

**HIGHER - ORDER GABOR SPECTRA**  
**A MATHEMATICAL MODEL FOR SIGNAL PROCESSING**

A Thesis  
Presented to  
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by

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**A MATHEMATICAL MODEL FOR SIGNAL PROCESSING**

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## THE PROBLEM

The Dynamic Characteristics of Speech and Image signals have been commonly exploited in several Signal Processing Application Systems by using feature extraction techniques, temporal filtering and several short-term Spectral and Cepstral representations. These applications demand high speed operation and high accuracy levels. The intense computational complexity of present analysis algorithms has been a deterrent to fulfillment of these requirements. The Noise component is another important factor resulting in pronounced degradations in the performance of the Signal Processing Systems. Several algorithms and methodologies have been proposed to mitigate the effect of noise on the accuracy and complexity of the signal analysis process. However these techniques are only aimed at extracting or improving very specific parameters of the input signals, thus necessitating the need for a composite system designed to work under near real-time conditions. This proposal describes a novel approach for computationally efficient signal feature extraction using the Higher Order Statistics of the Gabor Transform - Gabor Polyspectra.

The conventional Gabor representation transforms the input signal into a discrete set of time shifted and frequency modulated versions using the Fast Fourier Transform (FFT). Its computational complexity is of  $O(N \log N)$ . To further reduce this, the Gabor coefficients are obtained through the Arithmetic Fourier Transform (AFT), which has a complexity of  $O(N)$  real multiplications. The Higher Order Statistics are obtained from available signal information. This is then transformed to a multidimensional space using the proposed Gabor Transform and the feature vector consisting of a set of dominant harmonics and associated Gabor phase components is extracted. This feature vector has found useful applications in Speech Recognition and Image Segmentation Systems.

A Parallelized framework for the Gabor Polyspectra algorithm has been proposed and its application for Biomedical Imaging Applications has been discussed. The primary purpose of the Parallel Model is formulate the database and the associated Neural System required to model Vision Networks. The proposed system takes advantage of the fact that the operations of Human Vision Network closely resemble that of the Gabor elementary functions. This system has been one of the major research projects at the Waran Research Foundation.

# CHAPTER I

## ORIGIN AND HISTORY

### ***1.1 THE BASIC SIGNAL ANALYSIS METHODS***

#### **1.1.1 Spectral Analysis**

In basic terms Analysis means decomposing something complex into simpler, more basic parts. With respect to real world entities we find that there is a physical basis for modeling light, sound, and radio waves. This basis is dependent on the fact that these physical functions are made up of various amounts of different frequencies. Any process that quantifies the various amounts vs. frequency can be called Spectrum Analysis [1].

The Fourier transform of a function produces a spectrum from which the original function can be reconstructed by an inverse transform, making it reversible. The Spectrum preserves the magnitude of each frequency component and its phase. This information can be represented as a 2-D vector or a complex number, or as magnitude and phase. In graphical representations, often only the magnitude (or squared magnitude) component is shown. This is also referred to as a Power Spectrum. FFTs and the Power Spectrum [2,3] are useful for measuring the frequency content of stationary or transient signals. FFTs produce the average frequency content of a signal over the entire time that the signal was acquired. In order to measure frequency information that is changing over time, joint time-frequency functions such as the Gabor Spectrogram [4] are used.

Consider the application of Spectral Analysis on a random signal function. We find that the Fourier transform of a random waveform is random [5]. Some kind of averaging is required in order to create a clear picture of the underlying frequency distribution of the random signal. The data is therefore divided into time-segments of a chosen duration - Adaptive Sampling [6], and transforms (DFT) are performed on each one.

### 1.1.2 Cepstral Analysis

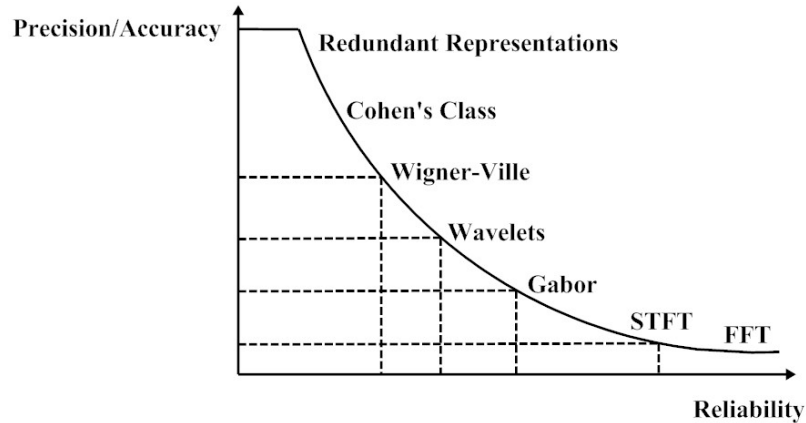
Cepstrum analysis is a nonlinear signal processing technique with a variety of applications in areas such as Speech and Image processing. It relies on the observation that a logarithmic signal spectrum is made up from the source and filter spectra added together [7]. The procedure for Cepstral analysis is to take the inverse Fourier transform of the logarithmic spectrum [8] and convert the signal back into the time domain. This time domain signal is not the same as the original signal used. A Frequency domain version of the signal is computed by further operating on the Cepstrum. The central part of the reflected Cepstrum is removed, the part that corresponds to the source, and a Fourier transform is performed to again generate a frequency domain version of the signal. This is manifested as a much smoother spectrum than the original; the degree of smoothing depends upon the number of Cepstral coefficients removed prior to the final Fourier transform.

