Analysis of Higher Order Spectra Compare to Second Order in Digital Signal Processing into the Multi Diversity System and its Applications

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Abstract

The key challenge faced by future wireless communication system is to provide high data rate wireless access at high quality of service .MIMO technology seems to meet this requirement. But practically the use of diversity technique in MIMO communication some problem arise. Due to this reason HOS based technique can be the future solution of MIMO communication instead of Diversity technique. In this study we describe about HOS, Limitation of Second Order Statistics over Higher Order Statistics its application in different field such as biomedical, geophysical sonar radar, communication and other signal processing field. In this paper we will discuss about higher order statistics of Second Order spectrum over Higher Order Spectrum; advantages, application, recent and previous works on higher order statistics in different signal processing field and also to predict the future research on higher order statistics and spectra on signal processing.

1. Introduction

In digital signal processing Higher Order Spectra plays an important role. Originally, higher order spectra were introduced as spectral representation of cumulants or moments of ergodic random process. They were used in an identification of nonlinear systems and non-Gaussian random process and phase coupling in wave-wave interaction, Signal processing aspects and application of HOS grew with the excellent books, paper, journals etc by scientists and researchers. During the years, HOS have been applied in many areas in achtocastic framework and their application has been extended to deterministic signals. Many of these contributions are now scattered in various journals and proceedings of conferences. Techniques for detection and classification using HOS have been proposed and many application contributions have been published journals that are outside the IEEE/IEE research collection.

The introduction of higher order Spectra is quite natural when analyzing the non-linearity of a system. A communication Engineer doing research on Multiple input multiple output (MIMO) wireless communication could benefit from an understanding of the capabilities of HOS in order to make better use of phase information, adapt to non-Gaussian noise or adapt to nonlinear channel characteristics .Similarly a biomedical engineer can use HOS to derive features from EEG and ECGsignals which represents output data from systems where the input is not known. The extraction of hidden information in a signal and to process finite number of data samples is the main objective of a signal processing. This can be done by the combining the development of mathematical formulation with their algorithmic implementation (either software or hardware) and their applications to real data. Power spectrum and correlation is being used as primary tools in the field of signal processing application for many years. In this study we describe about HOS, Limitation of Second Order Statistics over Higher Order Statistics its application in different field such as biomedical, geophysical sonar radar, communication and other signal processing field. Especially in this thesis we will discuss about total overview about the higher order statistics and spectrum and finally we will discuss about the pros and prospect of higher order statistics in the field of communication. So we strongly believe that it is very helpful for the learners of higher order statistics and one can earn enough knowledge about higher order statistics [1-4].

2. Estimation of HOS

Two methods for cumulants spectra estimation are presented next for the third-order case.

2.1 Indirect Method:

Let x(k), k=1, . . . ,N be the available data

Segment the data into K records of M samples each. Let $x^j(k)$,k=1, . . . ,M, represent the ith record

Subtract the mean of each record

Estimate the moments of each segment$x^j(k)$,s as follows

$$m_3^{x^i}(\tau_1,\tau_2)=\frac{1}{M}\sum_{l=l_1}^{l_2} x^i(l)x^i(l+\tau_1)\,x^i(l+\tau_2) \quad (1)$$

$$l_1=\max(0,-\tau_1,-\tau_2)$$

$l_1 = \min(M-1, M-2), |\tau_1| < L, |\tau_2| < L, i = 1,2, \ldots \ldots K$

Since each segment has zero-mean,its third-order moments and cunulants are identical,i.e.,

$c_3^{x_i}(\tau_1, \tau_2) = m_3^{x_i}(\tau_1, \tau_2)$.

Compute the average cumulants as

$\acute{c}_3^{x}(\tau_1, \tau_2) = \frac{1}{K}\sum_{i=1}^{K} m_3^{x_i}(\tau_1, \tau_2)$(2)

Where $L < M - 1 w(\tau_1, \tau_2)$ is atwo dimensional window of bounded support,introduced to smooth out edge effects [6-7]

The bandwidth of the final bi-spectrum estimate is $\Delta = \frac{1}{L}$. A good choice of cumulant window is

$w(\tau_1, \tau_2) = d(\tau_1)d(\tau_2)d(\tau_1 - \tau_2)$(3)

where

$$d(\tau) = \begin{cases} \frac{1}{\pi}\left|\sin\frac{\pi\tau}{L}\right| + \left(1 - \frac{|\tau|}{L}\right)\cos\frac{\pi\tau}{L} & |\tau| \le L \\ 0 & |\tau| > L \end{cases} \quad (4)$$

