^2}{2}} e^{-i2\pi ft} dt \quad (2.2.4)$$

In order to represent the local spectrum by S-transform, one expects a straightforward operation of averaging the spectrum after sometime so as to give the Fourier transform. It is simple to express as:

$$\int_{-\infty}^{\infty} S(\tau, f) d\tau = G(f) \quad (2.2.5)$$

Where  $G(f)$  is the Fourier transform of  $g(t)$ . This is obviously unique in relation to concepts of CWT and furthermore gives absolutely referenced phase data.

For the discrete case, the S-transform is a vector's projection characterized by the source (time series) onto a spanning arrangement of vectors. Spanning vectors' nature is not orthogonal and the S-transform, components are not independent. Here,  $g[kT]$  is the discrete time series such that  $k = 0, 1, \dots, N - 1$ .

The Fourier transform in discrete form is defined as

$$G\left[\frac{n}{NT}\right] = \frac{1}{N} \sum_{k=0}^{N-1} g[kT] e^{-\frac{iz\pi nk}{N}} \quad (2.2.6)$$

Each vector ( of the Fourier transform) is sorted into N localized vectors using component by component product with N shifted Gaussians to such an extent that the total of these N localized vectors is the first basis vector.

Discrete time source's  $g[kT]$ , S-transform is defined as (letting  $f \rightarrow n/NT$  and  $\tau \rightarrow jT$ )

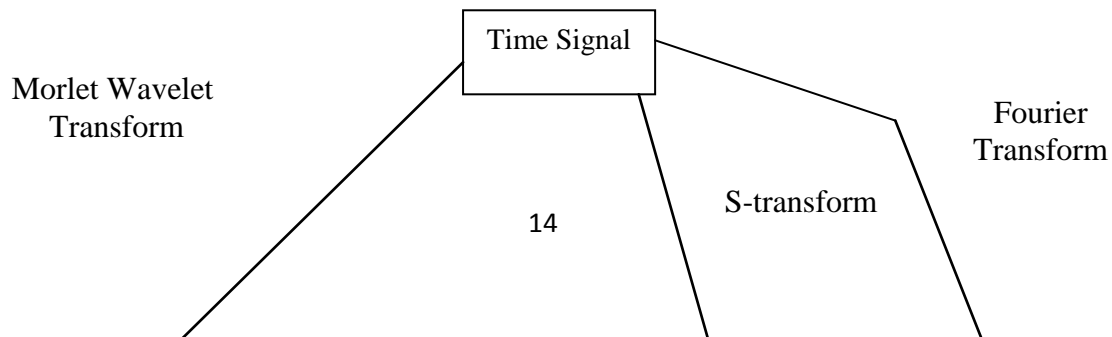
$$S\left[jT, \frac{n}{NT}\right] = \sum_{m=0}^{N-1} G\left[\frac{m+n}{NT}\right] e^{-\frac{2\pi^2 m^2}{n^2}} e^{\frac{iz\pi mj}{N}} \quad n \neq 0 \quad (2.2.7)$$

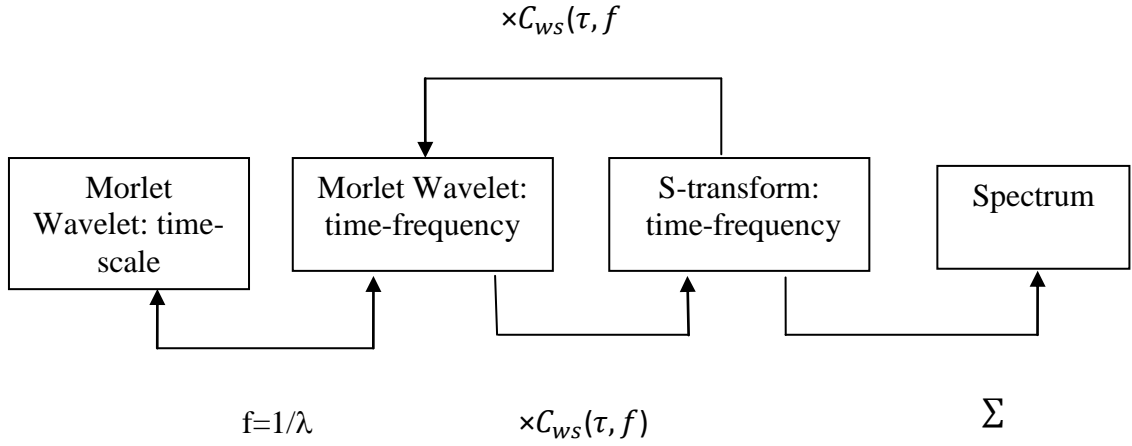
and for the  $n = 0$  voice, it is equivalent to the constant characterized as

$$s[jT, 0] = \frac{1}{N} \sum_{m=0}^{N-1} g\left(\frac{m}{NT}\right) \quad (2.2.8)$$

Where  $j, m,$  and  $n = 0, 1, \dots, N - 1$ . Hence, the inverse is exact as the equation (2.2.8) sets the steady time source's average into the zero frequency voice.

A new method of evaluating S-transform was introduced by considering its relationship with Morlet wavelet transform, the Fourier transform and their relations [8] as shown in Fig. 1.4. This approach was conceptualized from a view of wavelet point of. Also, the relationship was studied with continuous wavelet transform so as to overcome the limitation like, its constraint to linear frequency sampling [8].





**Figure 2.1:** The S-transform - Wavelet point of view

Further, to distinct from wavelet approach, a more effective representation was presented as an orthogonal set of basis function [9]. This method created a number of unique characteristics for S-transform, the important one was the absolutely referenced phase information which defined a discrete orthonormal S-transform.

An orthonormal change takes an N-point time source toward an N-point representation in time-frequency, in this way accomplishing the maximum efficiency. Also, every point of the outcome is linearly independent from some another point. This representation introduced new parameters like,  $w$  (a frequency variable typical of the center of a frequency band and parallel to the voice of the wavelet transform),  $\alpha$  (indicated frequency band's width), and  $\mu$  (localization in time indicated by a time variable). Thus, this representation defined the inner products between a time source as well as basis functions with the above said specification.

It is expressed as:

$$S\{h[kT]\} = S\left(\tau T, \frac{w}{NT}\right) = \sum_{k=0}^{N-1} h[kT] S_{[w,\alpha,\mu]}[kT] \quad (2.2.9)$$

So these  $S_{[w,\alpha,\mu]}$  basis functions do not have vanishing moments and are normalized to unit area.

### 2.3 COMPARISON WITH OTHER TIME-FREQUENCY ANALYSIS TOOLS

A non-stationary time series such as speech, electrocardiograms (here), genomic and seismic signal are increasing more significance as they contain time-limited events and noises. Inside and out investigation of such events requires the determination of time-local spectra.

These comparisons were studied [11]-

- **Comparison with Gabor Transform:** Window measure is the main contrast between Gabor Transform (GT) and S-transform. In case of GT, the windows estimate is a Gaussian function and in case of S-transform, it is defined as a component of frequency. S-transform results effectively in frequency space analysis when the frequency at input is low as the window size is relative to frequency. Exactly when the frequency at input is high, S-transform provides a superior definition in the time space.
- **Comparison with Wigner Transform:** Cross term is the principle issue of Wigner Transform which is due the auto-correlation function in the Wigner Transform function. This issue may make noise as well as distortion to signal examination. There are no cross term that can show up by utilizing S-transform examination which makes it an appropriate method to do signal adjustment or design filter.
- **Comparison with Short Time Fourier Transform:** The S-transform trademark for frequency dependent resolution permits the identification of the frequency burst (high). Whereas, as STFT includes consistent window width, it prompts the outcome having poorer definition.

## 2.4 ANALYSIS OF GAUSSIAN WINDOW IN TIME-FREQUENCY DOMAIN

During the past years, many researches were made on the characteristics of window function in TFRs. In the midst of linear TFR, STFT used a fixed sliding window that determined the tiling of time-frequency plane and WT used an adaptive window whose width changed with frequency thereby provided the progressive resolution [10]. In regards of S-Transform, the phase and amplitude version of WT or the STFT with a width-varying window was taken. This window function was Gaussian window that uniquely minimized the quadratic time-frequency moment with reference to time-frequency point [7]. This balanced Gaussian window minimised the time-frequency quadratic moment at a particular point. Also, the dimensions (both) were symmetric and there were no presence of lateral lobes.

The Gaussian window function in the continuous S-transform is expressed as [12]

$$S(\tau, f) = \int_{-\infty}^{\infty} m(t) \frac{|f|}{\sqrt{2\pi}} e^{\frac{-(\tau-t)^2 f^2}{2}} e^{-i2\pi f t} dt \quad (2.4.1)$$

where,  $\frac{|f|}{\sqrt{2\pi}} e^{\frac{-(\tau-t)^2 f^2}{2}}$  is the Gaussian window with variable width respect,  $\tau$  is time,  $f$  is frequency and  $m(t)$  is time-varying signal.

Further, Gaussian is allowed to be an element of translation  $\tau$  and dilation  $\sigma$  (or window width).  $S(\tau, f)$  becomes

$$S(\tau, f, \sigma) = \int_{-\infty}^{\infty} m(t) \frac{1}{\sigma\sqrt{2\pi}} e^{\frac{-(\tau-t)^2}{2\sigma^2}} e^{-i2\pi f t} dt \quad (2.4.2)$$

Simplification of  $S(\tau, f, \sigma)$  can be accomplished by including the limitation confining the window's width to  $\tau$  to be corresponding to the period (or frequency inverse).

$$\sigma(f) = \frac{1}{|f|} \quad (2.4.3)$$

The many purpose behind taking Gaussian window were taking after [12]:

- Fourier transform of a Gaussian will be Gaussian as it is symmetric in time and frequency;
- Gaussian function do not have side projections;
- About a time-frequency point, it particularly limits the quadratic time-frequency moment.

Window of S-transform satisfies the condition [14].

$$\int_{-\infty}^{\infty} d(\tau - t, f) d\tau = 1. \quad (2.4.4)$$

Due to this property, the time-frequency spectrum is invertible. Further, selecting the appropriate values of the window width; there can be a significant improvement in the time-frequency resolution.

## 2.5 STUDY ON INVERSE S-TRANSFORM

The inverse S-Transform is processed to recreate the filtered time series from the weighted S-transform. This analysis helps in aiding the signal and noise discovery consequently helping in the isolation and decomposition of signals. Inverse S-transform enables the data transformation efficiently.

The conventional S-transform can be easily inverted as it is absolutely invertible [14, 38], with one inverse Fourier transform. This grants quick as well as simple recovery of the sources (time series) from their S-spectrum. This is on the grounds that the S-transform windows fulfil the condition

$$\int_{-\infty}^{\infty} d(\tau - t, f) d\tau = 1. \quad (2.5.1)$$

The back manipulation of the spectrum is defined as a data-adaptive time-frequency weight function and is expressed as:

$$v(t) = \int_{-\infty}^{\infty} \int_{-\infty}^{\infty} S(\tau, f) F(\tau, f) e^{i\pi f t} df \quad (2.5.2)$$

where  $F(\tau, f)$  real and any complex function would control the phase spectrum.

Another approach was presented which avoided the time averaging and depended on the single consideration of every local spectrum as a time function [14] with the Gaussian window function  $k\sqrt{2\pi}/|f| d(\tau - t, f)$ . The filtered trace in similarity to above equation is communicated as:

$$v(t) = k\sqrt{2\pi} \int_{-\infty}^{\infty} \frac{S(t, f) F(t, f)}{|f|} e^{i2\pi f t} df \quad (2.5.3)$$

Here, the factor  $k\sqrt{2\pi}$  crosses out with the frequency dependent amplitude of the Gauss Window used to decide  $S(t, f)$  in contrast to equation (2.4.1). As a consequence, the signal localization in time is translated at once to the filtered time series. Further, a total reconstruction of the signals ought not be normal if the noise level is large as the components of signal will also be down-weighted.

