DOKUZ EYLÜL UNIVERSITY

GRADUATE SCHOOL OF NATURAL AND APPLIED SCIENCES

ROBUST ESTIMATOR BASED RECEIVER DESIGN IN DIGITAL COMMUNICATION SYSTEMS

by

Özge ŞENTÜRK

July, 2020

İZMİR

ROBUST ESTIMATOR BASED RECEIVER DESIGN IN DIGITAL COMMUNICATION SYSTEMS

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M.Sc. THESIS EXAMINATION RESULT FORM

We have read the thesis entitled "**ROBUST ESTIMATOR BASED RECEIVER DESIGN IN DIGITAL COMMUNICATION SYSTEMS**" completed by **ÖZGE ŞENTÜRK** under supervision of **ASST. PROF. DR. MEHMET EMRE ÇEK** and we certify that in our opinion it is fully adequate, in scope and in quality, as a thesis for the degree of Master of Science.

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ROBUST ESTIMATOR BASED RECEIVER DESIGN IN DIGITAL COMMUNICATION SYSTEMS

ABSTRACT

In this thesis, baseband and band-pass waveform design is proposed to transmit and receive binary information under non-Gaussian impulsive noise environment. The additive channel noise is modelled by α-stable distribution. Differing from the previous studies, the signal detection problem under α-stable noise is analysed by considering both symmetrical and skewed cases. It is shown that signal detection performance decreases when the noise exhibits asymmetric behaviour.

Once the destructive effect of skewness of the noise on communication is determined, two strategies are proposed to reduce the skewness of the channel noise. The first attempt is to add α-stable noise having the same impulsiveness and opposite skewness at the input of the receiver in order to symmetrize the resultant noise. This operation corresponds to stochastic resonance phenomena. As the second approach, the robust estimators are utilized to increase the signal detection performance under skewed impulsive noise by introducing novel waveform design which is primarily based on converting signal to be transmitted into an intentionally antipodal waveform. The receiver undoes the same operation and uses robust estimators to reduce the skewed α-stable noise on the deterministic signal to recover the transmitted binary information even if the channel noise distribution is not known in advance.

In order to expose the improvement of the proposed methods, coherent detection and non-coherent differential modulation based waveform design are proposed to illustrate the enhancement in bit error rate, respectively. The antipodal waveform design provides digital communication for not only skewed α-stable noise but also any non-Gaussian noise having symmetric and/or skewed distribution.

Keywords: Skewed α-stable distribution, robust estimators, stochastic resonance, digital communication

SAYISAL HABERLEŞME SİSTEMLERİNDE GÜRBÜZ KESTİRİCİ TABANLI ALICI TASARIMI

ÖZ

Bu tezde, Gauss olmayan dürtüsel gürültü ortamında ikili bilgi iletmek ve almak için temel bant ve bant geçiren dalga formu tasarımı önerilmektedir. Eklentisel kanal gürültüsü α-kararlı dağılım ile modellenmiştir. Önceki çalışmalardan farklı olarak α-kararlı gürültü altında sinyal tespit problemi, hem simetrik hem de eğik durumlar dikkate alınarak analiz edilmiştir. Gürültü asimetrik davranış gösterdiğinde sinyal tespit performansının düştüğü gösterilmiştir.

Gürültünün eğikliğinin haberleşme üzerindeki yıkıcı etkisi belirlendikten sonra, kanal gürültüsünün eğikliğini azaltmak için iki yaklaşım önerilmektedir. İlk yaklaşım, ortaya çıkan gürültüyü simetrik hale getirmek için, alıcının girişine aynı dürtüselliğe ve zıt eğikliğe sahip α-kararlı gürültü eklemektir. Bu durum stokastik rezonans olayına karşılık gelir. İkinci yaklaşım, gürbüz kestiriciler kullanarak, iletilecek sinyali antipodal bir dalga formuna kasıtlı olarak dönüştürmeye dayanan yeni dalga formu tasarımı sunarak eğik dürtüsel gürültü altında sinyal tespit performansını arttırmaktır. Alıcı aynı işlemi geri alır ve kanal gürültü dağılımı önceden bilinmese bile, iletilen ikili bilgiyi kurtarmak için deterministik sinyal üzerindeki eğik α-kararlı gürültüyü azaltmak için gürbüz kestiriciler kullanır.

Önerilen yöntemlerin gelişimini ortaya koymak için, sırasıyla bit hata hızında artışı göstermek için tutarlı tespit ve tutarlı olmayan diferansiyel modülasyon tabanlı dalga formu tasarımı önerilmektedir. Antipodal dalga formu tasarımı, sadece eğik α-kararlı gürültü için değil, aynı zamanda simetrik ve/veya eğik dağılımlı Gauss olmayan gürültü için sayısal haberleşme sağlar.

Anahtar kelimeler: Asimetrik α-kararlı dağılım, gürbüz kestiriciler, stokastik rezonans, sayısal haberleşme

CONTENTS

Page

LIST OF FIGURES

Page

CHAPTER ONE
INTRODUCTION

One of the main problems in the physical layer in digital communication is the modelling of the receiver according to conventional assumptions. The strongest assumption in the statistical signal processing for communication is that noise in the channel that determines the design of estimators, sensors and filters have a Gaussian distribution. However, many of the real life noise processes like atmospheric noise, underwater acoustic noise and several man made noise types are classified as non - Gaussian environment. The recent studies propose that the noise is ensured to exhibit non-Gaussian characteristic especially impulsive nature (Win et al., 2009).

As an overview, the signal detection problem is begun to be formalized in a non-Gaussian environment (Kassam & Thomas, 1987). Generally, the channel noise is assumed to be Gaussian to simplify design and implementation of detectors (Nikias & Shao, 1995). The impulsive noise contains outliers which cause the distribution to be heavy tailed (Zoubir et al., 2012). The appropriate model for heavy tailed distributions is Alpha stable distribution (SαS). In the presence of impulsive noise, designing of a linear detector according to the Gaussian assumption is not suitable for impulsive nature because the impulsive noise significantly decreases error performance (increasing error probability and rate of false alarm) (Nikias & Shao, 1995). To minimize those types of effects optimum and sub optimum detectors are extensively designed in the presence of symmetrical α-stable (SαS) noise (Nikias & Shao, 1995). In the general case, explicit-form of probability density function (pdf) of alpha stable noise does not exist (Kassam & Thomas, 1987). Hence for alpha stable noise, designing of only sub-optimum receivers are possible. Subsequently, a receiver design is proposed that includes analytical expression of a near optimal detector under impulsive noise (Kuruoglu et al., 1998). In symmetric alpha stable noise, sub optimum detection can be analysed to have low complexity by applying adaptive threshold (Saleh et al., 2012) and by defining some detectors such as Cauchy detector, soft limiter (Sureka & Kiasaleh, 2013). In different studies and approaches, performance of signal detection are observed where noise in the channel is thought as mixture of both SαS and Gauss distribution (Wang et al., 2008; Khalil et al., 2011).

The impulsive noise components that cannot be modelled by the Gauss distribution in the channel noise cause the receiver performance to drop dramatically. For this reason, the literature emphasizes the function of robust estimators as filters and the necessity of eliminating noise (Zoubir et al., 2012). A remarkable study introducing a weighted myriad filter which is one type of robust estimator is recommended for digital communication (Gonzales et al., 1996), and after that study is expanded to contain weighted median filters (Gonzales & Arce, 2002). In (Djurovic & Stankovic, 2002), L-filter based discrete Fourier transform (L-DFT) method is used to filter impulsive noise components and it is reported that the L-DFT has poor performance compared to weighted median / myriad filters despite the reduced complexity. Another robust estimator is defined in (Aysal & Barner, 2007) and it is reported that the meridian filter provides better robustness against the impulsive noise compared to the median and myriad filters. The meridian filter is modified to have an adaptive weighted form to improve filter performance (Stork, 2010).