This is known as the minimum bi-spectrum bias spectrum

2.2Direct Method:

Let x(k), k=1, . . . ,N be the available data

Segment the data into K records of M samples each. Let $x^j(k)$,k=1, . . . ,M, represent the ith record

Subtract the mean of each record

Compute the discrete Fourier transform $x^i(k)$ of each segment, based on M points, i.e.,

$x^j(k) = \sum_{n=0}^{M-1} x^i(n) e^{-j\frac{2\pi}{M}nk}$,k=0,1…………….M-1, i=1,2,…….,K

The discrete third-order spectrum of each segment is obtained as

$c_3^{x_i}(k_1, k_2) = \frac{1}{M} x^i(k_1)x^i(k_2)x^i(-k_1-k_2)$, $i = 1,2, \ldots \ldots \ldots K$ (5)

Due to the bi-spectrum symmetry properties,$c_3^{x_i}(k_1, k_2)$ need to be computed only in the triangular region $0 \le k_2 \le k_1, k_1 + k_2 < M/2$

In order to reduce the variance of the estimate note that additional smoothing over a rectangular window of size $(M_3 \times M_3)$can be performed around each frequency, assuming that the third-order spectrum is smooth enough, i.e.,

$c_3^{x_i}(k_1, k_2) = \frac{1}{M_3^2}\sum_{n_1=-^{m_3}/_2}^{^{m_3}/_2 - 1}\sum_{n_1=-^{m_3}/_2}^{^{m_3}/_2 - 1} c_3^{x_i}(k_1 +$ n1,k1+n2 (6)

Finally, the discrete third-order spectrum is given as the average overall third-order spectra, i.e.,

$c_3^{x_i}(w_1, w_2) = \frac{1}{K}\sum_{i=1}^{K} c_3^{x_i}(w_1, w_2)$, $w_i = \frac{2\pi}{M}K_i, i = 1,2$ (7)

The final bandwidth of this bi-spectrum estimate is $\Delta = {}^{M_3}/_{M}$, which is the spacing between frequency samples in the bi-spectral domain. For large N, and as long as

Δ=0, and $\Delta^2 N = \infty$ (8)

both the direct and the indirect methods produce asymptotically unbiased and consistent bi-spectral estimates, with real and imaginary part variances [4]:

$$\mathrm{var}\left(\mathrm{Re}\left[c_3^{x_i}(w_1, w_2)\right]\right) = \mathrm{Var}\left(\mathrm{Im}\left[c_3^{x_i}(w_1, w_2)\right]\right) = \frac{1}{\Delta^2 N} c_2^{x_i}(w_1)c_2^{x_i}(w_2)c_2^{x_i}(w_1 + w_2) \quad (9)$$

$$= \begin{cases} \frac{VL^2}{MK} c_2^{x_i}(w_1)c_2^{x_i}(w_2)c_2^{x_i}(w_1 + w_2) & \text{Indirect} \\ \frac{M}{KM_3^2} c_2^{x_i}(w_1)c_2^{x_i}(w_2)c_2^{x_i}(w_1 + w_2) & \text{direct} \end{cases} \quad (10)$$

where V is the energy of the bi-spectrum window.

From the above expressions, it becomes apparent that the bi-spectrum estimate variance can be reduced by increasing the number of records, or reducing the size of the region of support of the window in the cumulant domain (L), or increasing the size of the frequency smoothing window (M3), etc. The relation between the parameters M, K, L, M3 should be such that Equation 8 is satisfied [8-10].

2.3Parameter Estimation techniques using higher order spectra

An important means of finding the parameters of the process model in the frequency domain is to first find the magnitude and phase variation of the process model with frequency. An intermediate stage may be to find the bi-spectrum or tri-spectrum magnitude and phase estimates of the process [11].The process magnitude and phase may be estimated from the bi-spectrum magnitude and phase estimates of the process found [12-14].

The direct estimation of the process model parameters using higher order spectral techniques(without first estimating the process magnitude and phase) has been addressed, under the following topic headings:

The estimation of the parameters of an Auto Regressive Moving Average (ARMA) process model, in Z domain[15].

The estimation of the most appropriate order of the numerator and denominator polynomials in the ARMA process model [16].

The estimation of both the process parameters and time delay, in the discrete time domain [17].