In the case of speech recognition [10] for example, a filter bank is applied of which the center frequency of each bank is scaled according to the Mel scale. This scale takes into account the frequency resolution properties of the human ear. The inverse Fourier transform of the log output of this filter bank yields the Mel Frequency Cepstrum Coefficients (MFCC) [9]. The Cepstrum is also used for analysis of Biomedical Images [11].

## 1.2 *TIME-FREQUENCY REPRESENTATIONS*

We know that the Spectral density is a function of frequency and not a function of time. However, the spectral density of small "windows" of a longer signal may be calculated, and plotted versus the time associated with the window. Such a graph is called a Spectrogram Time Frequency Representation [12,13]. This is the basis for a number of spectral analysis techniques [14,15] such as the Short-time Fourier transform [16], Gabor Transform [17], Wavelets [19] and the Wigner-Ville Distribution [26]. Fig.1 shows the variations in the accuracy and reliability of these techniques.





**Figure 1:** Accuracy and Reliability of Time Frequency Techniques

### 1.2.1 Gabor Transform

The expansion of a signal into a discrete set of Gaussian elementary signals was originally suggested by Gabor in 1946, and the analytic expression for Gabor coefficients was later derived by Bastiaans [17]. An important property of the Gabor transform is that its coefficients reveal the localized frequency distribution of a signal or an image[18], instead of the global frequency information as provided by the coefficients of the Fourier transform. This has proven to be very useful for texture analysis [63], biomedical imaging [72], speech recognition [60] and other areas. The study of the Gabor transform will be useful not only for its own applications, but also for the understanding and applications of the wavelet transform since the two transforms are different manifestations of the same group representations theory.

### 1.2.2 Wavelets

A Wavelet is a kind of mathematical function used to divide a given function into different frequency components and study each component with a resolution that matches its scale [19]. The wavelets are scaled and translated into copies known as "daughter wavelets" of a finite length or fast-decaying oscillating waveforms known as the "mother wavelets" [20,21]. The Wavelet transforms have advantages over traditional Fourier transforms [22] for representing functions that have discontinuities and sharp peaks, and for accurately deconstructing and reconstructing finite, non-periodic and/or non-stationary signals.

Wavelet theory is applicable to several subjects [23]. It is now being adopted in many applications by replacing the conventional Fourier transform. An important application is its use for smoothing/denoising data based on wavelet coefficient thresholding. By adaptively thresholding the wavelet coefficients that correspond to undesired frequency components, smoothing and/or denoising operations can be performed. Wavelets have also enjoyed great success in Data Compression, Nondestructive Evaluation, Biomedical engineering [24], Turbulence Analysis and even Financial Analysis [21]. Further advancements have been made resulting in the Wigner-Ville Distribution [25].

### **1.2.3 Wigner-Ville Distribution**

The Wigner-Ville Distribution (WVD) is a signal transformation of an input time signal into a joint time-frequency domain that provides an excellent characterization of an input signal as well as its respective energy content [26]. In most cases the estimate of the Wigner-Ville Spectrum (WVS) of any Gaussian continuous-time Stochastic processes is treated using Cohen's class of time-frequency representations of random signals [12,27]. The discrete Wigner-Ville distribution can be implemented directly using standard Fast Fourier transform techniques [28]. For a non-negative frequency resolution of  $N$  points, only an  $N$  point FFT is needed. It is known that the WVD exhibits the highest signal energy concentration [29] in the timefrequency plane for linearly modulated signals, but the major problems are artifacts in the case of nonlinearly frequency modulated signals and the presence of cross-terms for multi-component signals.

## ***1.3 LIMITING FACTORS TO PERFORMANCE IN T-F DOMAIN***

The signal representations that have been mentioned are far from perfect. They are designed mostly under conditions where there is a trade-off between accuracy and computational time delay. In this proposal we introduce a system model that meets the needs of several Signal Processing applications with as few imperfections as algorithmically possible.

The performance limiting factors in the Gabor transform are inherent in its complex process. The Gabor elementary functions are not orthogonal to each other and an auxiliary function has to be employed in order to obtain the exact Gabor coefficients, a task which is computationally heavy. Another major disadvantage is that one has to divide by the Zak transform of the window function in order to calculate the Gabor coefficients [30,31]. The Zero theorem shows that if a function is continuous and decays sufficiently fast, its Zak transform will be zero somewhere in the unit square. The result is that for many windows of interest, including the Gaussian pulse, one will have to contend with either an analytic or a computational singularity when attempting to divide by the Zak transform of the window at some point in the domain of interest.

The limitations of Wavelets though not obvious, reveal themselves when used in various applications. From a theoretical viewpoint, Wavelet series are not optimal for representing images that contain objects with discontinuities along curves [32,33]. The existing Wavelet Pyramid Schemes have only a fixed number of directional elements and are independent of scale. With respect to scaling concepts, the traditional pyramids do not have highly anisotropic elements. The disadvantages mainly lay in the choice of window function required and its applications.