The discrete form of inverse S-transform becomes [10]

$$v[p] = \sum_{n=-N/2}^{\frac{N}{2}-1} \left\{ \frac{1}{N} \sum_{m=0}^{N-1} S[m, n] \right\} e^{(i2\pi np/N)} \quad (2.5.4)$$

Another approach was given to keep the time localization of the mask window called as Schimmel and Gallart's Inverse S-Transform [10]. It is expressed as:

$$v(t) = k\sqrt{2\pi} \int_{-\infty}^{\infty} \frac{S(t, f)}{|f|} e^{i2\pi f t} df \quad (2.5.5)$$

Although it provided better localization in time than the Stockwell's method but there were distortions in the retrieved signal.

## 2.6 APPLICATIONS OF S-TRANSFORM

The S-transform has discovered numerous applications in processing of signals as well as images. Some of the applications where S-transform has been widely employed are time-frequency filters, geophysics, medical imaging, electrical and mechanical engineering and climate and atmosphere.

### **2.6.1 Time-frequency filters**

To evaluate the signals in the time and frequency domains simultaneously, Time-frequency representation is a useful signal processing technique. Numerous works had been carried out in the past years in the development of TFRs covering the linear, the bilinear and others. Amidst the linear TFR, the two of the best known techniques were STFT and WT [15, 16]. Since S-transform is the powerful TFR, its performance was studied in time-frequency filters [10] and was found out that this technique gave better results in signal separation.

### **2.6.2 Medical Imaging**

The utility of s-transform can be best explained in the processing of non-stationary signals. In [18], it was found out that this technique is more effective in spectral analysis of real cardiovascular time series like systolic pressure for studying autonomic regulation where it correctly identified the occurrence of spectral components and produced high resolution in the recognition of the low frequency components. On the related note, S-transform was used in the context of medical imaging where a new local multiscale Fourier analysis was done by overcoming the limitation of Gabor, Fourier and wavelet transforms [17].

### **2.6.3 Signal Filtering**

In processing of signal, a filter is a device or procedure that expels some unacceptable parts or segments from a signal. In a class of signal processing, filtering [18] is defined as the characterizing highlight of filters responsible for the entire or fractional suppression of some fragment of the signal. Frequently, it implies clearing a few frequencies and not all; keeping in mind the end goal to smother interfering signals and lessen background noise. Be that as it may, filters do not only work in the frequency domain; particularly in the branch of image processing, different goals for filtering exists. In order to evacuate correlations, it can be done for specific frequency components and not for all without acting in the frequency domain.

Further in [19], studied the seismic response analysis of thin interbeds using generalized ST. Similar study has been done for analyzing and observing the airglow of gravity waves 1 in the field of geophysics [20].

Several power quality complications were analyzed using ST in the field of electrical engineering thereby proving it a significant tool as it showed good resolution in terms of frequency on the long period signal [21].

## **2.7 REVIEW OF S-TRANSFORM**

In this chapter, it has been analyzed and found out that S-transform serves as a better tool in time-frequency representation as it has locally referenced phase. The mathematical expression of S-transform, inverse, window function and its importance in time-frequency plane is discussed extensively. Then, the discrete version of the S-transform is studied and it is observed that many methods of evaluating the discrete S-transform are available in the literature. Also, various application areas of the S-transform are investigated. In this journey, it is found that S-transform has a sound application in medical imaging, geophysics, electrical and mechanical engineering and climate and atmosphere.

And finally, the utility of S-transform is searched in the area of ECG signal denoising particularly. As S-transform offers frequency dependent resolution with at the same time localizing the real and imaginary spectra and the explanation on the frequency spectrum in the S-transform is straighter forward, hence beneficial to remove the high frequency noises.

### **2.7.1 MOTIVATION OF THE THESIS**

What distinguishes the S-transform from other techniques is due to these reasons:

- Time-frequency axis
- linearity
- For S-transform, the width of Gaussian window is a function of  $f$  (varies with frequency); based on a moving and scalable localizing Gaussian Window
- No cross-terms may appear in S-transform which makes it appropriate method to design filter or signal modulation
- The S-transform feature of frequency dependent resolution permits the noticing of the high frequency burst.
- Uniquely joins the frequency dependent resolution with absolutely referenced phase so in this manner, the average (time) of the S-transform equals the Fourier spectrum.
- Event classification
- detection is similar

- Usage of the S-transform is simpler as it compares to an extension of the FFT algorithm
- Local amplitude spectrum as well as local phase spectrum is estimated simultaneously.
- It independently tests the positive frequency spectrum and the negative frequency spectrum.
- In the light of the absolutely referenced phase of the S-transform, it is achievable to characterize a channel instantaneous frequency function for each voice.
- Cross spectral examination can be possibly performed.

All these reasons contributed towards the study of ECG signal denoising using S-transform technique in this thesis work, hence the proposed work.

## CHAPTER 3

### DENOISING TECHNIQUE: S-TRANSFORM

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**M**ANY properties of S-transform has been stated in the previous chapter which described that it will not lose any valuable information and it can be reversed back easily. These properties have made S-transform valuable in a variety of signal tasks. As a super incredible space frequency technique, reconstruction method and a close contact with the Fourier transform, S-transform suits for biomedical signal processing greatly.

#### 3.1 INTRODUCTION

Electrocardiogram (ECG), a non-invasive method is utilized as a basic diagnostic tool for cardiovascular infections. It plays an important role in monitoring of patient and diagnosis attributable to its ease of use and non-invasive nature. Today, ECG signal processing is one of the challenging computational processes as various noises get inserted with it like channel noise, electrode motion, muscle artifacts and baseline wander [22, 23] during the acquisition and transmission of signals.

Muscle artifact is due the locomotion of muscles between skin and electrode. Electrode motion creates a motion defect as baseline changes due to changes in electrode-skin impedance. Baseline wander is introduced during coughing and breathing and also due to resultant movement of chest and arms/legs. The poor conditions of the channel can likewise initiate noise in the ECG signal amid its transmission. The clean ECG signal gives required data about the condition of the heart illness as well as ischemic changes that can happen along these lines giving significant data about the utilitarian points of interest of the heart. Keeping in mind the end goal to dependably and rapidly recognize the cardiac disorders, ECG would be considerably more helpful tool if all the undesirable noises that get installed in the signal during its acquisition is expelled as these noises corrupts the ECG signal and make the examination difficult. Henceforth, for further processing; the noise in ECG signals ought to upgraded. Here, the denoising of ECG signals is done utilizing Stockwell Transform (S-transform) to remove the drawbacks stated in chapter 2. For all the noises, this technique which is summed up approach can be applied during the acquisition and transmission of signals. There is no requirement of any prior information of signal in this method. The principle of this method is that the width of the Gaussian function differs with

change in frequency. Its fundamental three characteristics are: Frequency invariant amplitude response, progressive resolution and absolutely referenced phase information [7]. Besides, S-transform uses time-frequency axis [6]. This information on the frequency spectrum is very beneficial to remove the components of noise. Representation of the noisy ECG signal in the time-frequency domain is done by S-transform. For removing noises, masking as well as thresholding is done for noisy signal which is represented in time-frequency domain. These calculations are assessed for real noises like muscle artifacts, baseline wander, and electrode motion during its acquisition as well as the channel noises such as awgn noise and Rayleigh fading during its transmission. Experimental results show that this transform gives the best results in removing the noises with high SNR value.

### 3.2 THEORETICAL BACKGROUND

Stockwell et al. [7] introduced the S-transform in order to get a time domain signal in the time frequency representation. In S-transform, the changes in frequency allow the height and width of the analyzing window to vary. The resolution of S-transform depends on the frequencies. The continuous S-transform  $ST(\tau, f)$  of a signal  $m(t)$  is expressed as [13]

$$ST(\tau, f) = \int_{-\infty}^{\infty} m(t) \frac{|f|}{\sqrt{2\pi}} e^{\frac{-(\tau-t)^2 f^2}{2}} e^{-i2\pi f t} dt \quad (3.2.1)$$

The resulting spectrum when the time series  $m(t)$  is windowed with a window function (Gaussian function) or multiplied point by point,  $g(t)$  is

$$M(f) = \int_{-\infty}^{\infty} m(t) g(t) e^{(-2\pi f t)} dt \quad (3.2.2)$$

where, Gaussian function in generalized form is

$$g(t) = \frac{1}{\sigma\sqrt{2\pi}} e^{-\frac{t^2}{2\sigma^2}} \quad (3.2.3)$$

Further, Gaussian is allowed to be an element of translation  $\tau$  and dilation  $\sigma$  (or window width).

$$S(\tau, f, \sigma) = \int_{-\infty}^{\infty} m(t) \frac{1}{\sigma\sqrt{2\pi}} e^{\frac{-(\tau-t)^2}{2\sigma^2}} e^{-i2\pi f t} dt \quad (3.2.4)$$

As we can see, there are three independent variables in it which makes it an extraordinary instance of the multiresolution Fourier transform; it is additionally illogical as a tool for examination. In order to simplify, there is addition of the constraint which restricts the window's width to  $\sigma$  to be proportional to the period (or frequency inverse).

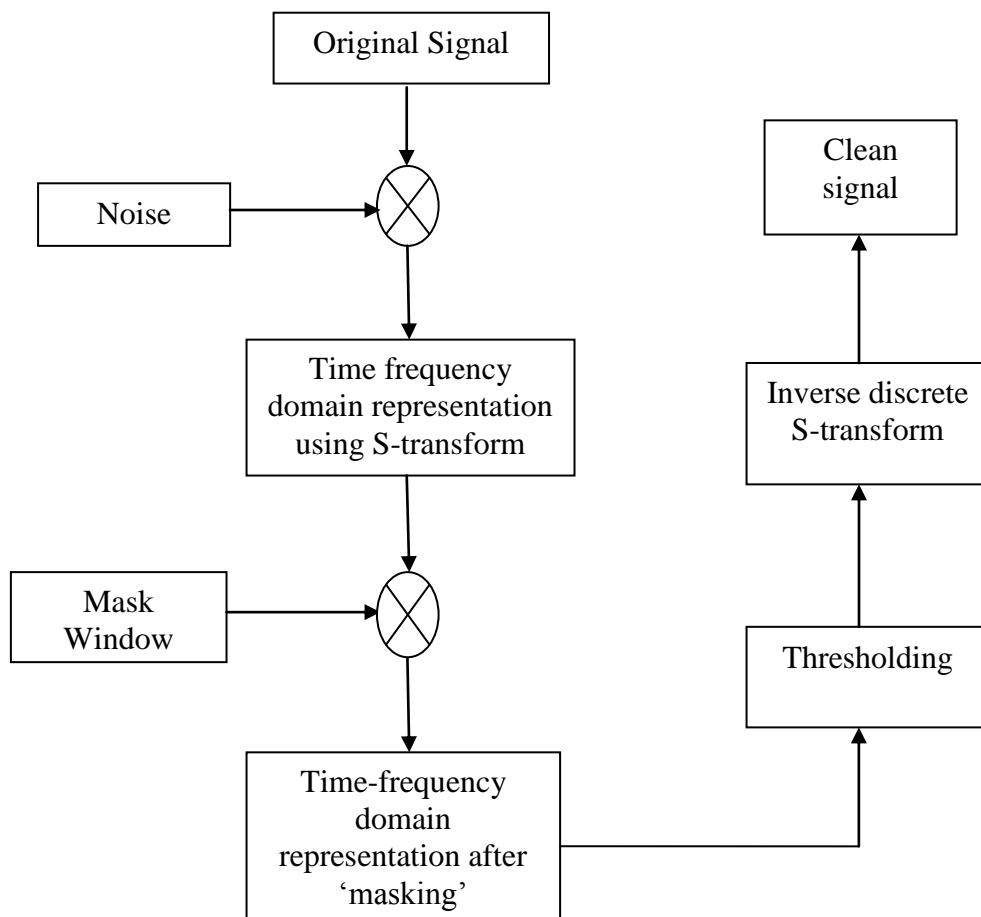
$$\sigma(f) = \frac{1}{|f|} \quad (3.2.5)$$

The many reason for taking Gaussian window were following [12]:

- Fourier transform of a Gaussian will be Gaussian as it is symmetric in time and frequency;
- Gaussian function do not have side projections;
- About a time-frequency point, it particularly limits the quadratic time-frequency moment.