The direct estimation of the time delay between two signals using higher order spectral techniques (without first estimating the process magnitude and phase).No other process dynamics are considered. These methods are divided into the following categories[18]:

Conventional time delay estimation techniques based on third order statistics. These methods involve maximizing the integral of a function that depends on the bi-spectral and cross bi-spectral phases of the input and output signals to the process [19].

Parametric time delay estimation techniques in the bi-spectral or tri-spectrum domain. These methods involve modeling the time delay by a polynomial and estimating the polynomial coefficients [20].

Time delay estimation techniques based on the cross-bi-spectral[16].

Time delay estimation techniques based on the mean fourth-cumulant criterion. This method is based on the tri-spectral domain.

Adaptive time delay estimation based on the parametric modeling of higher order cross-cumulants[18].

2.4 Robustness of the estimates using higher order spectra:

The higher order spectra of Gaussian signals is identically zero. Thus, if additive Gaussian noise of unknown spectrum is added to the process input or output, the estimation should not be affected[9].Successful identification of the process using higher order spectral methods requires

The input signal to the process is a non-guassian, zero mean, independent and identically distributed (i.i.d) random variable with finite dimensional, asymptotically stable linear transfer function.

The noise signals on the input and output of the process are i.i.d, possible mutually correlated, colored Gaussian or non Gaussian random variables (With a symmetric probability density function, if no-gaussian).In many practical situations, noise fulfils this criteria [13].

2.5 Blind System Identification:

Consider x(k) generated as shown in Figure 1. Estimation of the system impulse response based solely on the system output is referred to as blind system identification. If the system is minimum-phase, estimation can be carried out using SOS only. In most applications of interest, however, the system is a nonminimum phase. For example, blind channel estimation=equalization in communications, or estimation of reverberation from speech recordings, can be formulated as a blind system estimation problem where the channel is a nonminimum phase. In the following, we focus on nonminimum phase systems. If the input has some known structure, for example, if it is cyclo stationary, then estimation can be carried out using SOS of the system output. However, if the input is stationary independent identically distributed (i.i.d.) non-Gaussian, then system estimation is only possible using HOS In this section, we present following approaches based on the bicepstrum,. methods refer to the system of Figure 1, where the input v(k) is stationary, zero-mean non-Gaussian, i.i.d., nth-order white, and h(k) is a LTInonminimum phase system, with system function H(z). The noise w(k) is zero-mean Gaussian, independent of v(k). Consider a real process x(n) that is generated by existing a linear time invariant (LTI) system with impulse response h(k) with a stationery, zero-mean,non-gaussian process v(k) that is nth-order white,i.e.,

$$c_n^v(\tau_1, \tau_2, \dots \dots \dots . . \tau_{n-1}) = \Upsilon_n^v \delta(\tau_1, \tau_2, \dots \dots \dots \dots \tau_{n-1}) \qquad (11)$$

Via properties (P5) and (P6) and using Equation 8, the nth-order cumulant of the x(k), with n>2,equals

$$c_n^x(\tau_1, \dots \dots \dots . . \tau_{n-1}) = c_n^y(\tau_1, \dots \dots \dots . . \tau_{n-1}) + c_n^w(\tau_1, \dots \dots \dots . . \tau_{n-1}) \qquad (12)$$

$$= c_n^y(\tau_1, \dots \dots \dots . . \tau_{n-1})$$

$$= \Upsilon_n^v \sum_{k=0}^{\infty} h(k)h(k+\tau_1) \dots \dots \dots \dots \dots \dots h(k+\tau_{n-1})$$

Bi-spectral of x_K is

$$c_3^x(w_1, w_2) = \Upsilon_3^v H(w_1)H(w_2)H(-w_1 - w_2) \qquad (13)$$

2.6Bicepstrum-Based System Identification:

Let us assume that H(z) has no zeros on the unit circle. Taking the logarithm of $c_3^x(w_1, w_2)$ followed by an inverse 2-D Fourier transform, we obtain the bicepstrum bx(m, n) of x(k). The resulting bicepstrum is zero everywhere except along the axes, m=0,n=0, and the diagonal m=n, where it is equal to thecomplex cepstrum of h(k), i.e.[14]

$$b_x(m,n) = \begin{cases} h(m) & m \neq 0, n = 0 \\ h(n) & n \neq 0, m = 0 \\ h(-n) & m = n, m \neq 0 \\ \ln(c\Upsilon_n^y) & m = n = 0 \\ 0 & \text{elsewhere} \end{cases} \qquad (14)$$