The Wigner distribution has limitations for use in analyzing signals. Knowledge of the entire signal is required to compute the Distribution and there is no existing fast algorithm available to speed up the computation process. A Spectrogram based on the Wigner distribution will show interference artifacts. This results in a Wigner distribution spectrogram which shows noise in regions where there should be none. Comparative study between the Adaptive Spectrogram and the Wigner-Ville class reveals the Spectrogram to be more robust [31]. The distribution is negatively affected by important cross-terms [34], which limit its practical use. Cross-terms in most cases adequately reduce the smoothing operation of the distribution over time. Also the data-window used in the Wigner-Ville performs a frequency smoothing operation. We know that Fourier spectra are periodic with period equal

to the sampling rate, while the data-window is periodic in frequency with period equal to half the sampling rate. This may cause aliasing.

Considering the various Time-Frequency Representations and their Limitations, a Mathematical Model is proposed to overcome the inherent complexities. The model is based on obtaining Higher Order Statistics for the Gabor Transform - Gabor Polyspectra. The Gabor computations are reduced by replacing the FFT with a Number Theoretic Method to compute the Fourier coefficients. The Proposed model has shown positive results when applied to Speech Recognition and Image Segmentation. A Parallel implementation of the proposed Gabor System has been modeled to overcome the computational complexity when there a large number of inputs (Vision Networks).

## CHAPTER II

### THE GABOR TRANSFORM

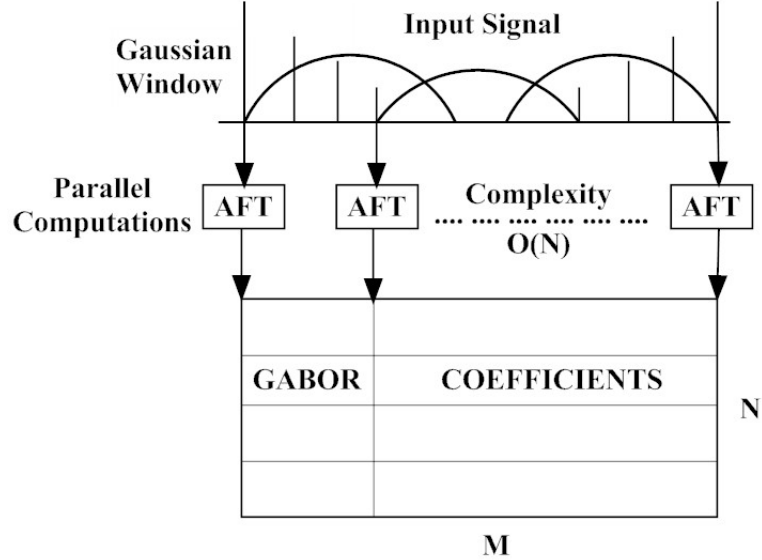
#### ***2.1 AN EFFICIENT GABOR ANALYSIS FRAMEWORK***

The Gabor transform was chosen as it is one of the better schemes for signal representation [18]. It decomposes the input signal into functions localized in both time and frequency, enabling us to study the signal modulation. Its major advantage is that it achieves the lower limit on the system entropy [18,35] which substantiates its use for a wide variety of applications. The majority of receptive field profiles of the mammalian visual system, speech synthesis mechanisms match well to this type of function [36]. The Gabor transform has been used for speech recognition, texture segmentation, image compression, biomedical image analysis and other areas as well.

##### **2.1.1 Gabor Computation using the Arithmetic Fourier Transform**

The conventional Gabor Transform [17,18,36,39] involves the multiplication of the input signal by a function which is biorthogonal to a Gaussian window. The input signal is decomposed and characterized by the respective time and frequency domain shifts. The required biorthogonal function is obtained with the help of the Fast Fourier Transform (FFT). This form of discrete Gabor transformation can be expressed in a matrix notation [18,39]. The complete Gabor coefficients can be found by multiplying the inverse of the Gabor matrix and the input signal. The Gabor matrix can be decomposed into the product of a sparse constant complex matrix consisting of the Fourier Coefficients and another sparse matrix which depends on the Gaussian window function.

Unfortunately, the biorthogonal function is nonlocal and the pre-multiplications involved are computationally intensive. To overcome this, the biorthogonal function is computed using the Arithmetic Fourier Transform.