The robust estimators like median, myriad and meridian filters are generally used to estimate location parameter. It is reported that parameter estimation and noise reduction from time-varying signals is one of the difficult problems in robust estimation (Zoubir et al., 2012). One approximation is formulations of myriad and meridian filters are updated to demonstrate a p-norm filter, and time-varying behaviours happen because the input data is placed through a temporal sliding window of specific length (Pander & Przybyla, 2012). In other studies, both L_p norm minimization and myriad filter are used at the receiver side of a single carrier communication (Mahmood et al., 2014b) and OFDM signal detection (Mahmood et al., 2014a). If the amplitude variation of the deterministic signal is not negligible compared with its average value, sliding window is not an appropriate approximation to filter the time varying signal. In a recent study, beyond the conventional methods of filtering which uses a sliding window, problem is considered as detection of location estimation. The samples of periodic sinusoidal carrier signal which have the same amplitude in each period, are grouped as repeated identical observations which have equal distance in time domain (Yang et al., 2018). A similar type of approximation is performed to design a near optimal detector for correlation detection (Zhang et al., 2018).

The common assumption in the literature is that channel noise in non-Gaussian environment exhibits symmetrical behaviour. Even though there was a primary initiative to detect signals under asymmetric noise (Kassam et al., 1982), there is not any study stressing the effect of asymmetry of non-Gaussian noise. This thesis tackles noise reduction problem of the sinusoidal signal under asymmetric α-stable noise using robust estimators. Inspired by non-coherent chaotic communication method known as differential chaos shift keying, a non-coherent digital communication based technique which is analogous to differential BPSK (DBPSK) is introduced and used, because both the reference and information bearing signals are affected from the channel noise and non-coherent detection is used rather than synchronous detection to show the effect of reducing noise at the receiver. In this thesis, it is also proposed that intentional impulsive noise is added to the receiver which has reverse skewness parameter to improve receiver performance. The results are shown with bit error rate simulations.

The thesis is organized as follows. The next section describes α-stable distributions and robust estimators. The necessity of intentional noise and performance improvement in terms of skewness parameter and generalized signal to noise ratio (GSNR) due to stochastic resonance phenomena are given. In chapter three, signal estimation under robust estimators with proposed sinusoidal location estimation method for both bandpass and baseband communication system are described. The simulations are performed and the results are concluded in the last chapter.

CHAPTER TWO

SIGNAL DETECTION IN NON-GAUSSIAN NOISE

In conventional signal processing applications, detection theory is utilized to decide whether a certain signal embedded in noise is present or not. The noise parameters may not be known in real world problems. In a general point of view, the random process as the noise sequence corrupting deterministic signal is modelled by its probability density function. However, if the analytical expression does not exist as is the case for α-stable distributions, characteristic function is used to describe the probability density function. In digital communication systems, detection theory provides to extract test statistic in order to determine receiver characteristics in both base-band and band-pass domain.

2.1 Alpha Stable Distribution

Although the channel noise is generally modelled with Gaussian distribution, additive non-Gaussian noise especially exhibiting impulsive behaviour is properly modelled by α-stable distribution.

One dimensional stable distribution can be expressed by its characteristic function as,

$$\varphi(\omega) = \begin{cases} exp\Big\{-\sigma^{\alpha}|\omega|^{\alpha}(1 - j\beta sgn(\omega) tan\frac{(\pi\alpha)}{2}) + j\mu\omega\Big\}, & \text{if } \alpha \neq 1 \\ exp\Big\{-\sigma|\omega|(1 + j\beta\frac{2}{\pi} sgn(\omega) ln|\omega|) + j\mu\omega\Big\}, & \text{if } \alpha = 1 \end{cases} \tag{2.1}$$

where

$$sgn(\omega) = \begin{cases} 1, & \text{if } \omega > 0 \\ 0, & \text{if } \omega = 0 \\ -1, & \text{if } \omega < 0 \end{cases} \tag{2.2}$$

where characteristic exponent α, skewness parameter β, scale parameter σ and the shift parameter μ tune the impulsiveness, asymmetry, the intensity and the location, respectively.

In the literature, scale is alternatively defined also as dispersion γ, having the relation γ=σ^α (Swami & Sadler, 2002). The distribution is said to be symmetric around the location μ if $\beta = 0$. Since the effect of shift is not under consideration, location parameter is discarded ($\mu = 0$). The probability density function (pdf) of the stable distribution can be found as (Janicki & Weron, 1994).

$$S_\alpha(x;\sigma,\beta,\mu) = \frac{1}{2\pi}\int_{-\infty}^{+\infty}\varphi(\omega)e^{-j\omega x}d\omega \tag{2.3}$$

There is not a closed form expression for density function except for the special cases which are Gaussian ($\alpha = 2$), Cauchy ($\alpha = 1$) and Levy ($\alpha = 1/2$, $\beta = 1$) distributions (Janicki & Weron, 1994).

The density function of Gaussian distribution is given as

$$S_2(x;\sigma,0,\mu) = \frac{1}{\sigma\sqrt{2\pi}}exp\left(-\frac{(x-\mu)^2}{2\sigma^2}\right). \tag{2.4}$$

The density function of Cauchy distribution is given as

$$S_1(x;\sigma,0,\mu) = \frac{2\sigma}{\pi\left[(x-\mu)^2+4\sigma^2\right]}. \tag{2.5}$$

The density function of Levy distribution is given as

$$S_{1/2}(x;\sigma,1,\mu) = \left(\frac{\sigma}{2\pi}\right)^{1/2}(x-\mu)^{-3/2}exp\left(-\frac{\sigma}{2(x-\mu)}\right). \tag{2.6}$$

These pdf functions are plotted in Figure 2.1. Any other stable density has pdf function determined numerically by the characteristic function (Samoradnitsky & Taqqu, 1994).

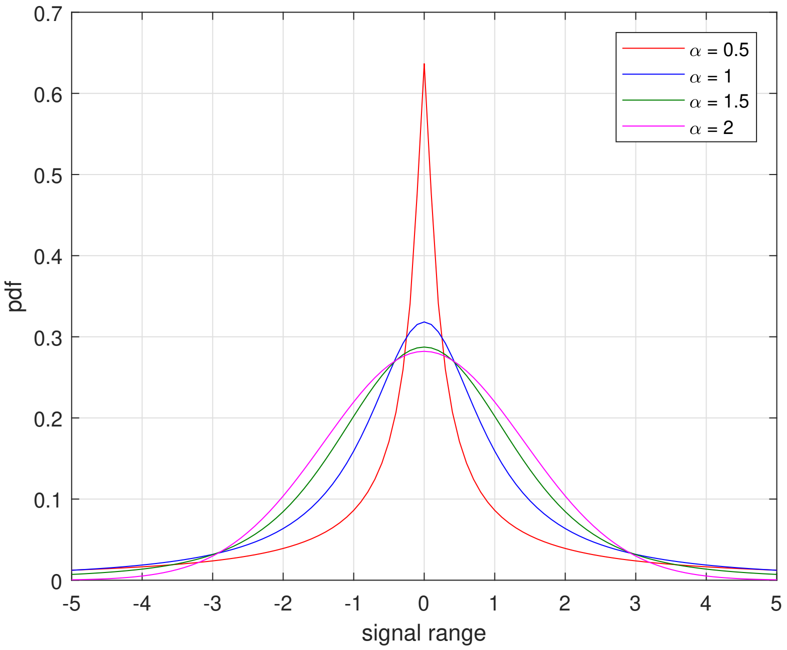

Figure 2.1 The variation on pdf with respect to α parameter ($\beta = 0$)

Alpha stable distribution is defined if α is in range $0 < \alpha < 2$. It means that the alpha stable random variables have infinite variance (second moment), so techniques which are used for Gaussian distribution are not applicable for alpha stable distribution. Thus, if X is a random variable, which has α-stable distribution, the property can be defined as,

$$\begin{aligned} E|X|^p &< \infty, \quad \text{if } p < \alpha \\ E|X|^p &\to \infty, \quad \text{if } p \geq \alpha \end{aligned} \tag{2.7}$$

where E is the expectation operator. The variance is finite for only Gaussian noise as a result of this property. An illustration of pdf according to different α and β parameter values are given in Figures 2.1 and 2.2