### 3.3 METHODOLOGY

The purpose of this algorithm [12] is to remove the noise components from ECG signal so as to enhance it which enables improved medical diagnosis. Fig. 3.1 represents the flowchart of the ECG signal denoising method.

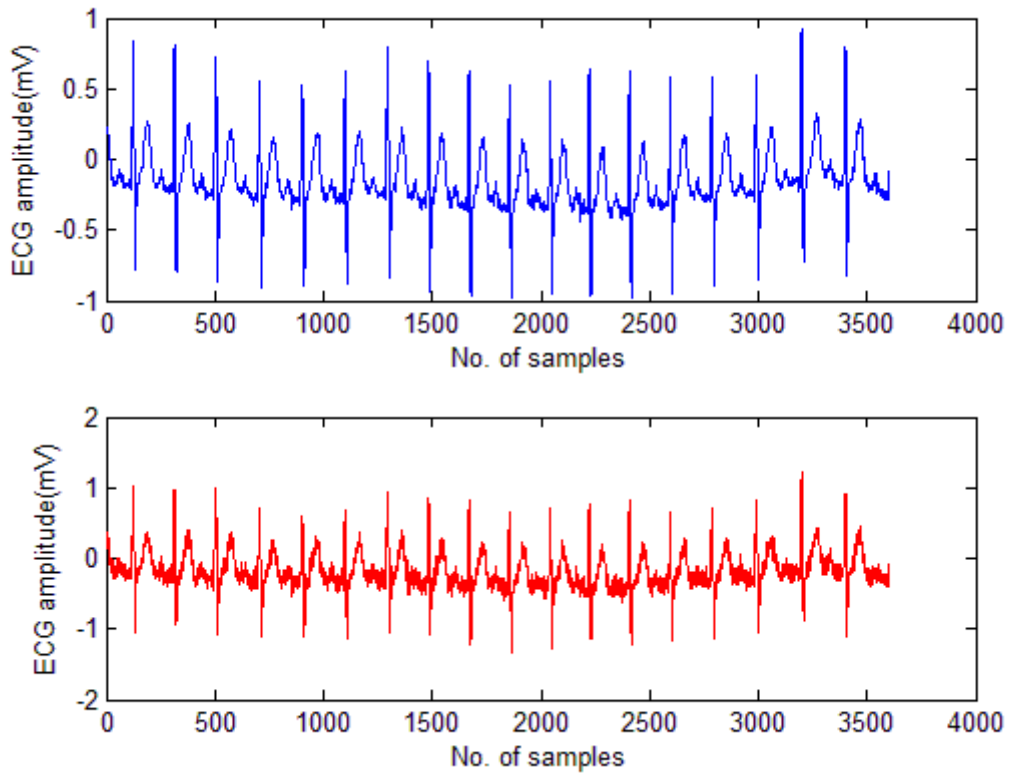


**Figure 3.1: Flowchart of ECG signal denoising method [12]**

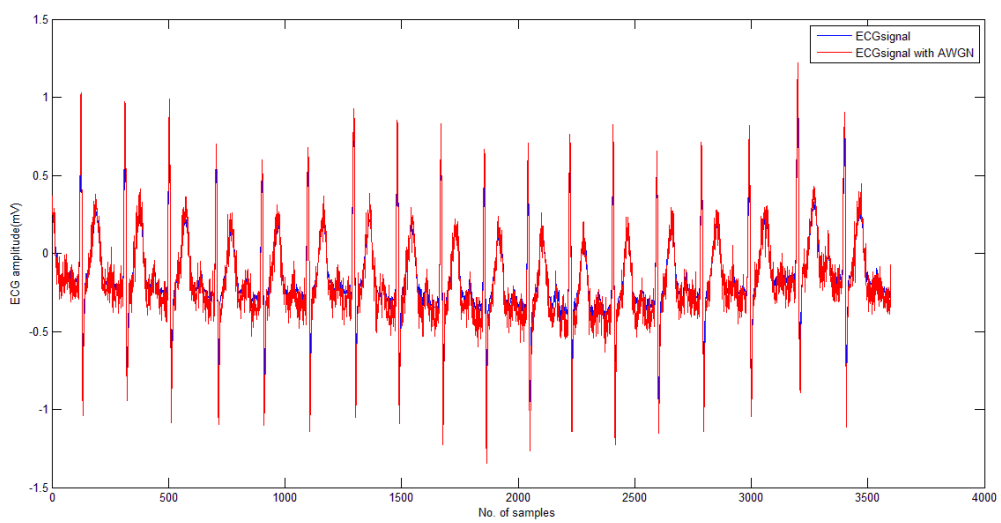
Different steps of the entire method are described as follows.

### Step 1: Adding noise to Original ECG signal:

For this step, the ECG signal is taken from MIT/BIH arrhythmia database and processed using software (MATLAB) as shown in Fig. 3.2.



**Figure 3.2: (a) Original (clean) ECG signal; (b) AWGN (at 10dB)**



**Figure 3.3: ECG signal + AWGN**

For experimental purpose, different noises are added to these signals such that  $m(t)$  represents the (clean) original ECG signal as well as  $n(t)$  represents the noisy signal. Therefore, the ECG signal with noise will be given by [12]-

$$st(t) = m(t) + n(t) \quad (3.3.1)$$

and is depicted in Fig. 3.3.

### Step 2: Time-frequency domain representation:

In order to obtain a time domain ECG with noise in the time-frequency representation, S-transform is used. In this step, discrete S-transform is applied on the noisy ECG signal.

By exploiting the proficiency of the fast Fourier transform and the convolution theorem, equation (3.2.2) is utilized to calculate the discrete S-transform. Assuming in equation (3.2.2), ( $f \rightarrow n/NT$  and  $\tau \rightarrow jT$ ), the S-transform is applied on the noisy discrete ECG series  $m(kT)$  which is given by-

$$ST \left[ jT, \frac{n}{NT} \right] = \sum_{h=0}^{N-1} m \left[ \frac{h+n}{NT} \right] e^{-\frac{2\pi^2 h^2}{n^2}} e^{\frac{i2\pi j}{N}} \quad (3.3.2)$$

where  $M \left[ \frac{n}{NT} \right]$  is the Fourier transform of  $m(kT)$  and  $j, h, n = 0, 1, \dots, N - 1$ . Flow-chart of the above equation is represented in Fig. 3.2.

and for the  $n = 0$  voice, it is equivalent to the constant characterized as

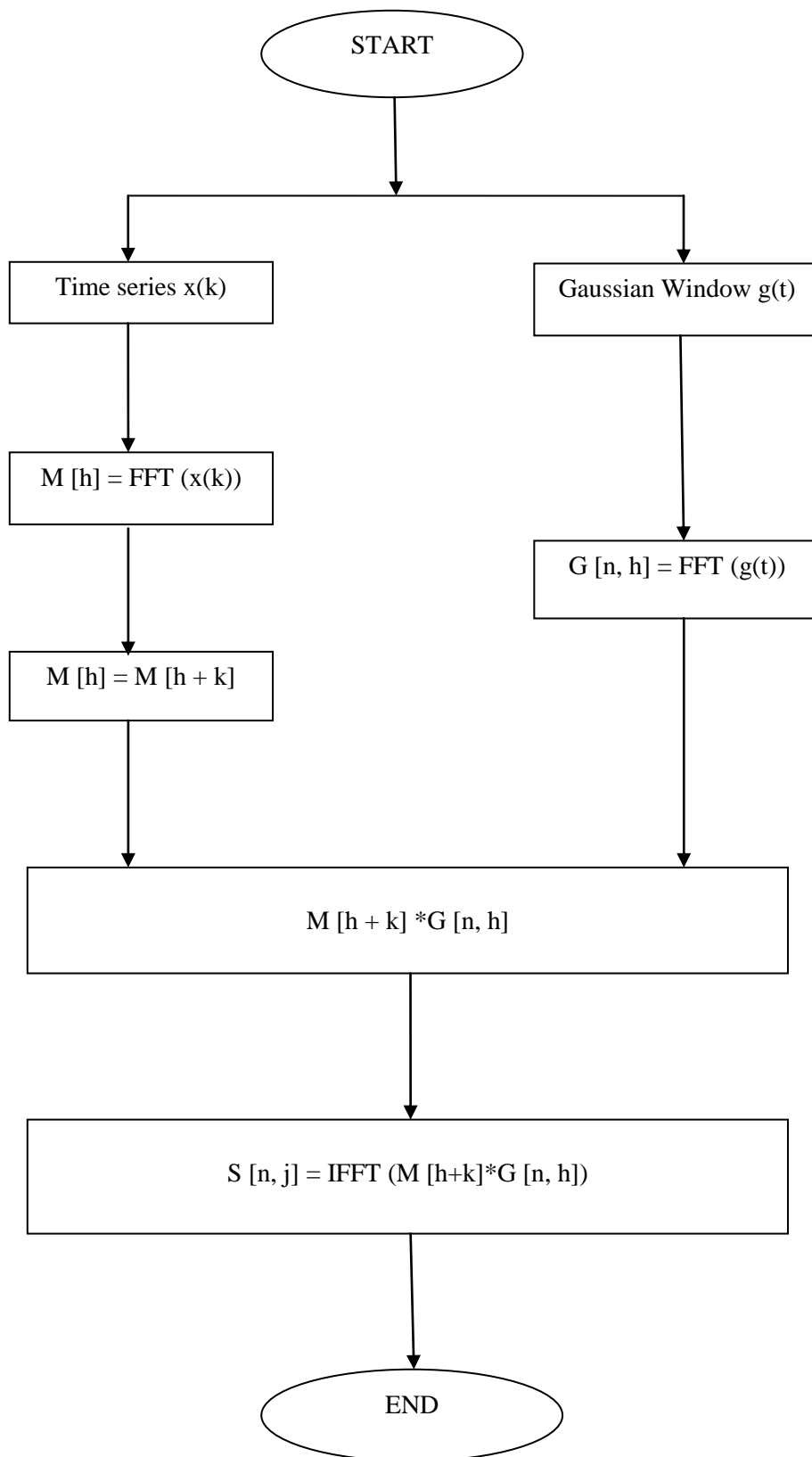
$$ST[jT, 0] = \frac{1}{N} \sum_{k=0}^{N-1} m \left[ \frac{h}{NT} \right] \quad (3.3.3)$$

The algorithm for the computing methodology of discrete S-transform is as follow:

**Algorithm:** Discrete S-transform [13]

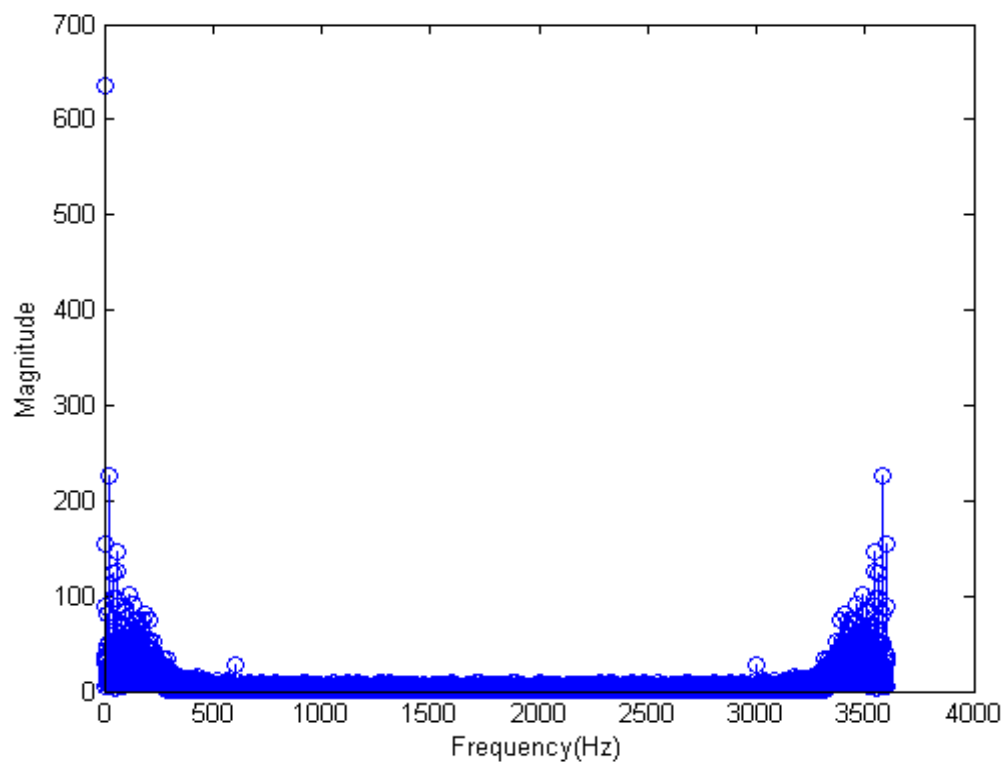
- Firstly, FFT is calculated of the N-point time signal.
- In order to make the voice frequency zero, shift the FFT spectrum. For a constant frequency, a ‘voice’ is a one dimensional function of time.
- The above shifted spectrum is multiplied by Gaussian window function (N-point).
- In order to get the corresponding voice frequency, N point IFFT is done.
- Above mentioned steps are repeated for every one of the frequencies.