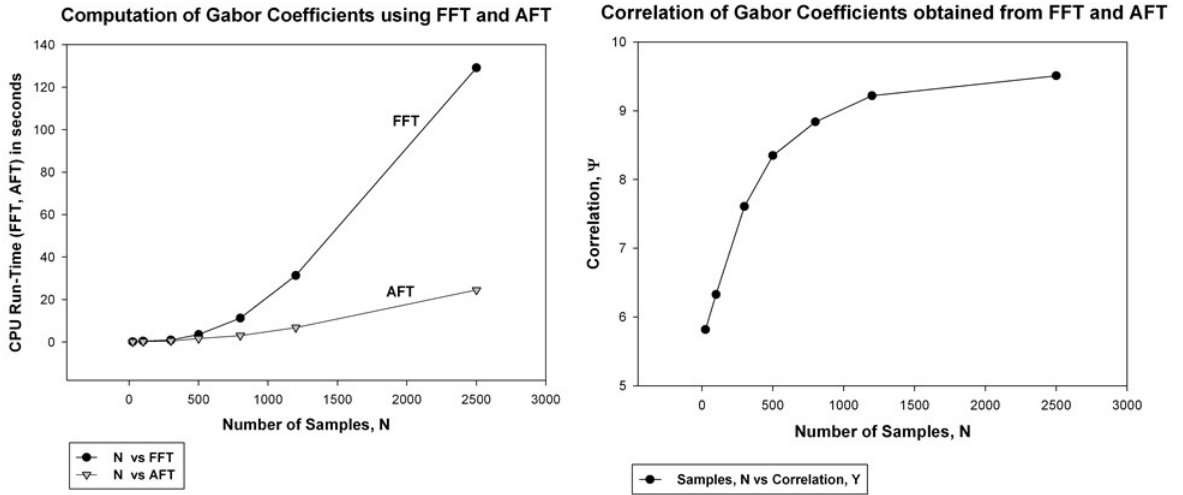


**Figure 2:** Implementation of the Gabor Transform using AFT

### Arithmetic Fourier Transform

The Arithmetic Fourier Transform (AFT) [40,41] computes the Fourier coefficients of a complex periodic function. It is based on the number-theoretic concept of Mobius inversion [42]. The Inversion formula has the advantage of eliminating many of the multiplications associated with computing the discrete Fourier coefficients. Its computations proceed in parallel and the individual operations are very simple. Except for a small number of scalings at one stage of the computation, only multiplications by 0, +1, and  $-1$  are required [40]. The AFT needs  $O(N)$  real multiplications and  $O(N^2)$  real additions with  $N$  being the number of samples [43].

In the Gabor Transform, the Fast Fourier transform is used for computation of the Biorthogonal function and its multiplication complexity is of  $O(N \log_2 N)$ . Using the FFT, we find that the overall complexity of the Gabor Transform is  $O(N \log N)$  [37,38]. In this thesis we propose an efficient Gabor expansion algorithm which replaces the FFT with the Arithmetic Fourier Transform. The algorithm reduces the overall multiplication complexity to  $O(N)$  as shown in the Fig.2.



**Figure 3:** CPU Run time and Correlation Factor of Proposed Gabor Algorithm

The time complexity and correlation factor for the Gabor AFT coefficients is represented in Fig.3. We notice that the run time is considerably lesser when compared to that required to compute the FFT coefficients. As the number of samples increases, the run time (in seconds) has decreased by more than half the time. Similarly the correlation between the Fourier coefficients obtained through FFT and AFT increases as the number of samples increases. Consider a speech signal containing 2000 samples, the graph shows a high value of correlation between the coefficients. With increasing sample numbers the Gabor-AFT model produces accurate results in faster time frames. The proposed Gabor expansion is applied to the input signal to extract the feature vector consisting of the dominant harmonics and the associated Gabor phase.

### 2.1.2 Gabor Phase Computation

Most state-of-the-art signal processing systems only utilize the magnitude of the Fourier transform of the time-domain signal segments. This means that the corresponding Fourier transform phases are discarded. However several studies [44,45] have indicated that it is a positive effort to directly model and incorporate the phase into the signal analysis process. We find that the phase obtained from a Fourier output cannot tolerate large changes in signal orientation, therefore a new local measure, referred to as the Gabor phase [46,47,48] has

been developed. The Phase information of Gabor filters is found to be more discriminative than that of the phase of the Fourier Transform. Similar to Fourier Coefficients, a Gabor response has a magnitude and an argument. The phase argument of the Gabor signal is determined by the ratio between the amplitudes of its quadratural components. This represents the unwrapped Short time phase components [45]. A Linear Predictive approach such as the Kalman Filter is used to obtain the required Principal Gabor Phase Components. This feature is essential in pitch determination and formant extraction of speech signals [49].

The Phase obtained from the Gabor filter takes advantage of the multi-resolution and multi-orientation characteristics inherent in the filters. It can be used to group related Gabor elements which simplifies the problem of target/background segmentation [46]. It also has useful applications in face recognition [47], vision networks [48] and speech recognition [49].

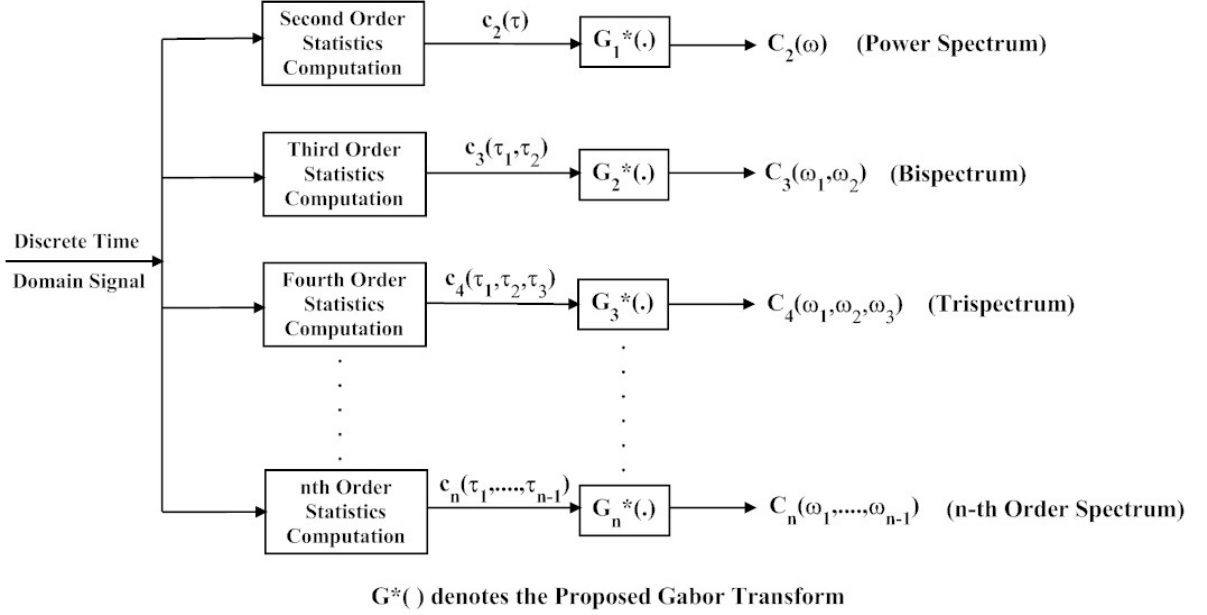
## ***2.2 MATHEMATICAL MODEL - GABOR POLYSPECTRA***