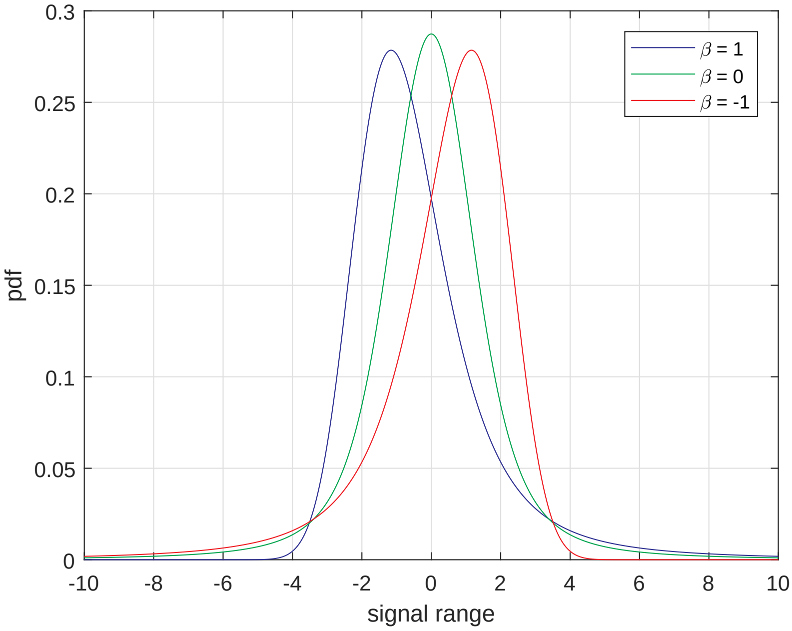

Figure 2.2 The variation on pdf with respect to β parameter (α = 1.5)

The other stable distribution properties are given as follows:

Property 2.1.1. Let $X_1 \sim S_\alpha(\sigma_1,\beta_1,\mu_1)$ and $X_2 \sim S_\alpha(\sigma_2,\beta_2,\mu_2)$ are independent random variables and addition of these two random variables are resulted in (Samoradnitsky & Taqqu, 1994).

$$X_1 + X_2 \sim S_\alpha(\sigma,\beta,\mu) \tag{2.8}$$

where $\sigma = ({\sigma_1}^\alpha + {\sigma_2}^\alpha)^{\frac{1}{\alpha}}$, $\beta = \frac{\beta_1{\sigma_1}^\alpha+\beta_2{\sigma_2}^\alpha}{{\sigma_1}^\alpha+{\sigma_2}^\alpha}$, $\mu = \mu_1 + \mu_2$.

Property 2.1.2. Let $X \sim S_\alpha(\sigma,\beta,\mu)$ and y is a real constant which is added to X random variable. The result can be shown as in Eq. (2.9) (Samoradnitsky & Taqqu, 1994).

$$X + y \sim S_\alpha(\sigma,\beta,\mu + y) \tag{2.9}$$

Property 2.1.3. Let $X \sim S_\alpha(\sigma,\beta,\mu)$ and c is a non-zero real constant which is multiplied by X random variable. The result can be shown as in Eq. (2.10) (Samoradnitsky & Taqqu, 1994).

$$\begin{aligned} &cX \sim S_\alpha(|c|\sigma, sign(c)\beta, c\mu) && \text{if} \quad \alpha \neq 1 \\ &cX \sim S_1(|c|\sigma, sign(c)\beta, c\mu - \tfrac{2}{\pi}c(\ln|c|)\sigma\beta) && \text{if} \quad \alpha = 1 \end{aligned} \tag{2.10}$$

Property 2.1.4. The effect of the skewness parameter can be given for $0 < \alpha < 2$ in Eq. (2.11) (Samoradnitsky & Taqqu, 1994).

$$X \sim S_\alpha(\sigma,\beta,0) \iff -X \sim S_\alpha(\sigma,-\beta,0) \tag{2.11}$$

Property 2.1.5. $X \sim S_\alpha(\sigma,\beta,\mu)$ is called as symmetric distribution only for the case $\beta = \mu = 0$ (Samoradnitsky & Taqqu, 1994).

Property 2.1.6. When $\alpha \neq 1$, $X \sim S_\alpha(\sigma,\beta,\mu)$ is called as strictly stable only for the case $\mu = 0$ (Samoradnitsky & Taqqu, 1994).

Property 2.1.7. When $\alpha = 1$, $X \sim S_1(\sigma,\beta,\mu)$ is called as strictly stable only for the case $\beta = 0$ (Samoradnitsky & Taqqu, 1994).

2.2 Antipodal Signal Detection

In digital communication, antipodal signalling, obviously corresponds to baseband binary phase shift keying (BPSK) modulation. Considering the set of observations in discrete time within a symbol duration, the baseband antipodal signal detection problem can be formulated as decision of DC level A having different sign as given in (2.12),

$$\begin{aligned} \mathcal{H}_0 &: x[n] = -A + w[n] \\ \mathcal{H}_1 &: x[n] = A + w[n] \end{aligned} \tag{2.12}$$

where n = 0, 1, . . . , N. The noise components w[.] are assumed to be independent and identically distributed and to have distribution w[.] $\sim S_\alpha(.;\sigma,\beta,0)$. The probability densities with respect to each antipodal signal reflecting the binary hypothesis is shown in Figure 2.3.

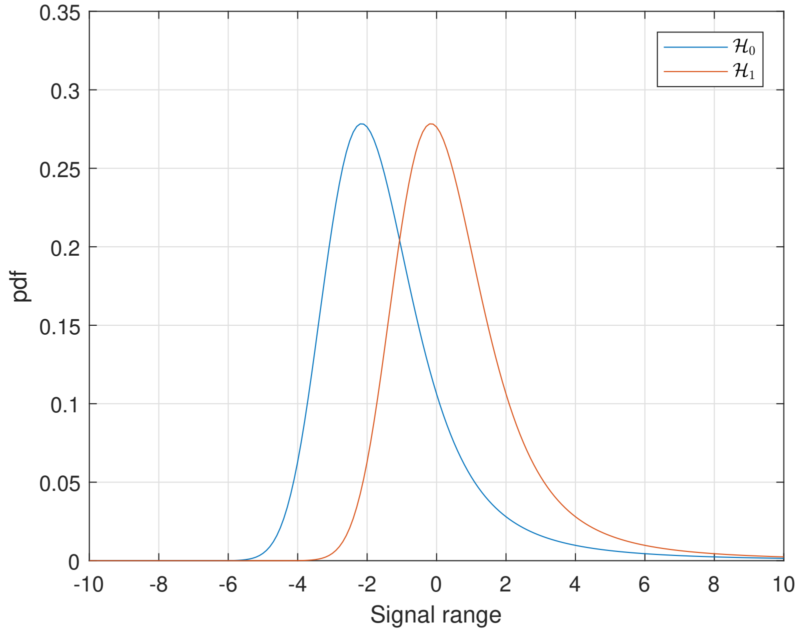

Figure 2.3 Binary hypothesis under α-stable noise

According to Figure 2.3, it is observed that conditional likelihood functions are not identical due to the asymmetry of the noise in the channel. The probability of error can be obtained as,

$$P_e = P(\mathcal{H}_1|\mathcal{H}_0)P(\mathcal{H}_0) + P(\mathcal{H}_0|\mathcal{H}_1)P(\mathcal{H}_1). \tag{2.13}$$

Since message bits are equally likely $P(\mathcal{H}_1) = P(\mathcal{H}_0) = 1/2$, the error probabilities are not equal and probability of error can be written as,

$$P_e = \frac{1}{2}P(\mathcal{H}_1|\mathcal{H}_0) + \frac{1}{2}P(\mathcal{H}_0|\mathcal{H}_1). \tag{2.14}$$

The probability of error can be approximated by substituting Eq. (2.6) and (2.12) in (2.14) as follows,

$$P_e = \frac{1}{4\pi}\left[\int_{-\infty}^{0}\int_{-\infty}^{\infty}\varphi(\omega)e^{-j\omega(x+A)}d\omega dx + \int_{0}^{\infty}\int_{-\infty}^{\infty}\varphi(\omega)e^{-j\omega(x-A)}d\omega dx\right]. \tag{2.15}$$

Although the error probability is a function of noise intensity, it is more convenient to express variation of error with respect to signal to noise ratio. Since the noise has infinite variance for α<2, the term "generalized signal to noise ratio (GSNR)" (Sureka & Kiasaleh, 2013) is defined as,

$$GSNR = 10\log\frac{A^2}{\gamma}\ . \tag{2.16}$$

For the sake of simplicity, dispersion is taken to be $\gamma = 1$. Then, the signal amplitude can be tuned for specified GSNR value as,

$$A = \sqrt{10^{\frac{GSNR}{10}}}. \tag{2.17}$$

The probability of error can be redefined as a function of GSNR as,

$$\begin{aligned} P_e(GSNR) = &\frac{1}{4\pi}\Big[\int_{-\infty}^{0}\int_{-\infty}^{\infty} e^{-\sigma^{\alpha}|\omega|^{\alpha}(1-j\beta sgn(\omega)tan\frac{(\pi\alpha)}{2}))}e^{-j\omega(x+\sqrt{10^{\frac{GSNR}{10}}})}d\omega\, dx \\ &+\int_{0}^{\infty}\int_{-\infty}^{\infty} e^{-\sigma^{\alpha}|\omega|^{\alpha}(1-j\beta sgn(\omega)tan\frac{(\pi\alpha)}{2}))}e^{-j\omega(x-\sqrt{10^{\frac{GSNR}{10}}})}d\omega dx\Big] \end{aligned} \tag{2.18}$$

where the impulsiveness is assumed to lie within the interval $1 < \alpha \leq 2$ and $\beta \in [-1, +1]$. Numerical simulations are given with respect to GSNR which illustrates the effect of noise parameters to error probability. In Figure 2.4, the probability of error for antipodal signalling under symmetric α-stable (SαS) distribution is illustrated with respect to various characteristic exponents.