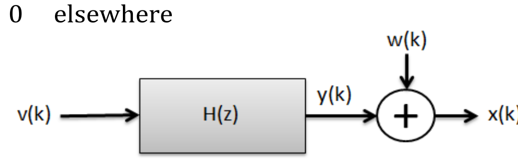

Figure 1. Single channel model

- where$h(n)$ denotes complex cepstrum, i.e., $h(n) = F_2^{-1}\{\frac{F_2[\tau_1 c_3^x(\tau_1,\tau_2)]}{c_3^x(w_1,w_2)}\}$where $F^{-1}(.)$denotes inverse Fourier transform. From Equation 14, the system impulse response h(k) can be reconstructed from bx(m, 0) (or bx(0,m), or bx(m,m)), within a constant and a time delay, via inverse cepstrum operations. The main difficulty with cepstrum operations is taking the logarithm of a complex number, i.e., ln(z)=ln(|z|)+jarg(z). The term arg(z) is defined up to an additive multiple of 2π. When applying log operation to$c_3^x(w_1, w_2)$, an integer multiple of 2π needs to be added to the phase at each (w_1, w_2), in order to maintain a continuous phase. This is called phase unwrapping and is a process that involves complexity and is sensitive to noise. Just using the principal argument of the phase will not result in a correct system estimate. To avoid phase unwrapping, the bicepstrum can be estimated using the group delay approach: $b_x(m, n) = \frac{1}{M} F_2^{-1}\left\{\frac{F_2[\tau_1 c_3^x(\tau_1,\tau_2)]}{c_3^x(w_1,w_2)}\right\}, \quad m \neq 0$ (15)
- with$b_x(0, n) = b_x(n, 0) F_2\{.\}$ and $F_2^{-1}\{.\}$denoting 2-D Fourier transform operator and its inverse, respectively. The cepstrum of the system impulse response can also be computed directly from the cumulants of the system output based on the equation
- $\sum_{k=1}^{\infty} kh(k)[c_3^x(m-k, n) - c_3^x(m+k, n +$ $k+kh-k[c3xm-k,n-k \quad -c3xm+k,n$ $= mc_3^x(m, n)$ (16)

- If H(z) has no zeros on the unit circle its cepstrum decays exponentially; thus, Equation (16) can be truncated to yield an approximate equation. An overdetermined system of truncated equations can be formed for different values of m and n, which can be solved for $h(k), k = \cdots \ldots \ldots \ldots \ldots, -1, 1, \ldots$ ...The system response h(k) can then be recovered from its cepstrum via inverse cepstrum operations. The above described bicepstrum approach results in estimates with small bias and variance as compared to many other approaches [19]. A similar methodology can be applied for system estimation using fourth-order statistics. The inverse Fourier transform of the logarithm of the trispectrum, or otherwise tricepstrum, tx(m, n, l), of x(k) is also zero everywhere expect along the axes and the diagonal m=n=l[14]. Along these lines it equals the complex cepstrum; thus, h(k) can be recovered from slices of the tricepstrum based on inverse cepstrumoperations.For the case of nonlinear processes, the bicepstrum is nonzero everywhere [20]. The distinctly different structure of the bicepstrum corresponding to linear and nonlinear processes can be used to test for deviations from linearity [21-22]

3. Estimation of HOS from MATLAB simulation

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We simulate a non-Gaussian ARMA process, and then estimate its cumulants. Time-series y is segmented into records of 16 samples each, with no overlap; biased estimates of the third-order cumulants are obtained from each segment and then averaged; the (i,j) element of cmat will contain the estimate ofC3y(i – n – 1,j – n – 1), for i,j = 1, . . ., 2 * n + 1. You can use the function cumtrue to compute and display the true cumulants. The contour plot in Figure.2 reveals the basic symmetry of third-order cumulants, namely C3y(□1,□□2) = C3y(□2,□1)). Other symmetry properties may be verified by using cumtrue to estimate the true cumulants of a linear process

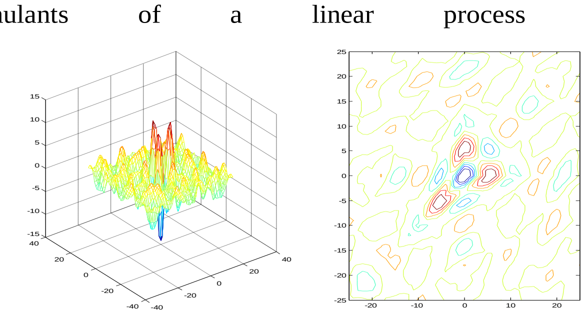

Figure 2. Estimated Third-Order Cumulants of an ARMA(2,1) Process (cumest)