There are several general motivations behind the use of Higher-Order Spectra in signal processing [50,51]. Some of them are:

- (1) To Detect and characterize nonlinear properties of signals.
- (2) To Identify and Reconstruct non-minimum phase systems.
- (3) To Extract information due to deviations from Gaussianity.

We know that most of the signals in the real world are non-Gaussian and thus have nonzero Higher-Order Spectra. It has been demonstrated [50] that a non-Gaussian signal can be decomposed into its Higher-Order Spectral functions where each one of them contains different information about the signals. For modeling Time-series data in signal processing applications, Second-Order Statistics (Power Spectrum) are exclusively used because they are usually the result of least-squares optimization criteria [51]. In the proposed system we take advantage of the properties of the Higher-Order Spectra in order to model the Time-Frequency data obtained from the Gabor Transform, shown in Fig.4. The Gabor





**Figure 4:** The Gabor Polyspectra Classification Map for a Discrete Signal.

Polyspectra thus obtained can be used in signal classification problems where distinct classification features can be extracted from the Higher-Order Spectrum domains.

### 2.2.1 Algorithm and the related Computational Complexity

Consider estimating the Higher-Order Spectra of a process when a finite set of measurements are given. While these approximations are straightforward, sometimes the required computations may be expensive despite the use of the Gabor-AFT Transform. We propose the algorithm used for computation of the Higher Order Statistics using the Gabor Spectra:

**Algorithm:**

Let  $X_1, X_2, \dots, X_L$  be the available data set.

1. Divide the data set in  $N$  samples of  $M$  observations, i.e.  $L = MN$
2. Obtain the mean/average of the  $N$  samples and subtract this value from the data within the respective observations in order to center the information.
3. Assuming that  $x_i(k), k = (0, 1, \dots, L - 1)$  is the data set per sample  $i = 1, 2, \dots, N$ , obtain an estimate of the  $n$ -th moment sequence.
4. Average the estimate over all the  $N$  samples.
5. Perform the Gabor Transform and generate the  $n$ -th Order Gabor Polyspectra.

The proposed Gabor Polyspectra preserves the true magnitude [52] and phase characteristics [53] of signals but the process is in some cases computationally intensive due to the heavy calculations involved in the moment estimations. Consider  $N$  data samples and an estimate of the  $k$ th order, the time complexity is said to be  $O(N^k)$  [69]. A parallel model has been discussed in the following sections to reduce this complexity. Also in our proposed algorithm the 2-D AFT is used to compute the discrete Gabor coefficients. The disadvantage with this system is the inherent non-uniform sampling constraint [43] in the AFT. This constraint does not allow the complete reconstruction of the original signal. The problem is dealt in the next section and the Post processing methods to overcome this have also been proposed.

### 2.2.2 Inverse and Non-Uniform Sampling Issues

For the continuous variable generalized Gabor Transform, the reconstruction or the inverse condition is straight forward [17,18] and it reveals a fundamental relation between the Gaussian window function and their biorthogonal functions. Considering the proposed algorithm, the inverse is first computed using two parameters separately - the Gabor Magnitude and Gabor Phase. The results are given below:

It was found that the main problem with the reconstruction from magnitudes [54] is that the set of all transforms with given magnitudes but arbitrary phases is not convex, in contrast to the set of all transforms with given phases and variable magnitudes. Therefore, the algorithm does not project onto convex sets, and there is no straightforward convergence proof. However when using the Phase components, there are many positive results on the reconstruction of random signals from the localized phase [55]. They also show convincingly that the localized Gabor phase is more useful than global phase. It has been proved [54,55] that reconstruction from phase factors is simpler than reconstruction from local magnitude. We conclude that the complete inverse of a signal can be obtained by combining the Gabor magnitude and the Gabor phase components.

Further it is necessary to test the robustness of the system under non-uniform sampling conditions [56]. The system was subject to a set of test vectors and then tested for accurate computation of the Gabor coefficients. Multiple test vectors containing the same number of coefficients were used. A Gaussian window of 16 seconds duration and centered at 0.8 seconds was employed by the AFT and the Zak Transform. The results showed that the coefficients obtained are very different in both methods and they clearly do not represent the Gabor Coefficients. There appears to be aliasing in the method which involves the AFT. It is evident that the reconstruction of the signal is not possible under these conditions. Therefore Post-processing methods must be employed to overcome the problems.