It is significant to observe that the error probability becomes apparently poorer when the noise characteristic is even slightly impulsive. The error performance is observed to be dramatically worse especially for decreasing characteristic exponent α, i.e., increasing impulsiveness.

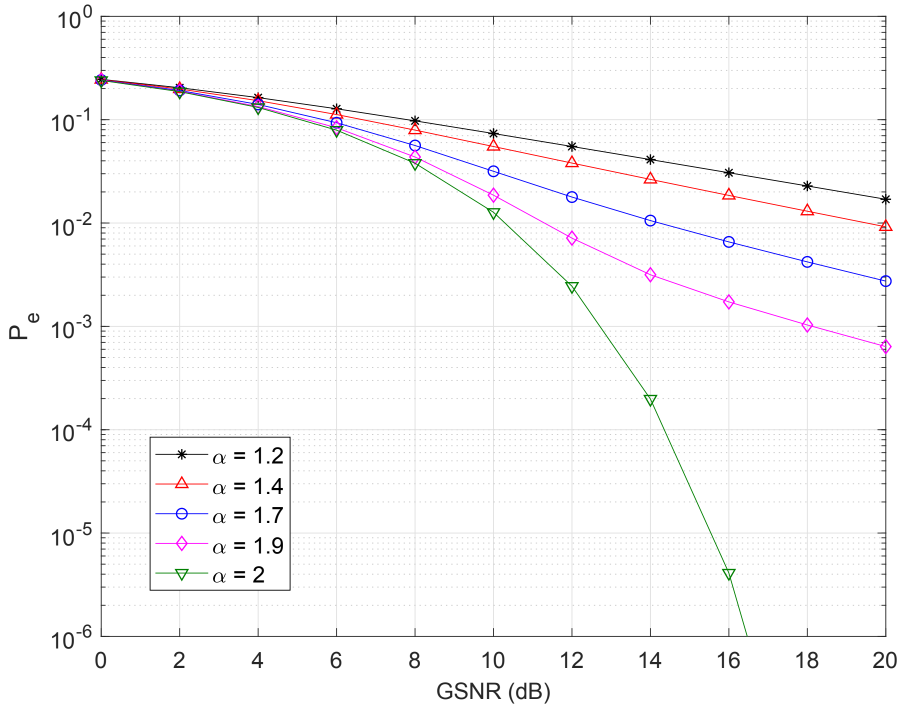

Figure 2.4 Probability of error under symmetric α-stable noise ($\beta = 0$)

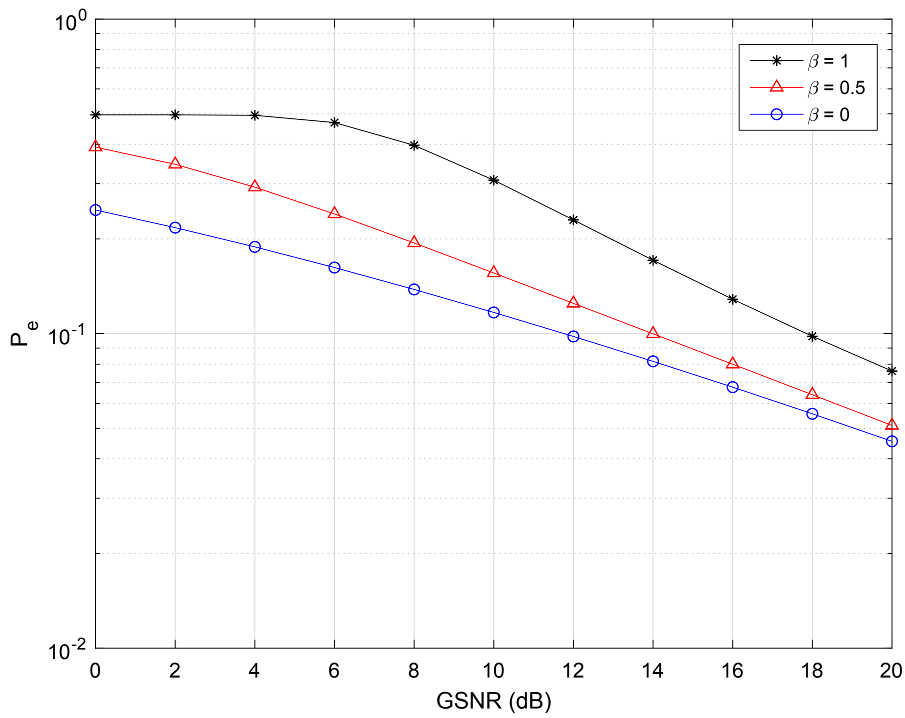

Figure 2.5 Probability of error for fixed $\alpha = 0.8$ by tuning β

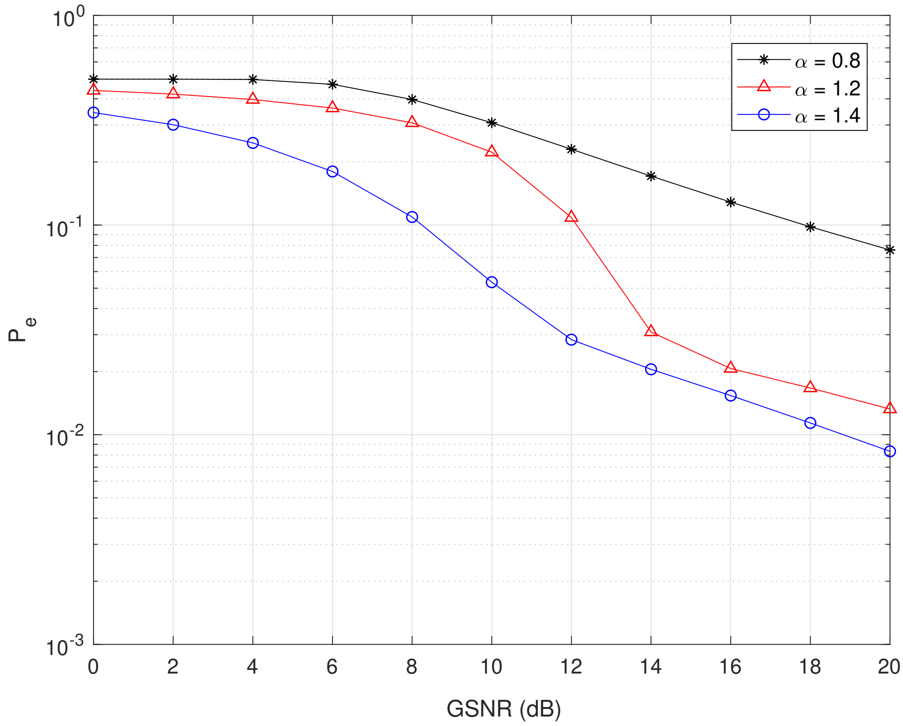

Figure 2.6 Probability of error for fixed β = 1 by tuning α

The effect of skewness on probability of error are investigated by tuning skewness for fixed characteristic exponent and tuning characteristic exponent for fixed skewness as shown in Figures 2.5 and 2.6, respectively. It is quite apparent that, probability of error gets worse when the stable noise becomes more skewed and / or more impulsive for fixed impulsiveness (Cek & Senturk, 2018).

It can be shown that the error performance can be improved at the receiver if the noise is converted to exhibit symmetric behaviour (Cek & Senturk, 2018). In addition to error probability, the receiver operating characteristics (ROC) gives a clue about how the skewness affects ROC curves which are shown in the next section.