Thereby, time-frequency domain representation using S-transform is obtained as shown in Fig. 3.8.

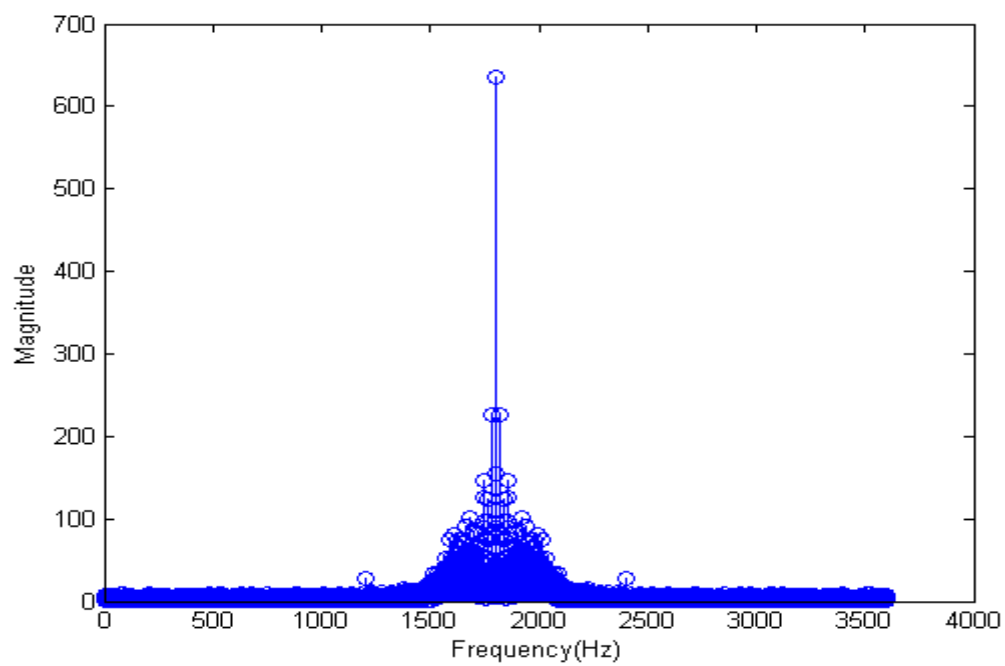


**Figure 3.4: Discrete S-transform [12]**

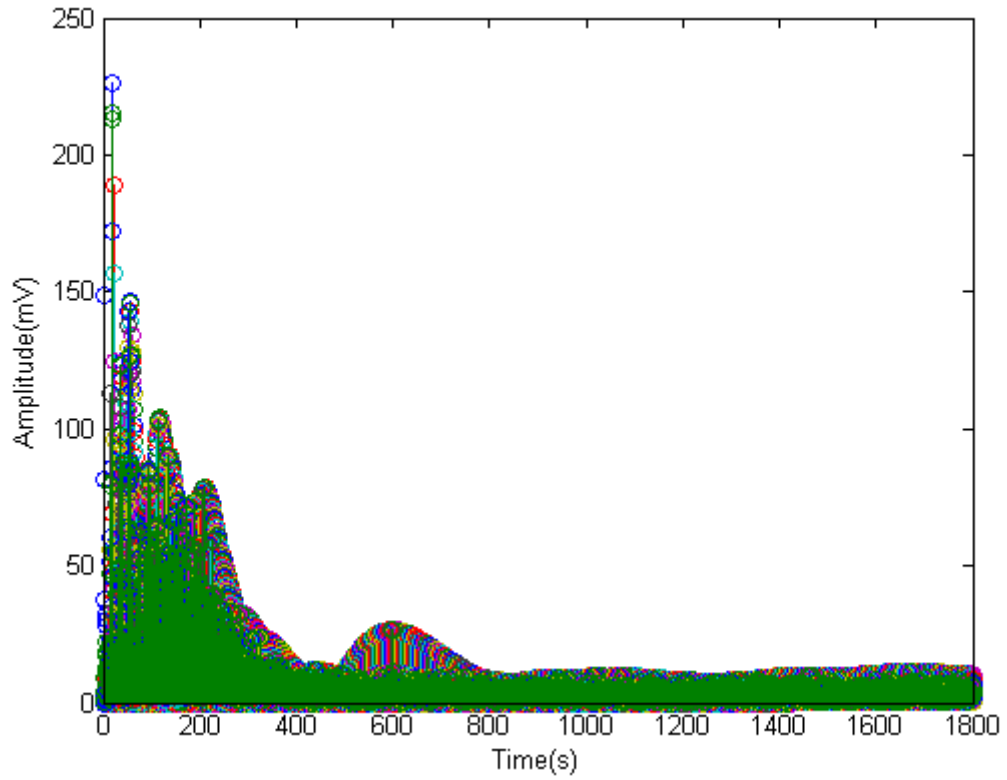
The following figures (3.5-3.7) are the outputs of each step of discrete S-transform utilizing MATLAB:



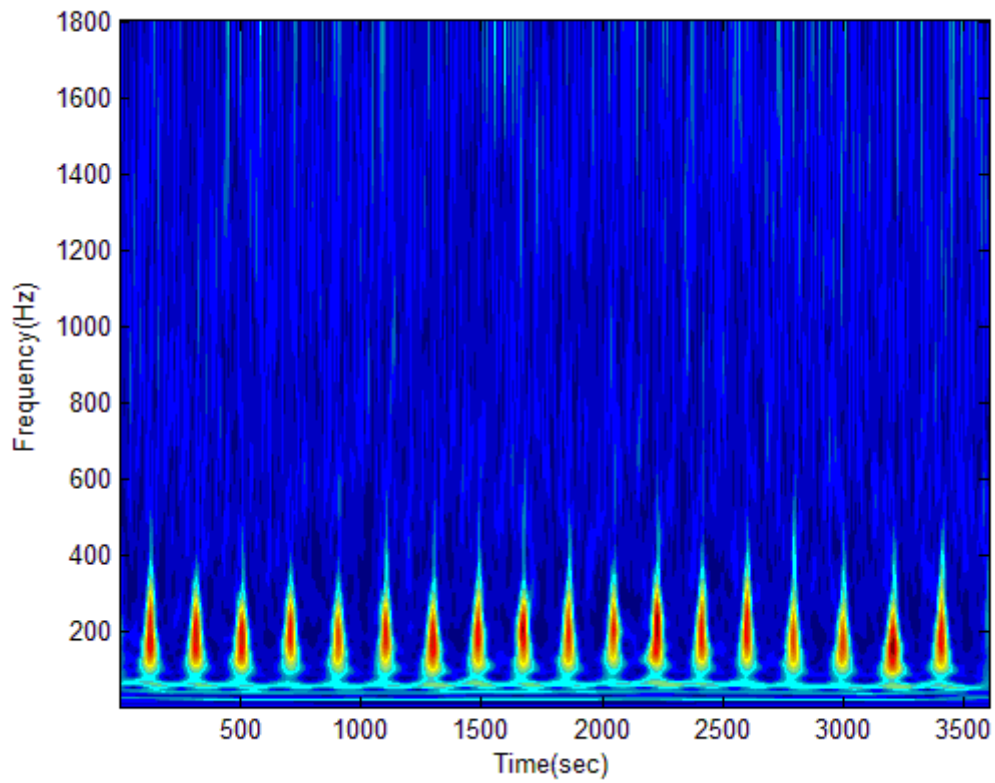
**Figure 3.5: Noisy ECG Signal in Frequency Domain**



**Figure 3.6: FFT shifted spectrum of noisy ECG signal**



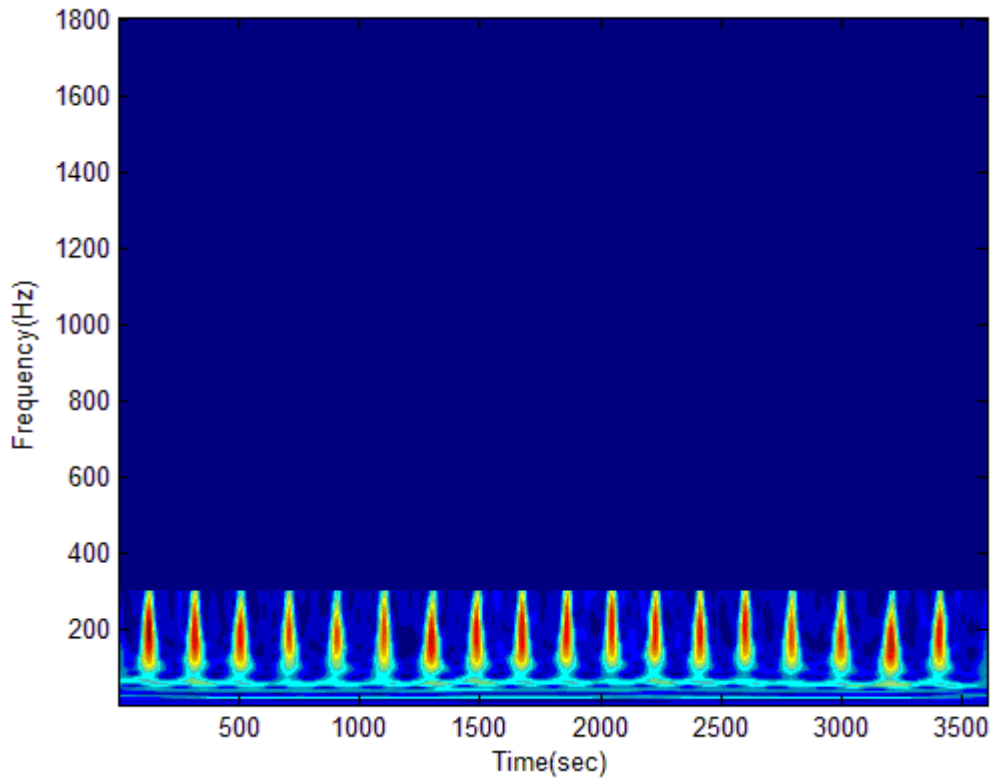
**Figure 3.7: Multiplication of shifted spectrum with Gaussian Window**



**Figure 3.8: Representation of noisy ECG in time-frequency domain signal utilizing S-transform**

### Step 3: Masking:

After taking IFFT, masking [13] is done. The purpose of this step is to expel the high frequency noises from the noisy ECG signal in time-frequency domain representation. ECG signals database taken from MIT-BIH Arrhythmia database [27] generally contains important information within 200 Hz. In order to do filtering, the frequency spectrum is multiplied by a mask window that is one near frequency and zero at noises.