Direct and indirect estimation of quadratic phase coupling signal is given below

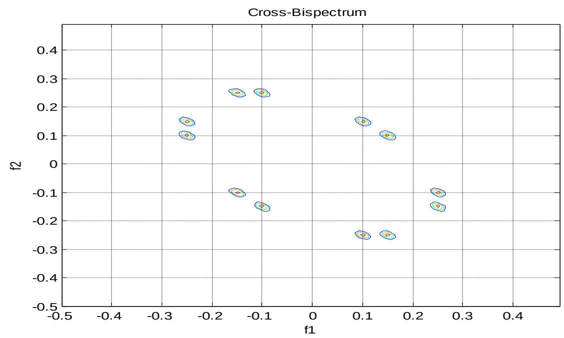

Figure 3. Indirect Estimate of the Bi-spectrum (bispeci)

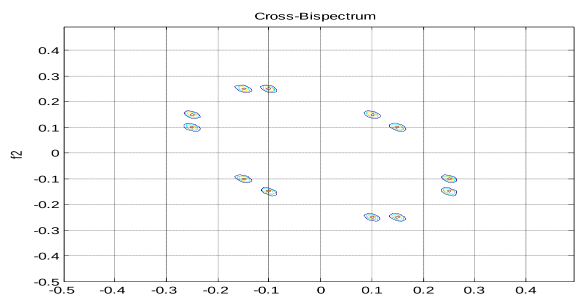

Figure 4. Direct Estimate of the Bi-spectrum (bispecdx)

Estimating Bicoherence:
Given estimates of the power spectra and the cross-bi-spectral, we can estimate the cross-bicoherence. It has been shown that consistent estimates of the power spectrum and the bi-spectral lead to consistent estimates of the bicoherence. Routines bicoher and bicoherx may be used to estimate the autobicoherence and the cross-bicoherence.

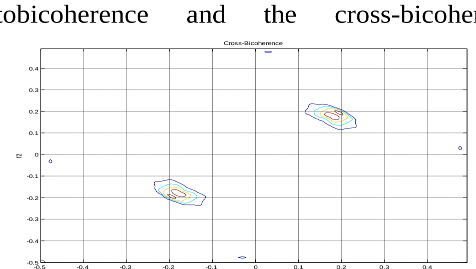

Figure 5. Cross-Bicoherence Estimate (bicoherx)

Estimation of 3rd order cumulants of ARMA process:

First, we will compute the theoretical third-order cumulants of an ARMA(2,1) process, with AR parameters, [1, –1.5, 0.8], and MA parameters, [1, –2]; we will then display the estimates using MATLAB's functions mesh or contour.

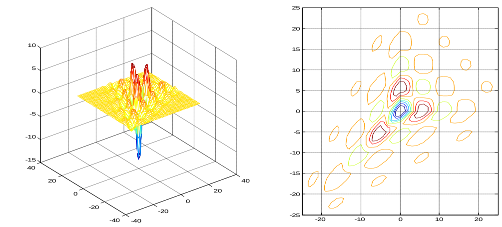

Figure 6. True Third-Order Cumulants of an ARMA(2,1) Process (cumtrue)

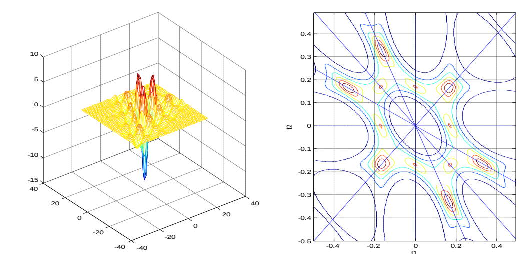

Figure 7. Bi-spectral of an ARMA (2, 1) Process (bispect)

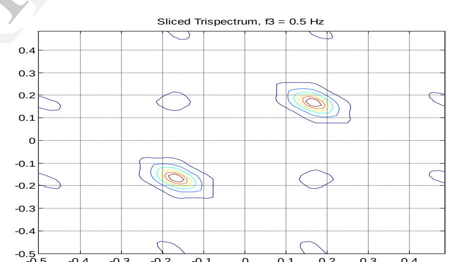

Figure 8. sliced Trispectrum at f3=0.5Hz

4. Application

1. InMobile Communication:
In communication signal processing, HOS can play a very important role. In many application, it is desired to extract some information from a signal corrupted by multiplicative noise .One such application lies in mobile communication. The mobile radio channel is a time varying multipath channel and is subject to physical propagation path loss. The time variation are caused by the medium changes vehicle moves. The propagation losses are related to both the atmospheric propagation and the terrain configuration .the multipath aspect is caused by the different scatters and reflectors such as buildings or trees that surround the mobile unit. As a result of these propagation phenomena typical envelope of a received mobile communication signal.