### **2.2.3 Post-Processing Methods to overcome Limiting Factors**

Several methods of obtaining the time-frequency representations of a signal from its arbitrarily spaced samples have been discussed so far. The problem arises when reconstruction of original signal is required. As mentioned before the non uniformity in sampling causes aliasing of the reconstructed signal. This distortion becomes particularly significant in cases when the sampling period after uniform sampling conversion is higher than what is required by the Nyquist criterion. The following are some methods that can be used to overcome this problem:

The simplest approach is to ignore the non-uniformity of sampling flow and relocate the signal samples on a uniform grid. The advantage of using such a simplified approach is that it allows the use of the standard formulation of discrete Gabor Transform. The problem tends to correct itself. The signal re-sampling approach [57] is based on the use of direct and inverse transforms. It involves the re-sampling of the signal from a non-uniform grid to a uniform one on the basis of a pair of direct and inverse discrete transformations for example - the general Discrete Fourier Transform and Inverse Discrete Fourier Transform. The new sampling grid is uniform and it is formed by taking into account the highest spectral frequency in the signal. However problems arise in rare cases when the number of new uniformly spaced samples is greater than the number of original samples.

More accurate results can be obtained if signal interpolation [57] is performed before calculation of the Gabor Coefficients. In this case, to obtain the Time-frequency representations without artifacts, the time intervals of the original sampling flow have to comply with the Nyquist limit.

The Proposed Gabor Polyspectra System finds applications in a number of areas due to the enhanced signal resolution and noise reduction properties. The next section deals with applications of the Gabor Higher Order Statistics for Speech Processing and Image Segmentation. A Parallel model of the system is proposed for applications in Biomedical Signal Processing and Vision Systems.

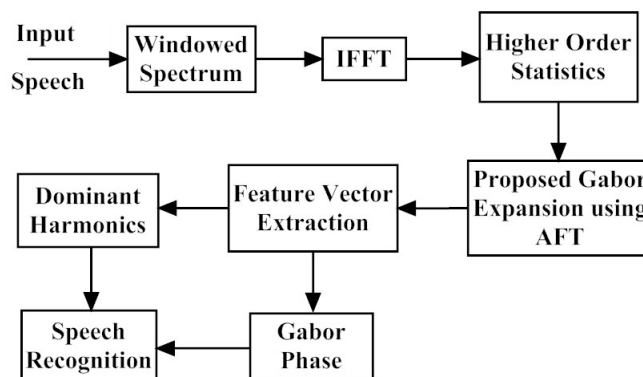
## CHAPTER III

### APPLICATION OF MODEL ON SPEECH AND IMAGE SAMPLES

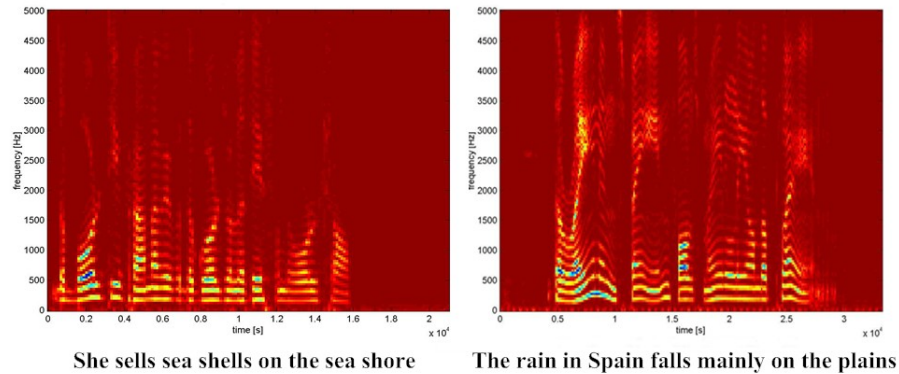
#### 3.1 SPEECH RECOGNITION

The System flow for the Speech Recognition System is as shown in Fig.5. The Windowed Spectrum of the noisy Speech signal is first obtained and this is followed by the application of the Inverse Fourier Transform. The coefficients obtained are used as the data-sets for determining the Higher-Order Spectra. If the noise is gaussian [58], the cumulant of the speech input is the cumulant of the clean speech signal. The same assumption can be if the noise has a symmetric p.d.f. [59] which is true for most of real noises. This property helps to reduce the noise factors and greatly increases signal resolution. The Statistical estimates thus obtained are used to compute the required Gabor Coefficients [60,61]. The recognition is based on the feature vector set obtained from the Gabor Polyspectra. The Dominant Harmonics and Gabor Phase are used simultaneously to differentiate and determine the spoken words.

In order to verify the validity of the algorithm described above we used a large number of test samples. The concentration was mainly to differentiate the similar sounding words(Homonyms) in a sentence. In the tests conducted, the acquired feature vector was



**Figure 5:** Speech Signal Feature Extraction

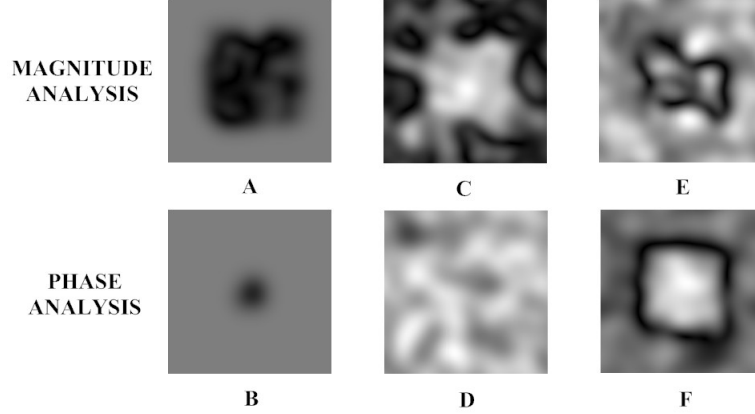


**Figure 6:** Gabor Spectra Obtained from the Test Sentences

used to set a threshold in order to separate these Homonyms. A sampling frequency of 8 kHz was selected and the frame size of the speech signal consisted of 500 to 1500 samples. The data used for the experiments contained speech signals recorded under varying noise conditions and containing similar sounding words. For example, the test sentences selected were similar to "She sells sea shells on the sea shore". Fig.6 shows the Gabor Time-Frequency representation acquired for the test sentences. The harmonics along with the associated phase were used to identify the individual components of the speech. It was seen that the harmonics and phase values were consistent for the same word sets under varying noise parameters. The overall accuracy of the proposed system for speech recognition shows positive results.