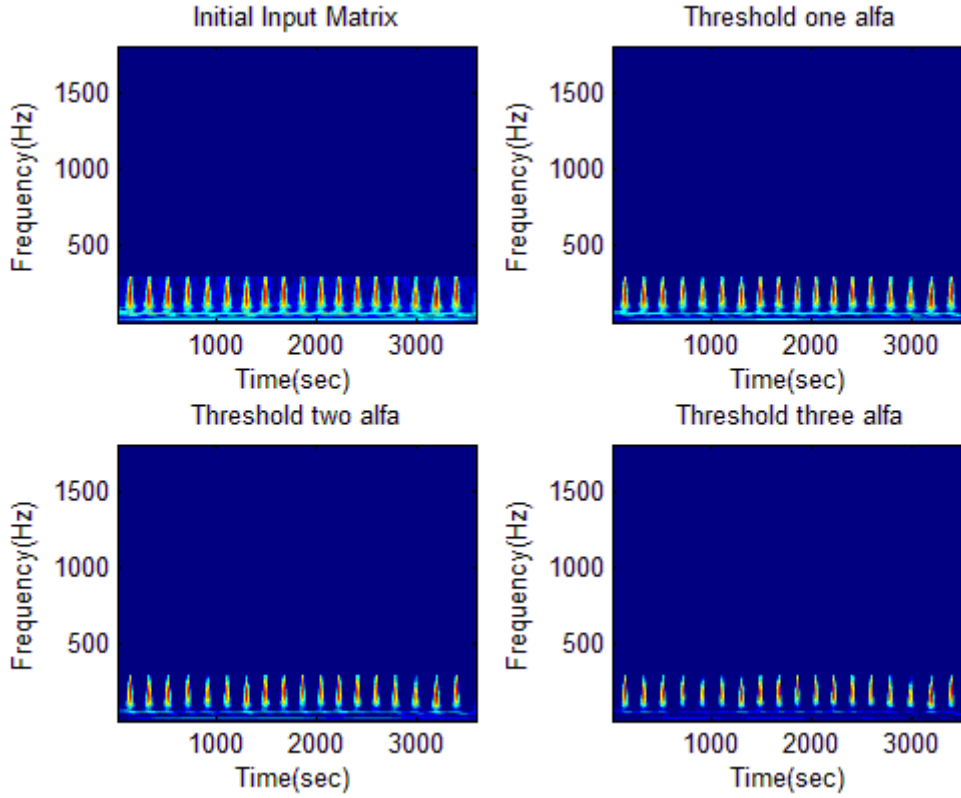


**Figure 3.9: Representation of noisy ECG signal in time-frequency domain after masking**

The bandwidth of a perfect ECG signal normally is 0.05-100 Hz [24]. In other words, a frequency domain masking is done such that below 200 Hz, the frequency components are held or more 200 Hz, the frequency components are expelled. Fig. 3.9 demonstrates the masked output of the noisy ECG signal in time-frequency representation.

### Step 4: Thresholding:

In the wake of masking, there are some background noises which exist in the ECG signal itself in the resultant ST matrix. Fig. 3.10 shows how a signal looks like after thresholding [25] with different levels. There are four figures: The initial signal matrix, Threshold level is one alfa, Threshold level is two alfa, Threshold level is three alfa



**Figure 3.10: Representation of noisy ECG signal in time-frequency domain with different threshold levels**

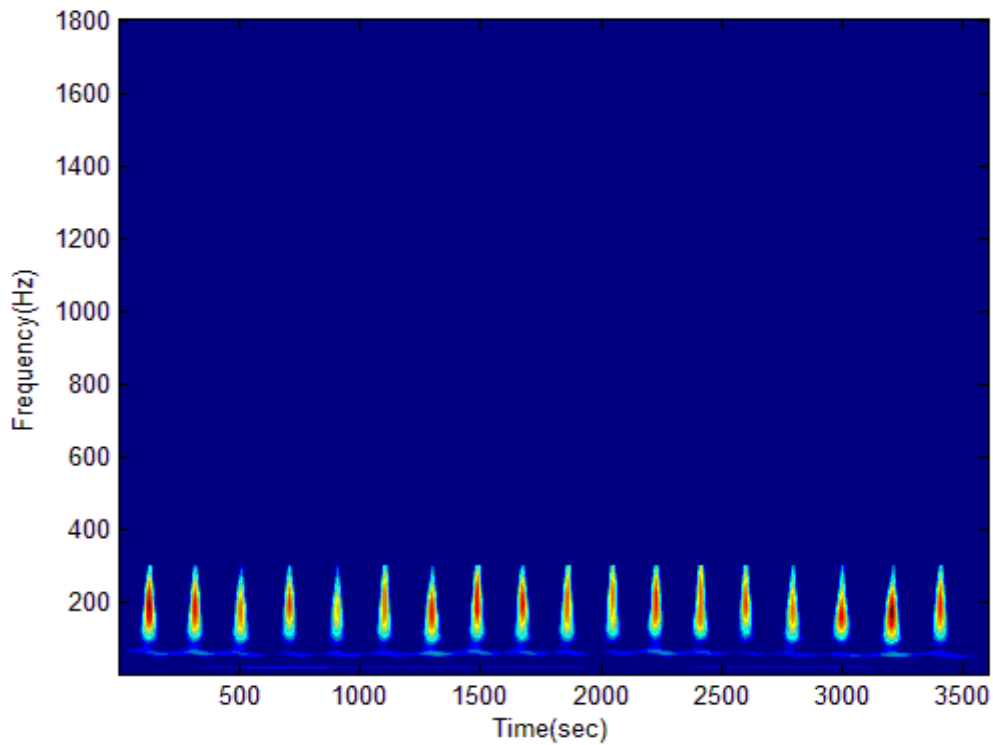
The rate of the thresholding implies the threshold level between the most extreme and least intensity of the initial signal. Thresholding is an approach to dispose of the impact of noise and to enhance the signal-noise ratio. That is, it is an approach to keep the significant data of the signal while dispose of the irrelevant part (under the condition that you pick a conceivable thresholding level). Fig. 3.11 shows how a signal looks like subsequent to masking and thresholding.

#### **Step 5: The inverse S-transform:**

In order to achieve the denoised ECG signal after masking and thresholding, inverse discrete S-transform is performed [12]. Note that, the signal changed over to time domain using the inverse S-transform preserves the time-frequency domain features after masking and thresholding as the S-transform is exactly invertible. The discrete inverse S-transform equation for all  $n$  as

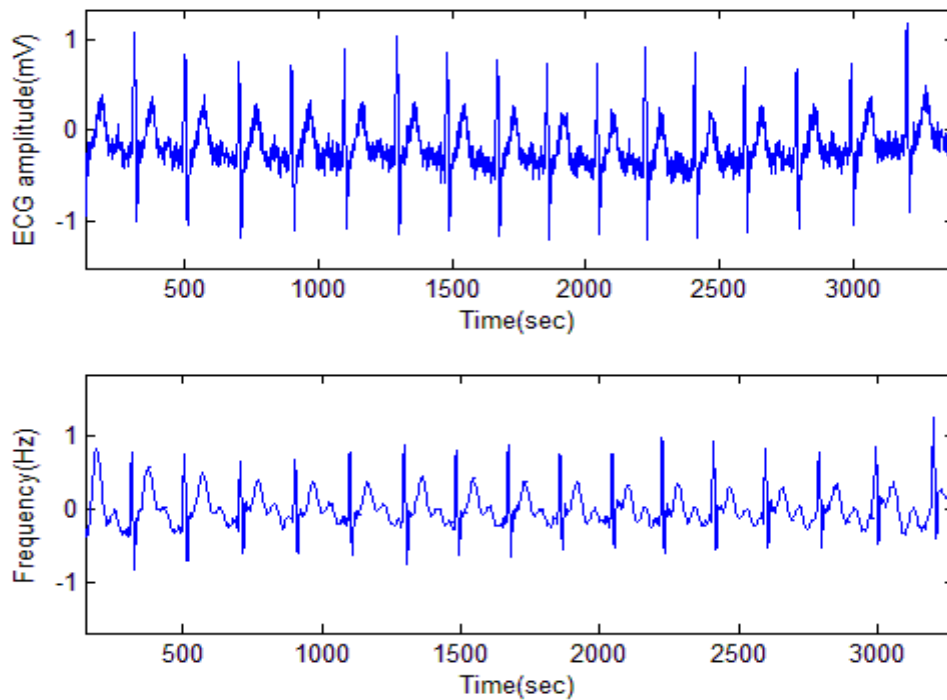
$$m[kT] = \frac{1}{N} \sum_{n=0}^{N-1} \left\{ \sum_{j=0}^{N-1} S\left[\frac{n}{NT} \cdot jT\right] \right\} e^{\frac{j2\pi nk}{N}} \quad (3.3.4)$$

where  $m[kT]$  is the denoised ECG signal. The value of  $S\left[\frac{n}{NT} \cdot jT\right]$  for  $n = 0$  is simply the average of  $m[kT]$ .



**Figure 3.11: Representation of noisy ECG signal in time-frequency domain subsequent to masking and thresholding**

Graphical representation of the original and the denoised ECG signal is shown in Fig. 3.12



**Figure 3.12: S-transform based denoising of ECG signals (beat no-215): (a) Input: Noisy ECG signal; (b) Output: Denoised ECG signal**

### 3.4 LIMITATIONS OF S-TRANSFORM

The S-transform was characterized with two limitations [39] on the window function explained below-

- Firstly, just a Gaussian window  $g(t, \sigma)$  is considered.
- Secondly, horizontal and vertical dilations of the Gaussian window is responsible for the frequency dependence of the analyzing window of the S-transform

The resolution of the S-transform, of the onset times of series can be enhanced by utilizing a smaller window, for instance, utilizing better controlled parameters of the Gaussian window. Nonetheless, when a window is limited in the time area, it definitely extends in the frequency domain, with ensuing loss of resolution in the frequency heading on the S-transform trading off the distinguishing proof of the entire series. One method for tending to this issue is to utilize additional parameters controlling the scale and the state of the examining window as opposed to simply just making the frequency inversely relative to the standard deviation  $\sigma$ .

### 3.5 PROPOSED WORK USING MODIFIED S-TRNASFORM

This thesis proposes a modified S-transform, which offers better time frequency resolution contrasted to the original S-transform. This is accomplished through the introduction of a new scaling parameter for the Gaussian window utilized in S-transform. This method gives good execution with high SNR value for various noises as discussed in chapter 4 when contrasted to S-transform.

The continuous S-transform  $ST(\tau, f)$  of a signal  $m(t)$  is expressed as-

$$ST(\tau, f) = \int_{-\infty}^{\infty} m(t) \left\{ \frac{|f|}{\sqrt{2\pi}} e^{-\frac{(\tau-t)^2 f^2}{2}} \right\} e(-2\pi i f t) dt \quad (3.5.1)$$

The normalizing factor of  $|f|/\sqrt{2\pi}$  in above equation makes sure that, when it is integrated over all the  $\tau$ ,  $ST(\tau, f)$  converges to  $M(f)$ , that is the Fourier transform of  $m$ -

$$\begin{aligned} \int_{-\infty}^{\infty} ST(\tau, f) d\tau &= \int_{-\infty}^{\infty} m(t) e(-2\pi i f t) dt \\ &= M(f) \end{aligned} \quad (3.5.2)$$

From above equation, it is showed that  $m(t)$  can be obtained from  $ST(\tau, f)$  as the S-transform is exactly invertible.

For the purpose of denoising, a better modification [40] of the continuous S-transform in equation (3.5.1) is given by-

$$MST(\tau, f, g) = \int_{-\infty}^{\infty} m(t) \frac{\sqrt{|fg|}}{\sqrt{2\pi}} e^{-\frac{|fg|(\tau-t)^2 f^2}{2}} e^{-i2\pi ft} dt \quad (3.5.3)$$

In this equation,  $g$  is a constant with units of frequency which is characterized by the user. And, Gaussian window's standard deviation varies as  $\sqrt{1/|f|}$ .