2.3 Receiver Operating Characteristics

The receiver operating characteristic (ROC) is the graphical representation which gives relations between the true positive rate and false positive rate which corresponds to probability of detection (P_D) and probability of false alarm (P_{FA}), respectively in detection theory. The curve shows the relationship between P_D on x axis and P_{FA} on the y axis. The variation of P_D with respect to P_{FA} is essential to be analysed in order to exhibit the effect of both skewness and impulsiveness of the noise together. Before analysing the effect of skewness, the false alarm and detection probabilities are expressed by approximate analytical expressions given in Eq. (2.19) and Eq. (2.20), respectively.

$$P_{FA} = P\{T > 0; \mathcal{H}_0\} = \frac{1}{2\pi}\int_0^{\infty}\int_{-\infty}^{\infty}\varphi(\omega)e^{-j\omega(x+A)}d\omega dx \tag{2.19}$$

$$P_D = P\{T > 0; \mathcal{H}_1\} = \frac{1}{2\pi}\int_0^{\infty}\int_{-\infty}^{\infty}\varphi(\omega)e^{-j\omega(x-A)}d\omega dx \tag{2.20}$$

where T is the test statistic obtained from Neyman Pearson test (Kay, 1993). Before analysing the effect of skewness, the noise is assumed to have symmetric α-stable distribution (β=0).

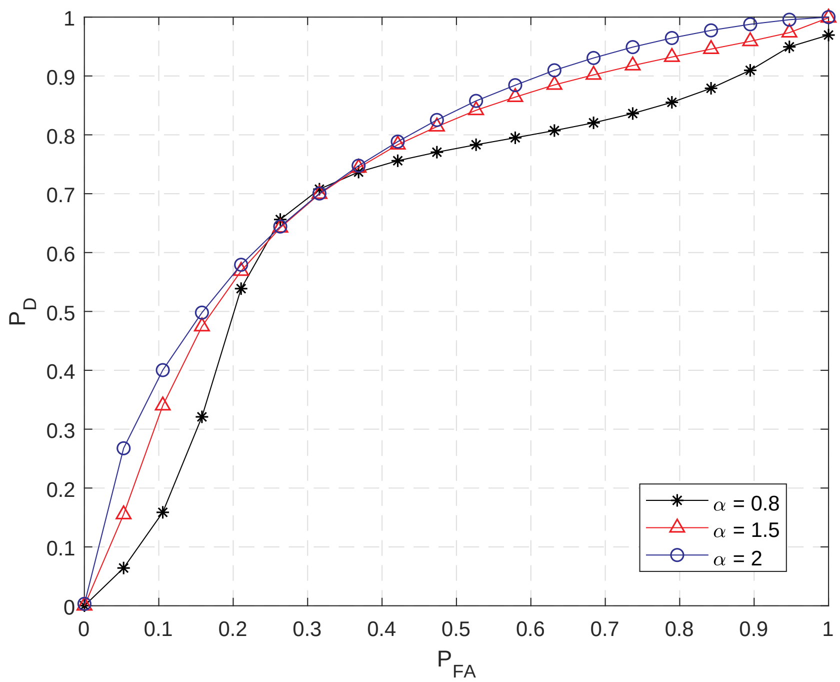

Figure 2.7 Variation of ROC characteristic with respect to different α values ($\beta = 0$)

The comparison of ROC curves including different characteristic exponent in terms of detection and false alarm probabilities are illustrated in Figure 2.7. It is clearly seen that when the impulsiveness of the noise is increased, i.e. α is decreased, the detection performance is poorer for fixed false alarm probability.

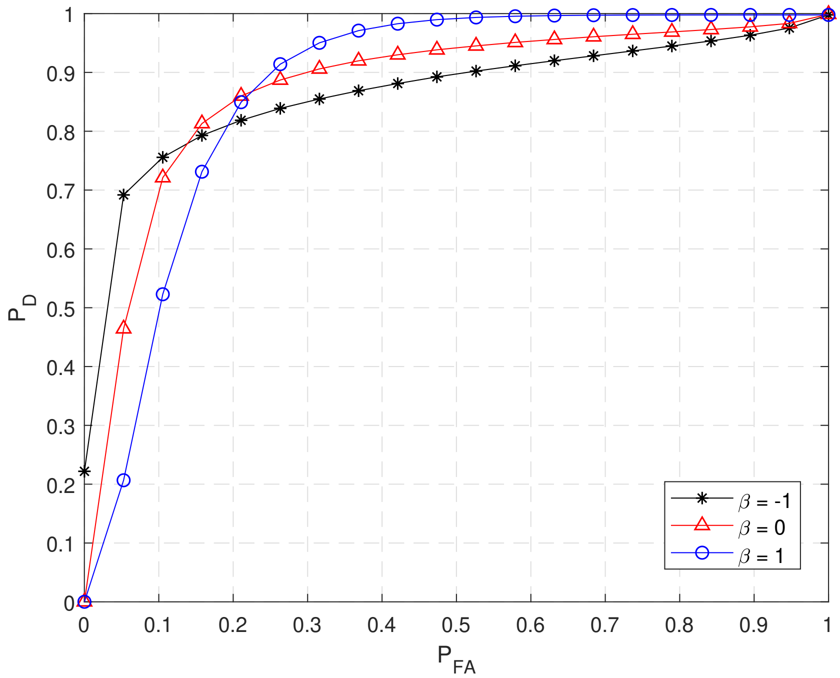

Figure 2.8 Variation of ROC characteristic with respect to different β values, (GSNR = 3 dB, α=1.5)

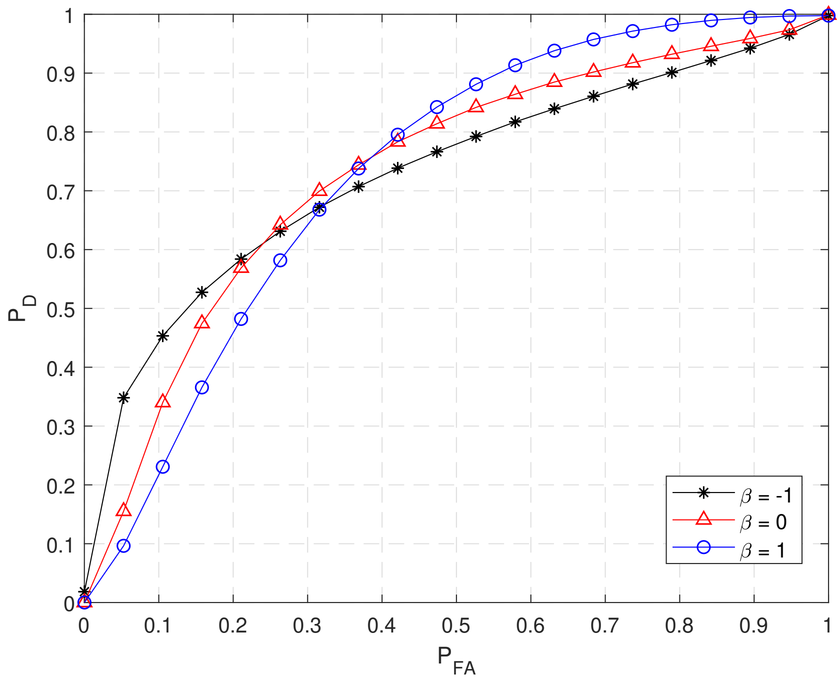

Figure 2.9 Variation of ROC characteristic with respect to different β values, (GSNR = -3 dB, α=1.5)

The investigation of ROC characteristics under skewed α-stable noise is shown in Figure 2.8 for fixed GSNR=3 dB and in Figure 2.9 for fixed GSNR=-3 dB, respectively. It is observed in both of plots that the detection performance alternates with respect the sign of the skewness and increasing false alarm probability. The negative skewness is observed to yield increased detection performance compared to both symmetrical and positive skewed stable noise whereas the detection performance becomes lowest when the false alarm probability is increased (Cek & Senturk, 2018).

Also, the effect of characteristic exponent and GSNR are illustrated in Figure 2.10 and Figure 2.11 for fixed skewness (β=1). It is obvious that detection probability increases with respect to false alarm probability when GSNR increases, as expected. When the noise exhibits more impulsive behaviour as shown in Figure 2.10 (α=0.8), the same behaviour is observed noting that the detection performance for the fixed false alarm rate decreases.