2. Research of HOS on Voice Activity Detection:
Voice activity detection (VAD) based on newly established properties of the higher order statistics (HOS) of speech. Analytical expressions for the third and fourth-order cumulants of the LPC residual of short-term speech are derived assuming a sinusoidal model. The flat spectral feature of these residual results in distinct characteristics for these cumulants in terms of phase, periodicity and harmoniccontent and yields closed-form expressions for the skewness.

3. MIMO Communication:
However with the integration of internet and multimedia application in next generation wireless communication the demand for wide band high data rate communication services is growing in the rapidly changing world, but the available radio spectrum is limited and the communication capacity needs cannot be meet without a significant increase in communication spectral or bandwidth efficiency. Higher data rates can be achieved only by designing more efficient signaling technique .Recent research in information theory has shown that large gains in capacity of communication over wireless channels are feasible in multiple input multiple output (MIMO) system as well as significantly enhances the system performance compared to conventional systems in fading multipath channel environments. TheMIMO channel which is shown in fig is constructed with multiple element array antennas at both ends of the wireless link. Broadly speaking all these MIMO techniques are based on paper handling of signals transmitted and received by an array of elements.

4.Biomedical Signal Processing:
The applications of HOS on biomedical signals are clustered according to the HOS property they must rely on, i.e., (1) the ability to describe non-Gaussian processes and preserve phase, (2) the Gaussian noise immunity, and (3) the ability to characterize nonlinearities. Ultrasound imaging distortions are estimated from the ultrasound echo and subsequently compensated for, to improve the diagnostic quality of the image. HOS have been used in modeling the ultrasound radio-frequency (RF) echo where schemes for estimation of resolvable periodicity as well as correlations among nonresolvable scatters have been proposed [22]. The "tissue color," a quantity that describes the scattered spatial correlations, and which can be obtained from the HOS of the RF echo. The skewness and kurtosis of mammogram images have been proposed in [18] as a tool for detecting micro calcifications in mammograms. In the second class are methods that process multicomponent biomedical signals, treating one component as the signal of interest and the rest as noise. HOS have been used to process lung sounds in order to suppress sound originating from the heart, and in to detect human afferent nerve signals, which are usually observed in very poor signal-to-noise ratio conditions.

5. Classification
Pattern or signal classification can be done working directly with the pattern or signal samples, or with attributes related to them. It is difficult to handle additive colored Gaussian noise with traditional approaches. A new approach (Giannakis and Tsatsanis, 1992), that is blind to additive colored or white Gaussian noise, works with a vector of cumulants or polyspectra, and extends correlation–based classification to HOS-based classification. It is based on the important fact that estimates of cumulants or polyspectra are asymptotically Gaussian. Consequently, one is able to begin with an equation like

$$\text{Estimateof HOS} = \text{HOS} + \text{estimation error} \quad (17)$$

6. Harmonic Retrieval:
The estimation of the number of harmonics and the frequencies and amplitudes of harmonics from noisy measurements is frequently encountered in several signal processing applications, such as in estimating the direction of arrival of narrow-band source signals with linear arrays,and in the harmonic retrieval problem.

5.Conclusion

During the past two decades spectrum estimation techniques have proved essential to the creation of advanced communication, sonar, radar, speech biomedical, geophysical and imaging systems. These techniques only use second order statistical information, which means that we have been assuming that the signal are inherently Gaussian. Most real-world signals are not Gaussian. It is no wonder, therefore that spectral techniques often have serious difficulties in practice. There is much more information in a stochastic non-Gaussian or deterministic signal then conveyed by its auto-correlation or spectrum .Higher order spectrum which are defined in terms of the higher order statistics of a signal contain this additional information. In this thesis an overview of higher order spectral analysis and its application in signal processing has been presented.Signal processing algorithms based on higher order spectra are now available for use in commercial and military applications. The emergence of low cost very high speed hardware chips and the ever-growing availability of fast computers now demand that we have been doing in the past from signals, so that better decisions can be made. All of the new algorithms that have been developed using higher order spectra are application driven.

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