- When  $|f| = |g|$ , the standard deviation is only equal to  $1/|f|$
- When  $|f| < |g|$ , the window's standard deviation is less than  $1/f$
- When  $|f| > |g|$ , the window's standard deviation is greater than  $1/f$

### 3.5.1 DISCRETE MODIFIED S-TRANSFORM:

For the discrete form of  $m$ , it is represented by  $\hat{m}$ . The discrete modified S-transform [40] of  $\hat{m}$ , characterized by  $\widehat{MST}$ , is obtained using the convolution theorem in equation (3.5.2)-

$$\widehat{MST} \left[ jT, \frac{n}{NT} \right] = \sum_{h=-N/2}^{\frac{N}{2}-1} \widehat{M} \left[ \frac{h+n}{NT} \right] e^{\left[ \frac{-2\pi^2 h^2}{|np|} \right]} e^{\left[ \frac{+2\pi i h j}{N} \right]} \quad (3.5.4)$$

Here, the number of points in the time series is given by  $N$ ,  $T$  is the sampling interval,  $j$  is a discrete time index ( $j = \tau/T$ ), the discrete frequency indices are  $n$  and  $p$  ( $n = fNT, p = gNT$ ), and the DFT of  $\hat{m}$  is the  $\widehat{M}$  –

$$\widehat{M} \left[ \frac{n}{NT} \right] = \frac{1}{N} \sum_{k=0}^{N-1} \hat{m}[kT] \exp \left[ \frac{-2\pi i n k}{N} \right] \quad (3.5.5)$$

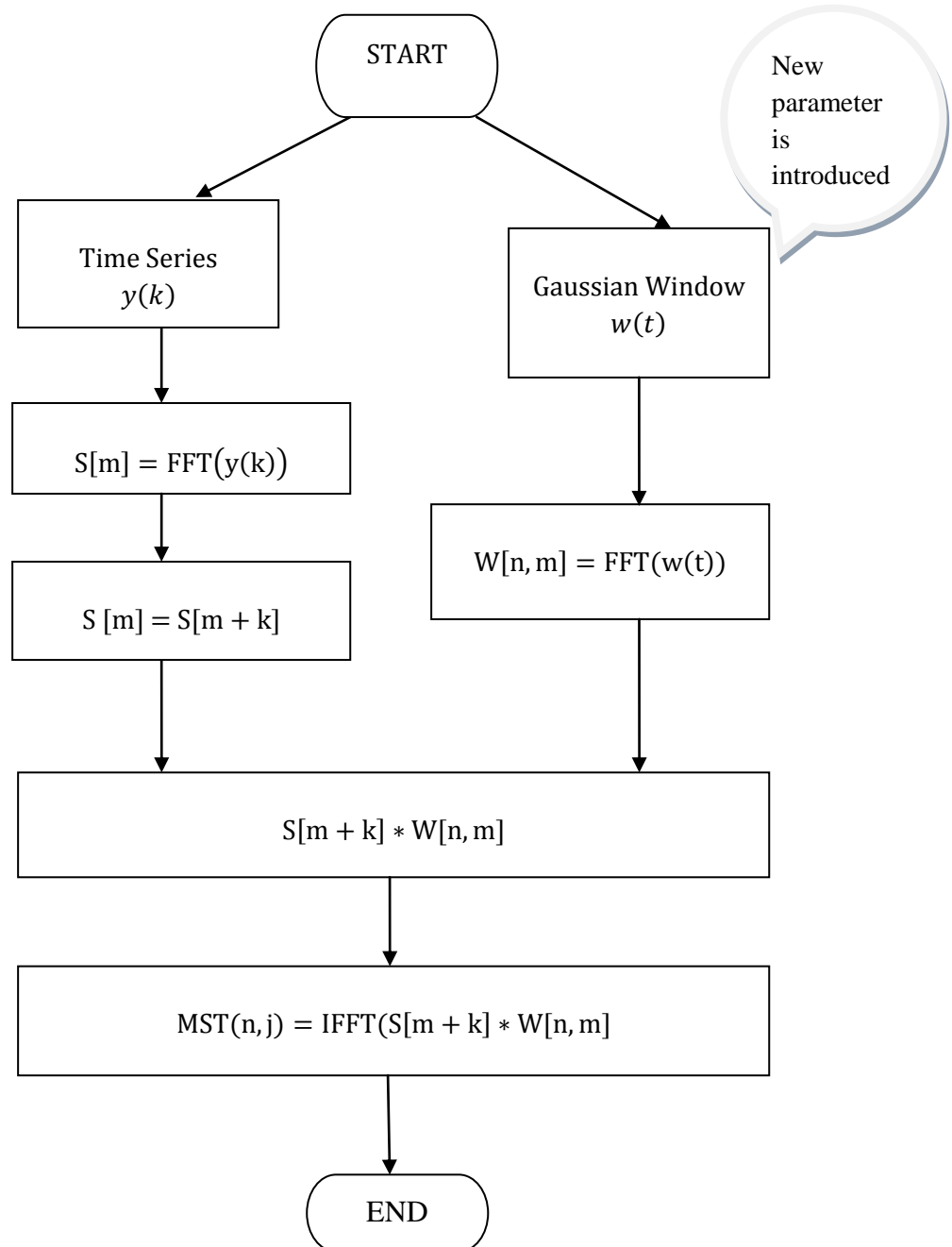
In the above equation,  $k = t/T$ . As in the S-transform, for the special case when  $n = 0$ ,  $\widehat{MST}$  is set equivalent to the average of  $\hat{m}$ .

### 3.5.2 METHODOLOGY

The purpose of this algorithm is to remove the noise components from ECG signal so as to enhance it more when contrasted to S-transform. The same algorithm is followed as described in the methodology of S-transform with the introduction of new scaling parameter when computing the Gaussian Window.

The following steps are stated below-

- Original Signal + Noise :  $s(t) = h(t) + n(t)$
- Time – frequency representation using Modified S-transform
- Mask window
- Time-frequency domain representation after masking
- Time-frequency domain representation after thresholding
- Time domain representation
- Denoised ECG signal



**Figure 3.13: Proposed Work using Modified S-transform**

This technique gives good experimental results with high SNR value for various noises as when contrasted to S-transform which is demonstrated in chapter 4. Fig. 3.13 represents the block diagram of the proposed work using Modified S-transform.

## CHAPTER 4

### RESULTS AND DISCUSSION

---

**T**HIS chapter demonstrates the performance analysis of denoising of ECG signals using S-transform technique and the proposed method using Modified S-transform. The calculations are tried on MIT-BIH (Massachusetts Institute of Technology–Beth Israel Hospital) Arrhythmia database [20] and MIT-BIH noise stress database [21].

These databases are sampled at 360Hz. Different noises are added falsely to the ECG signal that outcomes in 5dB and 10dB SNR. These noisy ECG signals are denoised utilizing the algorithm stated in chapter 3 using the S-transform technique and the proposed method using Modified S-transform, thus the comparison is evaluated.

The execution of this technique is assessed in view of the Signal to Noise Ratio (SNR). It is defined as the measure that differentiates the level of desired signal to the level of background noise. It can be represented as the follows-

$$SNR_{dB} = 10 * \log_{10} \left( \frac{P_{signal}}{P_{noise}} \right) \quad (4.1)$$

where,  $P_{signal}$  represents the power of original (clean) signal and  $P_{noise}$  represents the power of noise signal

The SNR improvement is acquired by calculating the difference in SNR values at the input and output of the denoising technique as

$$SNR \text{ improvement} = oSNR - iSNR$$

where, oSNR and iSNR represent the SNR at output and input levels.

The technique is tested on various noises that are for the most part inserted with ECG motion amid its transmission and acquisition i.e. additive white Gaussian noise, Rayleigh fading, muscle artifacts noise, electrode motion noise and baseline wander noise.

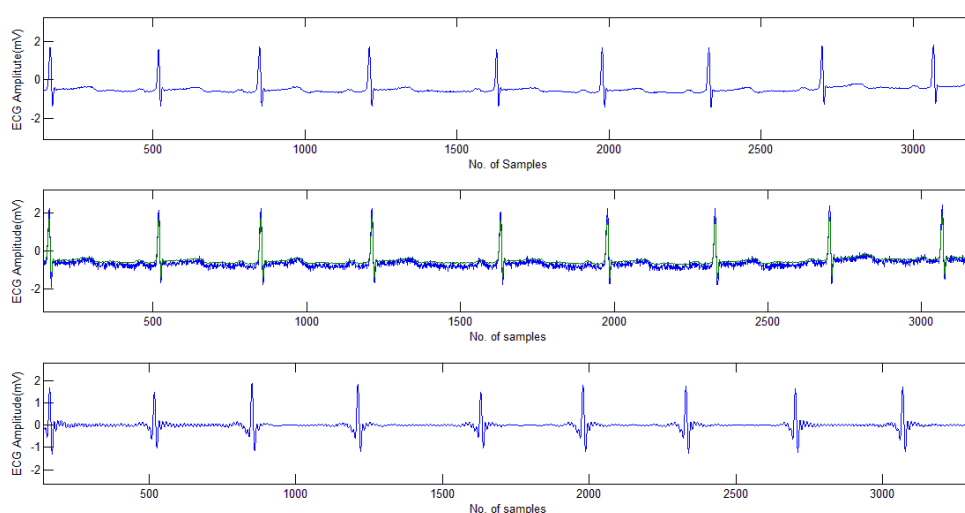
The programming work of above said schemes will be simulated in the signal processing platform of

- MATLAB Version R2013a

- Processor Intel(R) Core i3 System type and
- 64-bit operating system

#### 4.1 Performance results with AWGN

AWGN is utilized to demonstrate noise acquainted because of poor channel conditions. It is falsely added to ECG information from MIT/BIH database. Fig. 4.1(a) demonstrates the original ECG clean signal (beat no. 115), Fig. 4.1(b) demonstrates the ECG to which AWGN is included bringing about a SNR of 10dB. Fig. 4.1(c) illustrates the denoised ECG signal utilizing the proposed method using Modified S-transform.



**Figure 4.1: Denoising of ECG signal with AWGN (a) ECG signal (Clean) (b) ECG signal with Noise (c) Denoised ECG signal utilizing modified S-transform**

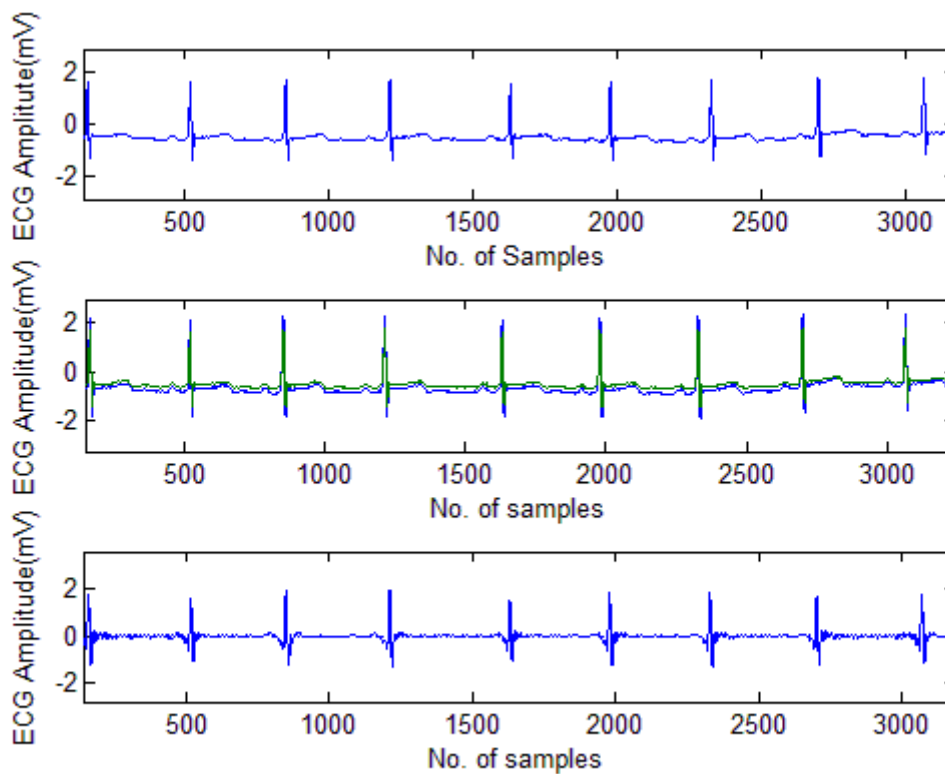
**Table 4.1: Performance results with AWGN**

MIT/BIH Tape No.	5 dB		10 dB	
	ST	MST	ST	MST
	Improved SNR	Improved SNR	Improved SNR	Improved SNR
115	7.3255	10.227	10.3613	13.8724
121	5.5977	7.7068	7.1908	15.3429
215	7.8621	14.5769	14.6452	20.0957

Table 4.1 shows SNR comparison for ST and MST with AWGN. The table contains relative outcomes for 3 unique arrangement of information loaded from the MIT/BIH database. From the outcomes, it is obvious that the proposed technique performs better, with a higher SNR. For example, the outcomes utilizing database/Tape No: 215 demonstrate that for 10dB input SNR, S-transform gives improved SNR of 14.6452dB. Meanwhile, the modified S-transform has improved SNR of 20.0957dB.