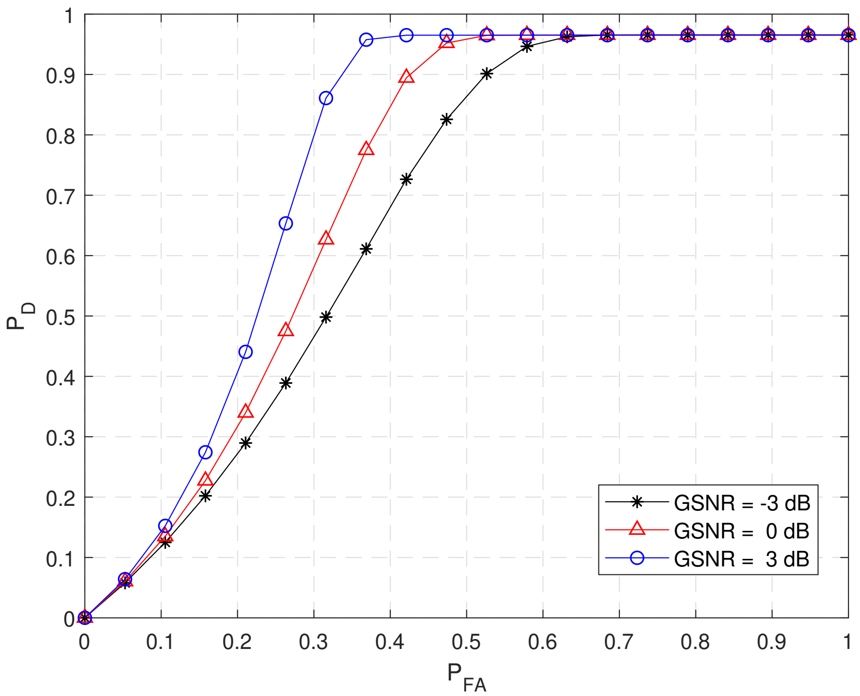

Figure 2.10 Variation of ROC characteristic with respect to different GSNR values (α = 0.8, β = 1)

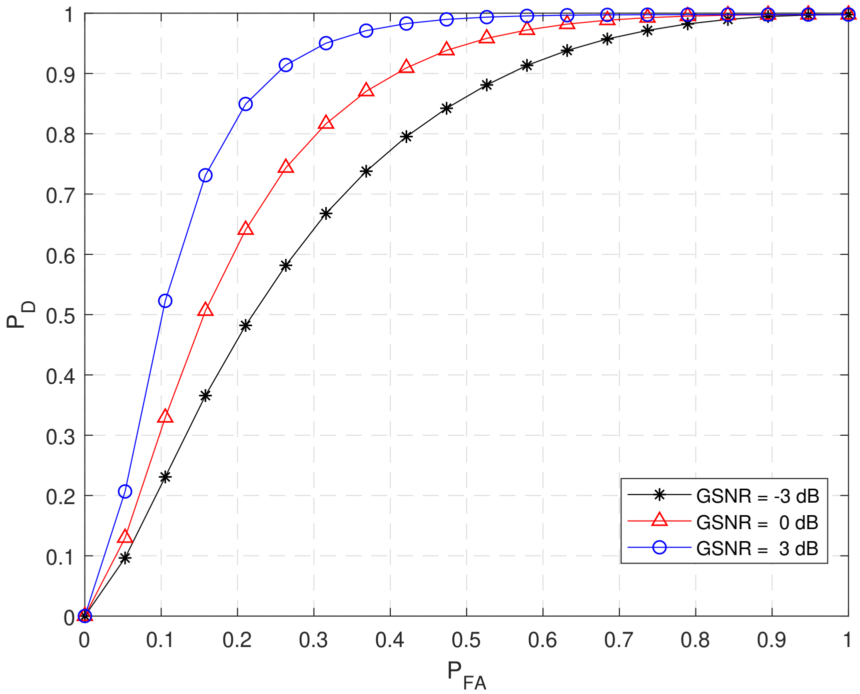

Figure 2.11 Variation of ROC characteristic with respect to different GSNR values ($\alpha = 1.5, \beta = 1$)

2.4 Stochastic Resonance in Skewed α-Stable Noise

Improvement on detection of deterministic signal provided by adding noise at an optimum intensity can be described as stochastic resonance phenomenon. In other words, stochastic resonance occurs when the random noise provides a better system performance in non-linear systems (Mcdonnell et al., 2008). In the literature, stochastic resonance is widely used to detect the weak signals. According to uncontrollable noise intensity, noise-induced stochastic resonance is in limited range in most applications, so the parameter-induced stochastic resonance is found in more study areas (Jiao et al., 2016, July).

At the receiver, intentional noise having different skewness is added to the channel noise exhibiting skewed impulsive distribution in order to achieve stochastic resonance, and improvement in receiver performance occurs when the asymmetry value of the added noise is in contrast to the asymmetry of the noise in the channel. The error performance becomes better when the impulsive noise is symmetric. In this case, intentional noise should be designed to bring total symmetry to zero.

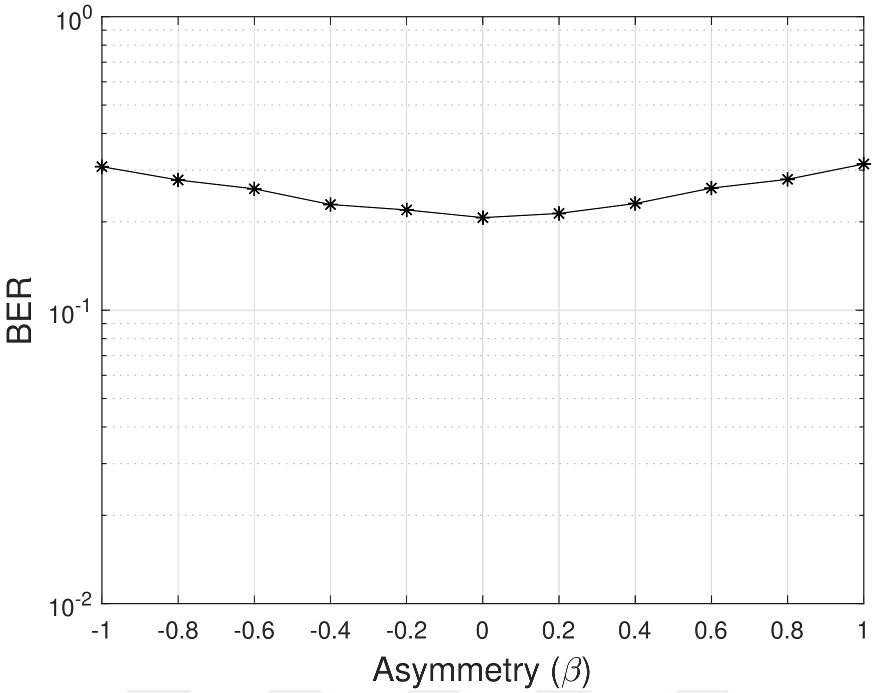

Figure 2.12 Bit error rate performance change according to β parameter (α = 1.4)

The error performance becomes better when the impulsive noise is symmetric so, intentional noise should be designed to bring the total symmetry to zero. Figure 2.12 shows the receiver performance which becomes better when the impulsive noise is symmetric. The BER performance improvement increases if impulsiveness decreases but the effect of β is more apparent when the impulsiveness increases.

By adding intentional noise components with the same characteristic exponent which has distribution $w_m[.] \sim S_\alpha(\alpha, \beta_m, \sigma_m, 0; x)$ the signal in the receiver is obtained as follows

$$r[n] = s[n] + w[n] + w_m[n]. \tag{2.21}$$

The noise is $w_r[n] = w[n] + w_m[n]$ obtained as a result of the above equation and the asymmetry and scaling values of the noise $w_r[.] \sim S_\alpha(\alpha, \beta_r, \sigma_r, 0; x)$ are given in Eq. (2.22)

$$\beta_r = \frac{\beta\sigma^\alpha + \beta_m\sigma_m^\alpha}{\sigma^\alpha + \sigma_m^\alpha}, \qquad \sigma_r = (\sigma^\alpha + \sigma_m^\alpha)^{\frac{1}{\alpha}}. \tag{2.22}$$

This situation corresponds physically to the stochastic resonance event and it is determined that the performance reaches the best value in combination of the asymmetry parameter and noise intensity that provides resonance. It is proposed to add intentional noise at the receiver having opposite skewness to increase the receiver performance.