### ***3.2 IMAGE SEGMENTATION***

Image Segmentation is an important visual feature for a wide range of image processing applications. Most of the earlier analysis techniques concentrated on statistical, geometrical, and structural approaches, recently, model-based and signal processing techniques have been explored [63,64]. The Gabor Transform has been found to show accurate results for boundary and texture discrimination [63,64]. This is because the Gabor function is generally acknowledged to mimic some characteristics of the human cortical simple cells, and therefore has been found to play a successful role in the area of texture analysis [63].



**Figure 7:** Comparison of Gabor Magnitude and Phase Components for Boundary Detection

The analysis can be divided into two main stages: one in which the local computations extract the statistical attributes of the image, and the second in which these measurements are used for grouping and/or segregation. The developed mathematical framework is found to be suitable for this purpose. The Gabor Polyspectra is applied to a set of images and the respective magnitude and phase components are used for segmentation [65,66]. The Fig.7 shows the application of the extracted features for the purpose of texture analysis, grouping and segregation. The test gray scale images (A,B) are normalized in the range [0-127], (C,D) in the range [0-255] and (E,F) in the range [0-511]. We notice that at lower ranges (A,B) the acquired magnitude components produce clearer boundaries as compared to that produced by the phase components. However at higher ranges (E,F), the phase components produce significant results. The middle order ranges produce better results when subject to preprocessing methods [65].

In comparison with the conventional methods the proposed algorithm is more efficient due to the novel and successful utilization of the Higher-Order statistics of the Gabor Transform. The Higher-Order Statistics have been found to show increased signal resolution and reduction in noise artifacts. Also the proposed model for image texture analysis plays an important role in understanding the psychophysical performance of the Vision Systems.

## CHAPTER IV

### PARALLEL COMPUTATION OF GABOR COEFFICIENTS

#### 4.1 GABOR POLYSPECTRA IN A PARALLEL LINUX CLUSTER

In an effort to further lessen the computational complexity of the System, a parallel model of the Gabor Transform in a Linux Environment using MPI Libraries has been proposed. The main applications of this proposal is to provide accurate results when the input signal size is very large i.e. greater than 10,000, for example in Vision Networks [67].

Consider  $n$  to be the number of nodes, say 100,  $L$  to be the number of input samples - 10,000,  $M$  and  $N$  to be the respective frequency and time domain shifts - 100, 100. These parameters are distributed to all the nodes and they are then segregated into two main clusters. One computing the Gaussian Window Function,  $H$  and the other, the Arithmetic Fourier coefficients,  $E$ . The  $H$  and  $E$  matrices obtained are multiplied with one another and the inverse of the acquired matrix forms the required Biorthogonal function. On completion of the inverse operation the two clusters are ready to receive the input samples. The inputs are first divided into two segments and fed into the clusters in a sequential manner. The Biorthogonal matrix is multiplied with the input samples to produce the Gabor coefficients.

On first look, the optimum solution might be to have as many nodes as possible [68,69], but in reality this is not the case. A calculated trade-off between the number of nodes, interconnectivities and specified data rate along with prior information about the input size, sets the optimal functioning of the Parallel System. The basic framework in Fig.8 shows the connections across the various nodes and accounts for the stability of the computations.