## 4.2 Performance results with Rayleigh Fading

In this experiment, the poor conditions of channel which can also initiate noise to ECG when it is transmitted is modelled in the presence of Rayleigh fading. This fading is generated by falsely adding it to ECG information from MIT/BIH database. Fig. 4.2(a) demonstrates the original ECG clean signal (beat no. 115), Fig. 4.2(b) demonstrates the ECG to which Rayleigh fading is included bringing about a SNR of 10dB. Fig. 4.2(c) illustrates the denoised ECG signal utilizing proposed method using Modified S-transform.



**Figure 4.2: Denoising of ECG signal with Rayleigh Fading (a) ECG signal (Clean) (b) ECG signal with Noise (c) Denoised ECG signal utilizing modified S-transform**

Table 4.2 shows SNR comparison for ST and MST using Rayleigh fading. The table contains relative outcomes for 3 unique arrangement of information taken from the MIT/BIH database. For example, the outcomes utilizing database/Tape No: 215 demonstrates that for 10dB input SNR, the S-transform gives improved SNR of 11.6977dB though the modified S-transform gives improved SNR of 17.4171dB.

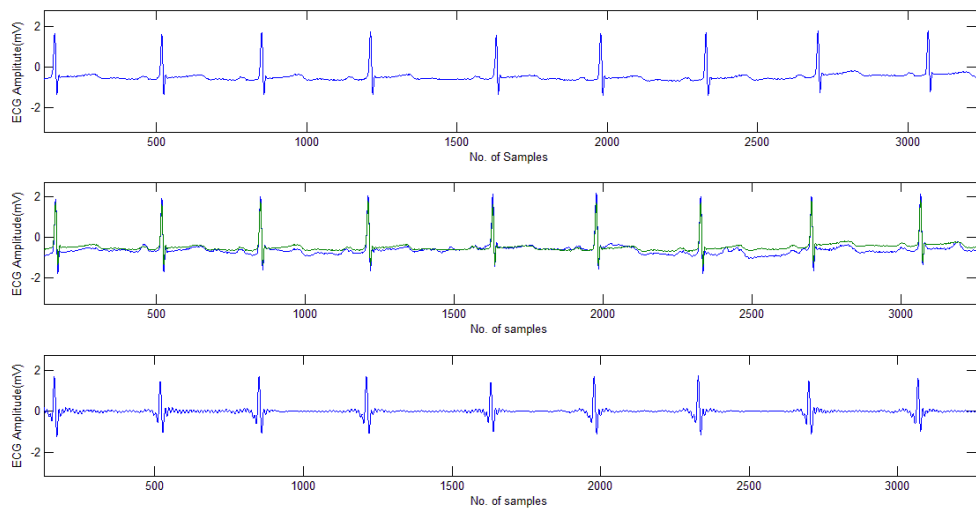
**Table 4.2: Performance results with Rayleigh Fading**

MIT/BIH Tape No.	5 dB		10 dB	
	ST	MST	ST	MST
	Improved SNR	Improved SNR	Improved SNR	Improved SNR
115	6.3195	7.4381	7.9572	11.2112
121	5.9305	10.1684	7.388	14.7845
215	10.1652	13.1639	11.6977	17.4171

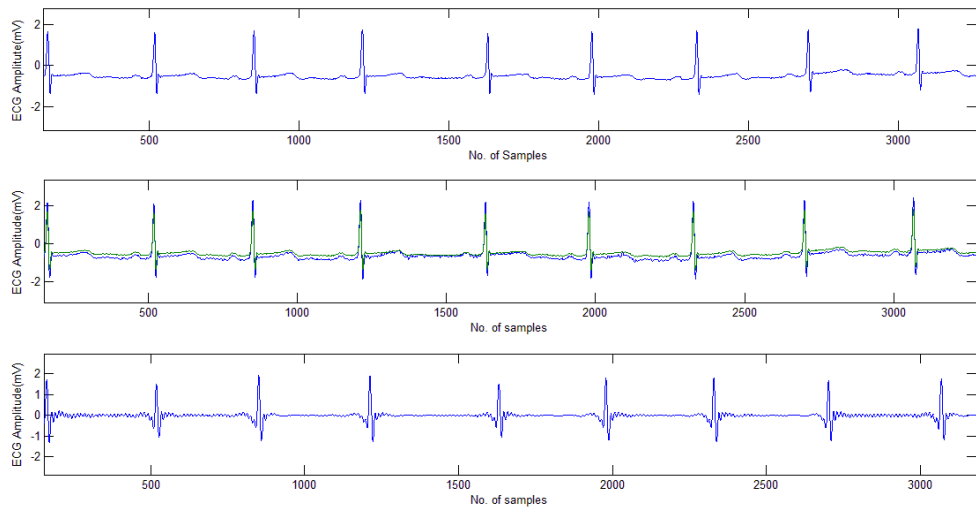
### 4.3 Performance results with Real case noises

Real case noise, for example, Muscle Artifacts (MA), Electrode Motion (EM), and Baseline Wander (BW) are more plausible amid obtaining of ECG. Muscle artifact is due the locomotion of muscles between skin and electrode. Electrode motion creates a motion defect as baseline changes due to changes in electrode-skin impedance. Baseline wander is introduced during coughing and breathing and also due to resultant movement of chest and arms/legs. These sorts of noises are huger amid stress test. For assessing modified S-transform technique, these noises are loaded from the Noise stress database and included to ECG information from MIT/BIH database.

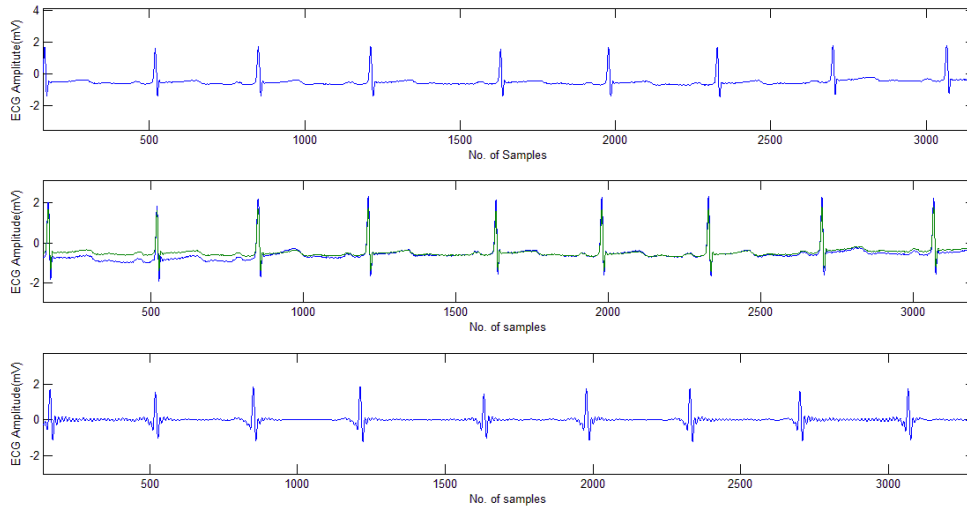
Fig. 4.3 demonstrates the performance outcomes for EM noise. Fig. 4.3(a) demonstrates the Original ECG clean signal (Beat No: 115) and Fig. 4.3(b) demonstrates the ECG to which EM noise is included bringing about a SNR of 10dB. Fig. 4.3(c) demonstrates the output of proposed method. Similarly, Fig. 4.4(a) – 4.4(c) demonstrates the experiment outcomes for MA noise and Fig. 4.5(a) – 4.5(c) demonstrates the experiment outcomes for Baseline Wander noise. The frequency components of real case noises are in the same range as that of the original ECG signal [21].



**Figure 4.3: Denoising of ECG signal with Electrode Motion: (a) ECG signal (Clean) (b) ECG signal with Noise (c) Denoised ECG signal utilizing modified S-transform**



**Figure 4.4: Denoising of ECG signal with Muscle Artifacts: (a) ECG Signal (Clean) (b) ECG signal with Noise (c) Denoised ECG signal utilizing modified S-transform**



**Figure 4.5: Denoising of ECG signal with Baseline Wander: (a) ECG signal (Clean) (b) ECG signal with Noise (c) Denoised ECG signal utilizing modified S-transform**

The denoised signal illustrated in Fig. 4.3 – 4.5 shows that the modified S-transform removes these noise components and achieves time frequency domain filtering by utilizing a suitable mask and subsequently displays enhancement in the signal quality in a better way.

Table 4.3 shows SNR comparison for ST and MST using Electrode Motion noise. Table depicts that the proposed method provides better improvement in SNR. For example, performance outcomes for database/Tape No: 115 demonstrate that for 10dB input SNR, the S-transform technique has an improved SNR of 10.2976dB though the modified S-transform output has a higher improved SNR of 15.9946dB. The comparative outcomes for other database likewise demonstrate that the proposed method is superior in performance with higher SNR.

**Table 4.3: Performance results with EM**

MIT/BIH Tape No.	5 dB		10 dB	
	ST	MST	ST	MST
	Improved SNR	Improved SNR	Improved SNR	Improved SNR
115	8.1364	10.5544	10.2976	15.9946
121	2.2464	6.331	9.0159	14.9512
219	1.7212	4.1014	5.1529	8.3509

Table 4.4 shows SNR comparison for ST and MST using Muscle artifacts noise. Table depicts that the proposed method provides better improvement in SNR. For example, performance outcomes for database/Tape No: 115 demonstrate that for 10dB input SNR, the S-transform technique has an improved SNR of 15.4401dB though the modified S-transform output has a higher improved SNR of 20.4517dB. The comparative outcomes for other database likewise demonstrate that the proposed method is superior in performance with higher SNR.

**Table 4.4: Performance results with MA**

MIT/BIH Tape No.	5 dB		10 dB	
	ST	MST	ST	MST
	Improved SNR	Improved SNR	Improved SNR	Improved SNR
115	5.9624	11.8853	15.4401	20.4517
121	6.2317	10.0072	7.6453	11.0104
215	7.6036	14.9332	9.4709	16.95

Table 4.5 shows SNR comparison for ST and MST with baseline wander. Table depicts that the proposed method provides better improvement in SNR. For example, performance outcomes for database/Tape No: 115 demonstrate that for 10dB input SNR, the S-transform technique has an improved SNR of 10.698dB though the modified S-transform output has a higher improved SNR of 11.8208dB.