BER performance improvement using stochastic resonance is given in Section 3.5 where robust estimators are utilized.

CHAPTER THREE
SIGNAL DETECTION USING ROBUST ESTIMATORS

Basically, digital communication systems consist of three main sections: channel, transmitter and receiver. The transmitter transmits the message generated by the information source over the channel. At this point, the signal is disrupted due to undesirable conditions in the channel and transmitted to the receiver. The receiver has the task of working to create the original signal by various methods (Haykin, 2014). Typical digital communication scheme is given in Figure 3.1. Since source encoding and channel encoding are not concentrated on this study, raw binary information is considered to transmit the baseband and/or bandpass message.

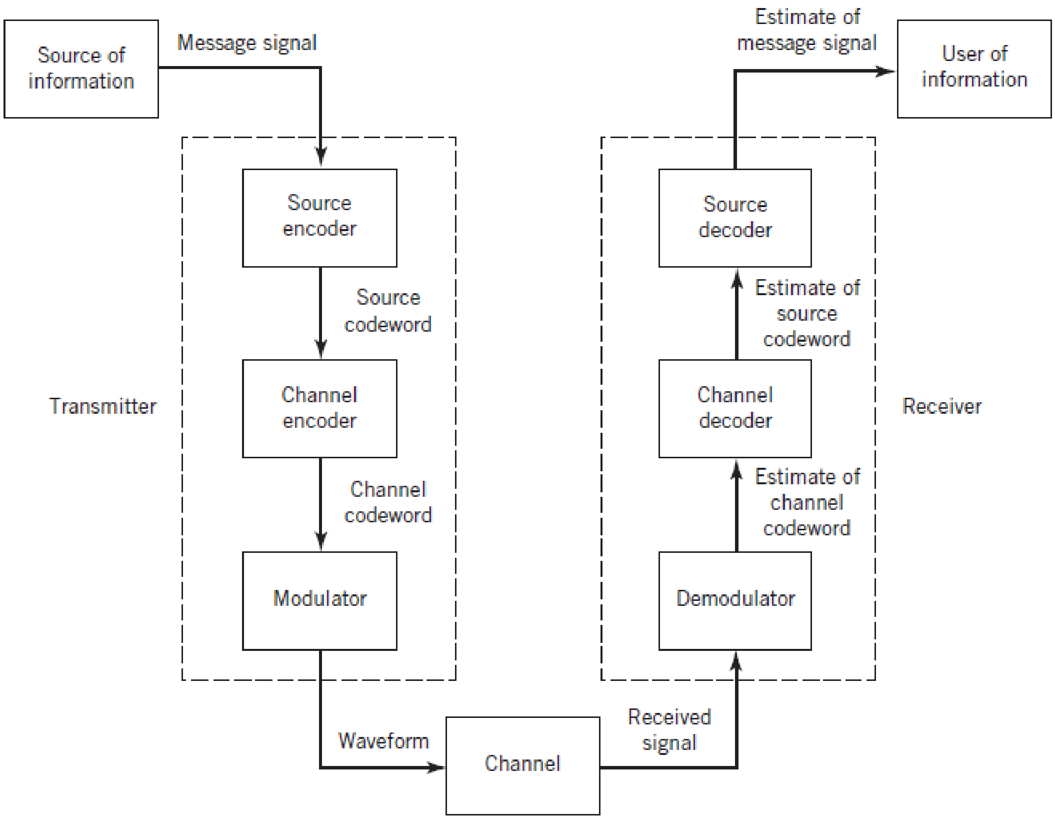

Figure 3.1 Block diagram of a typical digital communication system (Haykin, 2014)

Communication system can be characterized as baseband and bandpass with respect to modelling based on unmodulated and modulated signal, respectively. If no modulation is applied to transmit the signal, it is called a baseband system, and if it is moved to a higher frequency band than the frequency band it is in, it can be called a bandpass system. In baseband system, no frequency shifting is needed to transmit signal.

Digital modulation is the process of converting a bit stream into a waveform for transmission over a specific channel. Digital modulation techniques are required for wireless communication and provide higher information capacity, security and quality compared to analog communication systems.

Phase Shift Keying (PSK) is one of the digital modulation techniques. This technique is used to transmit data by changing phase of the reference signal which has constant frequency. PSK is more robust to additive noise than the Amplitude Shift Keying (ASK). ASK uses symbols with different amplitudes and is sensitive to additional noise. On the other hand, PSK is much more bandwidth efficient than Frequency Shift Keying (FSK) because different FSK uses different frequency symbols that are not bandwidth efficient. The simplest modulation waveform can be expressed as binary PSK which corresponds to transmitting and receiving antipodal waveforms.

3.1 Coherent and Non-Coherent Systems

A digital communication system can be classified with detection techniques. If there is a phase information for transmitted carrier at the receiver, the system is expressed as coherent. This system employs coherent detection, and both frequency and phase are synchronized and it is also known as synchronous detection. Generally coherent system includes phase recovery circuit which provides reproducing the transmitted signal. Unlike coherent systems, non-coherent systems do not require phase information and synchronism is not needed for this type of systems.

The creation of demodulation carrier for coherent systems can be done using various techniques. The use of these techniques complicates the design of the receiver. If system is non coherent, it becomes simpler to design when compared to coherent systems but error probability becomes worse.

3.2 Differential Binary Phase Shift Keying (DBPSK)

Binary data in typical BPSK system are represented with two different phases and signals. These signals $s_1(t)$ and $s_2(t)$ are expressed as in Eq. (3.1) with phases 0 and π,

$$\begin{aligned} s_1(t) &= \quad Acos(2\pi f_c t), \qquad 0 \le t \le T \\ s_2(t) &= -Acos(2\pi f_c t), \qquad 0 \le t \le T \end{aligned} \tag{3.1}$$

where A is the amplitude, f_c is the carrier frequency, and T is the signal duration. Typical BPSK waveform, modulator and demodulator are given in Figures 3.2, 3.3 and 3.4 respectively.

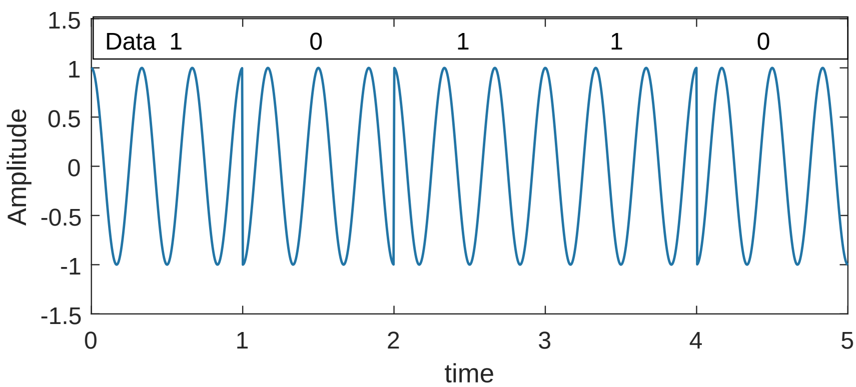

Figure 3.2 Typical BPSK waveform

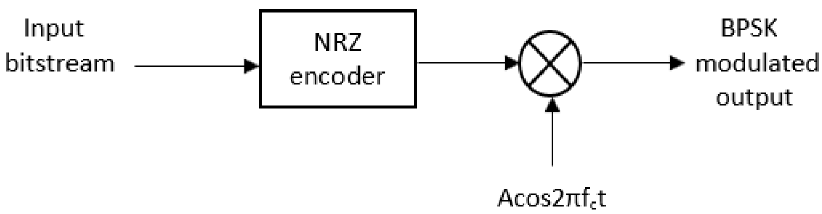

Figure 3.3 Diagram of BPSK modulator

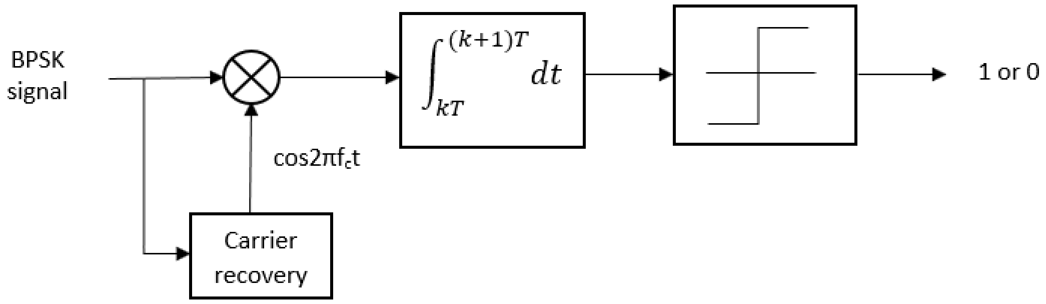

Figure 3.4 Diagram of BPSK coherent demodulator

Non-coherent detection does not require phase information, so DBPSK system can be demodulated non-coherently. In DBPSK system, input bits are first differentially encoded and modulated with BPSK modulator. Received signal $r(t)$ can be non coherently demodulated after differentially decoding. Regarding to unknown phase, it can be assumed that $x_1(t)$ and $x_2(t)$ are orthogonal and have the same energy (Haykin, 2014) which are phase shifted versions of transmitted signal $s_1(t)$ and $s_2(t)$, respectively. Received signal can be expressed as,