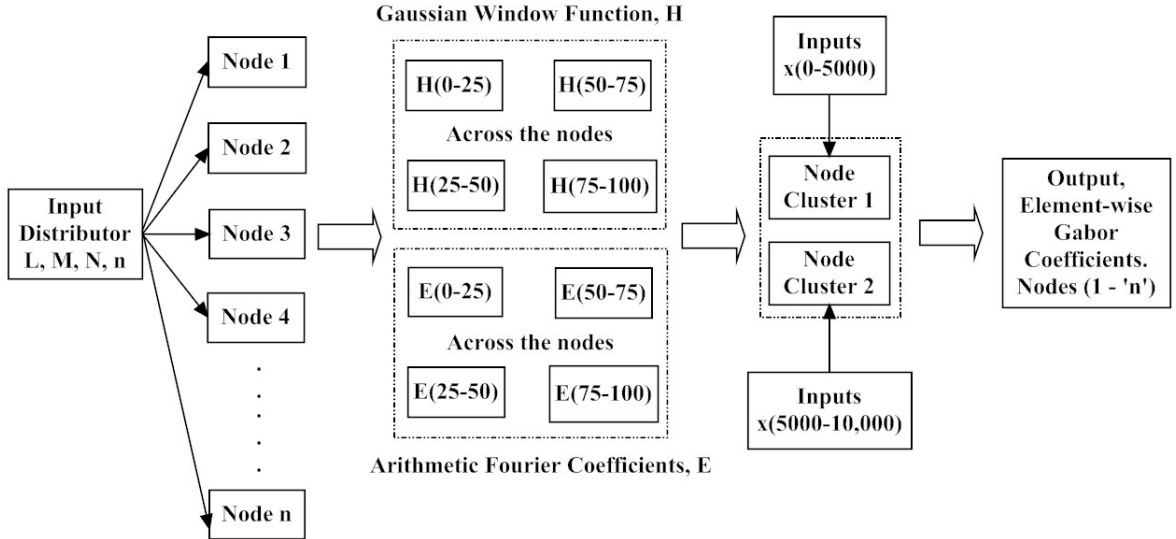


Figure 8: Parallel Model for the Gabor Transform

## 4.2 APPLICATION FOR BIOMEDICAL SIGNAL PROCESSING

### 4.2.1 Tissue Characterization of Ultrasound Images

It is believed that different biological structures are composed of peculiar textures. If this texture is reflected in the ultrasound image it should be possible to differentiate tissue composition by texture discrimination techniques. Most Ultrasound images of high-frequency (30-40 MHz) are blurred in both the axial and lateral directions due to the finite resolution of the imaging system [70]. A convenient model commonly used to represent this blurring is to express each Ultrasound signal  $y(n)$  as a product of the system function  $h(n)$  and tissue reflectivity function  $x(n)$ . The additive noise term  $\eta$  must also be accounted for.

These acquired images can be analyzed using the Gabor Polyspectra Algorithm to overcome the blurring effects and obtain the texture characteristics. First, separate (1-D) functions for the axial and lateral profiles are to be estimated using the Higher-order spectral technique [71]. This process is said to enhance the resolution of the Ultrasound Images and reduce the noise artifacts of the imaging system. Subsequently, the Gabor Transform is implemented on the estimated data sets, simultaneously in the axial and lateral direction. This can be useful in discriminating the image textures [62]. It is conceivable that features

such as hair follicles in the dermis and fingerprints on the surface of the finger can be more clearly displayed.

#### **4.2.2 Analysis of Myoelectric Signals**

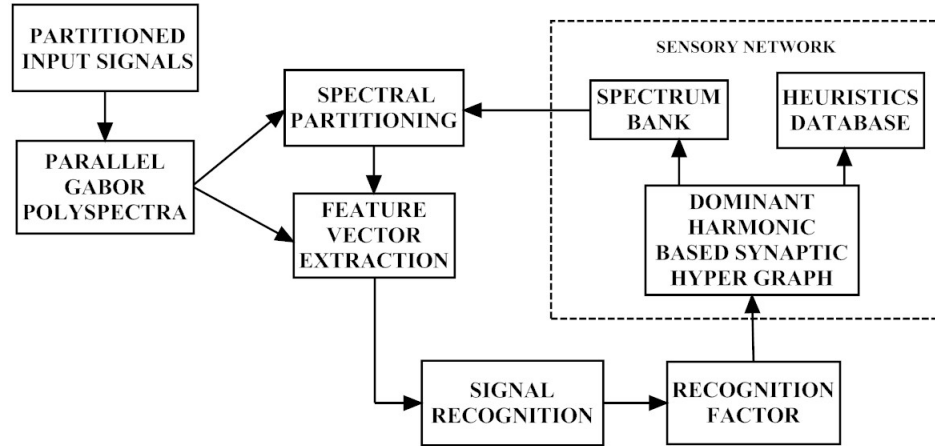
The Myoelectric Signal is the electric manifestation of neuromuscular activity [72,73] and is collected non-invasively on the skin via appropriate electrodes. The complex signal is stochastic in nature and depends on the anatomical and physiological properties of the contracting muscle [73]. With regard to medical applications, it is well established that the Surface Myoelectric Signal recordings from an amputees residual muscles can be used to control prosthesis movements [73]. Various techniques have been employed for processing these signals, such as auto regressive (AR) modeling, pattern recognition techniques, discrete wavelet transform [72] and various artificial neural network architectures together with other feature extraction schemes. Although the existing methods achieve high rates of accurate classification, they require substantial computations.

The parallel implementation of the proposed Gabor Polyspectra algorithm can be used to overcome these computational limitations. The Myoelectric Signals, detected using appropriate electrodes, are subject to Feature Extraction and Classification using the proposed algorithm. We can deduce that the Higher-Order Gabor Spectra will improve the signal resolution and also decrease the variation [73] among different signals in the same class. This enables us to classify the patterns more accurately.

#### **4.2.3 Database Formation for Modeling Neural Networks**

This work is inspired by the Brain Modeling initiatives at the Waran Research Foundation [74]. The Vision Sensory Network is widely known to resemble the Gabor elementary functions [62]. Based on this, a database is formed as shown in Fig.9, using the Gabor Polyspectra, to train the Neural Network [75]. The defined parallel network model is implemented to overcome the computational limitations.

The input signal is to be distributed among the nodes of the cluster and then subject to



**Figure 9:** Database Formation for modeling Vision Networks

Higher-Order Spectral partitioning. The features are extracted and the recognition factor is computed. The test signal vectors will include specific objects like cubes, spheres and abstract 3-D shapes. The consistency of the recognition factor is to be plotted to obtain the feasibility of the proposal in a parallel environment. Using the results of the parallel Gabor implementation, the Higher Order Statistics aim to show promising results in modeling the Visual Network.

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