**Table 4.5: Performance results with BW**

MIT/BIH Tape No.	<b>5 Db</b>		<b>10 dB</b>	
	ST	MST	ST	MST
	Improved SNR	Improved SNR	Improved SNR	Improved SNR
115	6.6906	15.3647	10.698	11.8208
215	9.7579	16.8911	12.0266	10.8213
219	1.2562	4.6565	1.1329	6.1805

## CHAPTER 5

### CONCLUSIONS AND FUTURE SCOPE

---

**T**HE reasoning draws conclusions however does not make the conclusions certain, unless the mind finds it by the way of experience which gives the thinking that will protect the conclusions made. Consequently, the analytical and simulation studies made and revealed in the past sections are used to make an arrangement of inferences. The concluding remarks are incorporated into the accompanying segment alongside future extent of the work.

#### 5.1 CONCLUSION

ECG signal improvement is fundamental for programmed or manual processing of ECG. Fourier transforms are constrained to the examination of stationary time series. In order to overcome this constraint, time-frequency analysis were created. This dissertation embodies the result of denoising of ECG signals based on Stockwell Transform (S-transform) and the proposed work based on Modified Stockwell Transform (MST).

The methodology stated in chapter 3 is a summed up way to deal with ECG signal improvement utilizing S-Transform. This technique need not require any reference motion as auxiliary signal as well earlier data like R peak position. Elimination of noise parts from the time-frequency domain representation of ECG signal is done via masking and thresholding. This thesis presented a modified S-transform and the improvement is accomplished through the presentation of another scaling parameter for the S-transform Gaussian window. The techniques are assessed for various noises during transmission of signals like additive white Gaussian noise, Rayleigh fading and during acquisition of signals like Muscle Artifacts, Electrode Motion and Baseline Wander at two different SNR levels i.e., 5dB and 10dB. Programming work of above said methods is simulated in the signal processing platform of MATLAB Version R2013a. Simulation results demonstrate that the proposed technique performs with better SNR when contrasted to S-transform which is normally utilized as a denoising technique for an ECG signal. The proposed work proves to be excellent time-frequency tool for biomedical signal processing greatly.

## 5.2 FUTURE SCOPE

The Modified S-transform based technique being the superior as discussed in this thesis, can be advanced as a useful arrangement by achieving the about to be mentioned steps-

- Improve the ability of the transform with the goal that it can be likewise connected for the less regular Power line Interference.
- Clinical assessment of the technique by gathering information from ECG machines in ordinary and stress test conditions. This assessment can be utilized to learn about the adequacy of the strategy for uncertain real life ECG securing situations.
- An equipment usage of the system should be possible for interfacing it with ECG acquisition condition for applications in real situations.
- Examination of time series from diverse areas.

## ***LIST OF PUBLICATIONS***

---

- [1] 2017 Denoising of ECG signal using Modified S-Transform. *Sadhana - Acad. Proc. Eng. Sci.* (Communicated)

## REFERENCES

---

- [1] Sayadi O, Shamsollahi MB (2008). ECG denoising and compression using a modified extended Kalman filter structure, *IEEE Trans Biomed Eng*, 55(9), 2240–8.
- [2] Thakor NV, Zhu YS (1991). Application of adaptive filtering to ECG analysis: noise cancellation and arrhythmia detection, *IEEE Trans Biomed Eng*, 38(8), 785–94.
- [3] Barros AK, Mansour A, Ohnishi N (1998). Removing artifacts from electrocardio-graphic signals using independent component analysis, *Neurocomputing*, 22, 173–86.
- [4] Ho CYF *et al.* (2003). Fuzzy multiwavelet denoising on ECG signal, *Electro Lett*, 39(16), 1163–4.
- [5] S. Poornachandra (2008). Wavelet-based denoising using subband dependent threshold for ECG signals, *Digital Signal Processing*, 18(1), 49-55.
- [6] R. G. Stockwell (2007). Why use the S-transform? In Pseudo-Differential Operators: PDEs and Time-Frequency Analysis, ser, *Fields Institute Communications, Wong, Ed. AMS*, 52, 279-309.
- [7] Stockwell R, Mansinha L, Lowe R (1996). Localization of the complex spectrum: the S-transform, *IEEE Trans Signal Process*, 44(4), 998–1001.
- [8] Ventosa S *et al.* (2008). The S-transform from a wavelet point of view, *IEEE Trans Signal Process*, 56(7), 2771–80.
- [9] Stockwell RG (2007)). A basis for efficient representation of the S-transform, *Digital Signal Process*, 17(1), 371–93.
- [10] Pei SC, Wang PW (2010). Discrete inverse S-transform with least square error in time-frequency filters, *IEEE Trans Signal Process*, 58(7), 3557–68.
- [11] S-transform theory. Available at: <https://en.wikipedia.org/wiki/S-transform>
- [12] M.K Das, S. Ari (2013). Analysis of ECG signal denoising method based on S-transform, *IRBM*, 34, 362–370
- [13] Samit Ari, Manab Kumar Das, Anil Chacko (2013). ECG signal enhancement using S-transform, *Computers in Biology and Medicine*, 43, 649-660
- [14] Schimmel M, Gallart J (2005). The inverse S-transform in filters with time-frequency localization, *IEEE Trans Signal Process*, 53(11), 4417–22.

- [15] D. Gabor, *Theory of communication*, J. Inst. Elect. Eng 1946, 93(26), 429–457.
- [16] S. Qian and D. Chen, *Joint Time-Frequency Analysis: Methods and Applications*, Englewood Cliffs, NJ: Prentice-Hall, 1996.
- [17] Zhu H *et al.* (2003) A new local multiscale Fourier analysis for medical imaging, *Med Phys*, 30, 1134–41.
- [18] Varanini M *et al.* (1997). Spectral analysis of cardiovascular time series by the S-transform, *Comput Cardiol*, 24, 383–6
- [19] Gao JH, Chen WC, Li YM, Tian F (2003). Generalized S-transform and seismic response analysis of thin interbeds, *Chinese J Geophys*, 46, 526–32.
- [20] Stockwell RG, Lowe R (2001). Airglow imaging of gravity waves 1. Results from a small network of OH nightglow scanning imagers, *J Geophys Res Atmosphere*, 106(D15), 17185–203.
- [21] Dash PK, Panigrahi BK, Panda G (2003). Power quality analysis using S-transform, *IEEE Trans Power Deliv*, 18, 406–11.
- [22] M. Blanco-Velasco, B. Weng, and K. E. Barner (2008). ECG signal denoising and baseline wander correction based on the empirical mode decomposition, *Computers in Biology and Medicine*, 38(1), 1-13.
- [23] M. Z. U. Rahman, R. A. Shaik, and D. V. R. K. Reddy (2011). Efficient sign based normalized adaptive filtering techniques for cancelation of artifacts in ecg signals: Application to wireless biotelemetry, *Signal Processing*, 91(2), 225-239.
- [24] R. Rangayyan, *Biomedical Signal Analysis: A Case-Study Approach*, Wiley India Pvt. Ltd., 2009
- [25] Thresholding. Available at: <http://robotics.eecs.berkeley.edu/~sastry/ee20/index.html>
- [26] MIT-BIH arrhythmia database. [Online]. Available: <http://www.physionet.org/physiobank/database/mitdb/>.
- [27] MIT-BIH noise stress database. [Online]. Available: <http://www.physionet.org/physiobank/database/mitdb/>.
- [28] G. Friesen *et al.* (1990). A comparison of the noise sensitivity of nine qrs detection algorithms, *IEEE Trans. Biomed. Eng*, 37(1), 85-98

- [29] Y.-C. Yeh and W.-J. Wang, QRS complexes detection for ECG signal: the Difference Operation Method Computer Methods and Programs in *Biomedicine*, 91(3), 245-254.
- [30] Husn- Hsien Chang Jose M. F. Moura “Biomedical signal processing,” ed. Myer Kutz, in Biomedical engineering and design handbook, 2nd edition, volume 1, McGraw Hill. 2010
- [31] R. U. Acharya, J. S. Suri, J. A. E. Spaan, and S. M. Krishnan, *Advances in Cardiac Signal Processing*, Springer, 2007.
- [32] C. L. Stan\_eld and W. Germann, *Principles of Human Physiology*, Media Update, Pearson Education, Limited, 2008.
- [33] A. J. Moss and S. Stern, *Noninvasive electrocardiology: clinical aspects of Holter monitoring*, ser, Frontiers in cardiology, W.B. Saunders, 1996.
- [34] Wikipedia: electrocardiography. [Online]. Available: <http://en.wikipedia.org/wiki/Electrocardiography>
- [35] Diagram of the human heart. Available at: <https://en.wikipedia.org/wiki/Heart#/media/File>
- [36] I. G. Khan, *Rapid ECG Interpretation*, Saunders, 2003
- [37] Manab Kumar Das, Electrocardiogram signal analysis for heart beat pattern classification. Ph.D Thesis, National Institute of Technology, Rourkela, INDIA, 2015
- [38] Janssen A (1991). Optimality property of the Gaussian window spectrogram, *IEEE Trans Acoustics Speech Signal Process*, 9(1), 202–4.
- [39] Said Assous and Boualem Boashash (2012). Evaluation of the modified S-transform for time frequency synchrony analysis and source localisation, *EURASIP Journal on Advances in Signal Processing*, 49
- [40] C.R Pinnegar, L. Mansinha (2003). Time-local spectral analysis for non-stationary time series: The S-transform for noisy signals, *World Scientific*, 3(3), 357-364.

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---

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Publication

---

**3** Assous, Said, and Boualem Boashash. "Evaluation of the modified S-transform for time-frequency synchrony analysis and source localisation", EURASIP Journal on Advances in Signal Processing, 2012. % **1**  
Publication

---

**4** Stockwell, R.G.. "A basis for efficient representation of the S-transform", Digital Signal Processing, 200701 % **1**  
Publication

---

**5** Krishna, Y. Murali; Khasim, N. Sayedu and Raja, V. Naveen. "Low Complex Adaptive Fast Converged Kalman Filter for Cardiac ECG % **1**

Artifacts Elimination", International Journal of Signal Processing, Image Processing & Pattern Recognition, 2014.

Publication

---

6

Pinnegar, C. R., and L. Mansinha. "Time-Local Spectral Analysis for Non-Stationary Time Series: The S-Transform for Noisy Signals", Fluctuation and Noise Letters, 2003.

Publication

---

<% 1

7

Mohamed, Azah, Mohammed Abdol, and Mohammad Fuad. "Power Quality Disturbance Detection and Source Prediction Using Advanced Signal Processing Techniques", Modelling Simulation and Identification, 2010.

Publication

---

<% 1

8

Jaya Bharata Reddy, M., Rama Krishnan Raghupathy, K.P. Venkatesh, and D.K. Mohanta. "Power quality analysis using Discrete Orthogonal S-transform (DOST)", Digital Signal Processing, 2013.

Publication

---

<% 1

9

Zahra Moravej. "A new approach for fault classification and section detection in compensated transmission line with TCSC", European Transactions on Electrical Power, 01/2011

Publication

---

<% 1

10

IFMBE Proceedings, 2009.

Publication

<% 1

11

Anita P.. "ECG Feature Extraction Using Wavelet Based Derivative Approach", Communications in Computer and Information Science, 2011

Publication

<% 1

12

Submitted to University of Wales Swansea

Student Paper

<% 1

13

Suriya Kaewarsa. "Detection of Power Quality Events Using DOST-Based Support Vector Machines", International Symposium on Computer Science and its Applications, 10/2008

Publication

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Submitted to Ahlia University

Student Paper

<% 1

15

Lecture Notes in Electrical Engineering, 2016.

Publication

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16

K. Wozniak. "Tracking of instantaneous spectrum components using time-frequency methods", 2008 Conference on Human System Interactions, 05/2008

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17

[www.biomedicalcomputationreview.org](http://www.biomedicalcomputationreview.org)

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---

18

Submitted to Birla Institute of Technology

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---

19

Courmontagne, Philippe, Samir Ouelha, and Fabien Chaillan. "On time-frequency representations for underwater acoustic signal", 2012 Oceans, 2012.

Publication

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---

20

Submitted to SASTRA University

Student Paper

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---

21

A. Camina. "PRO-p GROUPS OF FINITE WIDTH", Communications in Algebra, 1/1/2001

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