$$r(t) = \begin{cases} x_1(t), & s_1(t) \text{ transmitted for } 0 \le t \le T \\ x_2(t), & s_2(t) \text{ transmitted for } 0 \le t \le T. \end{cases} \tag{3.2}$$

Block diagrams for DBPSK modulator and demodulator are given in Figures 3.5 and 3.6, respectively.

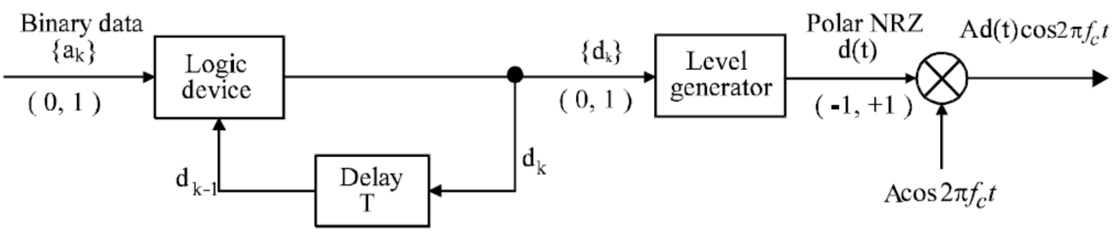

Figure 3.5 Block diagram of DBPSK modulator (Xiong, 2006)

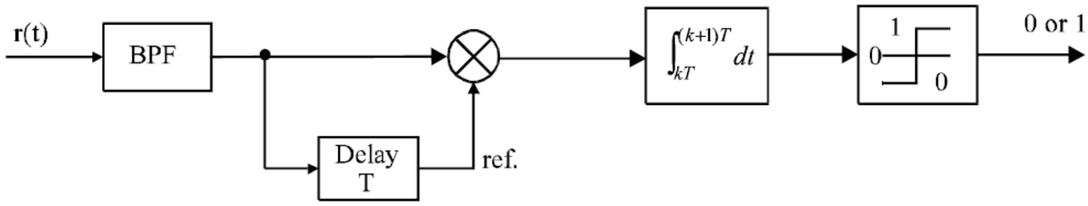

Figure 3.6 Block diagram of DBPSK demodulator (Xiong, 2006)

The proposed communication system in this thesis can be considered as analogous to modified DBPSK. Non-coherent detection used at the receiver causes the effect of the proposed skewed α - stable noise suppression to be more apparent since the reference and the information bearing signals are both affected by the channel noise.

3.3 Robust Estimator Types

Robust estimators, also known as M estimators, were originally developed in the theory of robust statistics which are the class of maximum-likelihood (ML) type estimators and these estimators have significant place among the robust signal processing techniques (Aysal & Barner, 2007). Robust non-linear estimators have critical importance for applications involving impulsive processes (e.g., communications systems, switching systems, biomedical signal processing radar clutter, ocean acoustic noise as mentioned before) as heavy tailed non-Gaussian distributions are utilized in order to model the underlying signals (Zoubir et al., 2012).

The set of samples are given as $X_1, X_2 \ldots, X_N$ is given as a robust estimator of location parameter θ which minimizes the Eq. (3.3)

$$\hat{\theta} = \arg\min \sum_{i=1}^{N} \rho(X_i - \theta) \tag{3.3}$$

where ρ is defined as a cost function (Arce, 2005). The shape of ρ determines the behaviour of estimator. The θ value can be examined for some special function of $\rho(x)$, especially to define the robust estimators. If cost function is equal to $\rho(x) = |x|$, that refers to sample median and if $\rho(x) = log[k^2 + x^2]$, where k is the linearity parameter, in this case equality is called as sample myriad. The shaping $\rho(x)$ is the significant point for the success of robust estimators and directly affects estimation accuracy (Arce, 2005).

Let a set of N independent samples $X_1, X_2, \ldots, X_n, \ldots, X_N$ and each one has the Gaussian distribution with variance σ^2. Be given as $\hat{\theta}$ is the ML estimation of location and can be obtained as (Arce, 2005),

$$\begin{aligned} \hat{\theta} &= \arg\min \sum_{i=1}^{N} (X_i - \theta) \\ &= \frac{1}{N} \sum_{i=1}^{N} X_i \\ &= mean\{X_i\}. \end{aligned} \tag{3.4}$$

It can be seen that sample mean process yields ML estimation from observations. Three types of robust estimators which are median, meridian and myriad estimators are described respectively in the next part.

3.3.1 Median Estimator

Median filter is moving along the horizontal axis by a symmetrical window on a discrete time signal $x[n]$. The filter takes an equal number of data from both left and right sides and sorts the data from the smallest to the largest. Then, the middle value becomes filter output (Arce, 2005). For this, the filter creates a fixed length window vector which determines the observation interval. The observation window centred at n is given as,

$$x[n] = [x[n - M_l], \ldots, x[n + M_r]] \tag{3.5}$$

The window may generally be come across as symmetric about $x[n]$ which corresponds to right window length M_r and left window length M_l to be equal to each other. The total window size becomes $M_l + M_r + 1$. Since the window is mostly assumed to be symmetric $M_l = M_r = M_1$ and the filter output is given as,

$$y_{med}[n] = MEDIAN\Big(x\Big[n - M_1\Big], \ldots, x\Big[n + M_1\Big]\Big). \tag{3.6}$$

3.3.2 Meridian Estimator

Meridian filter is derived by ML estimation under Cauchy distribution spacial case of Generalized Cauchy Distribution corresponding to $\lambda = 1$ where λ is the tail parameter, and the cost function is equal to $log(\delta + |u|)$. δ is the robustness parameter because the meridian filter is likelihood based and has an exact result about being unbiased, consistent and efficient in meridian statistic (Aysal & Barner, 2007).

Consider a set of M samples $x[n - M_1], \cdots, x[n], \cdots, x[n + M_1]$ each obeying the Meridian distribution. The ML estimate of location, η, or sample meridian filter is given as,

$$\begin{aligned} y_{mer}[n] &= MERIDIAN\Big(\Delta; x\Big[n - M_1\Big], \ldots, x\Big[n + M_1\Big]\Big) \\ &= arg \quad \min_{\eta \in R} \sum_{i=n-M_1}^{n+M_1} \log[\Delta + |x[i] - \eta|] \end{aligned} \tag{3.7}$$

where Δ is referred as the medianity parameter which determines the behaviour of filter and is also a tunable parameter. Under impulsive noise, if medianity parameter takes small values, the filter becomes more robust (Pander & Przybyla, 2012).

3.3.3 Myriad Estimator

The myriad filter can be defined as a ML estimation of location which is derived from the stable model having a cost function which can be represented as $\log[K^2 + X^2]$ where K is a tunable parameter which decides the behaviour of filter. The myriad filter properly exhibits optimally properties in several impulsive models (Arce, 2005). It provides highly efficient filtering under non-Gaussian noise, especially for α-stable distributed noise. Myriad filter is derived by ML estimation including special case of Cauchy distribution as meridian filter corresponding to $\lambda = 2$ (tail parameter).

Consider a set of M samples $x[n]$ which are identically distributed and independent with a fixed positive (tunable) value of K, and the output of the myriad filter is given as,

$$\begin{aligned} y_{myr}[n] &= MYRIAD\Big(K; x\big[n - M_1\big], \ldots, x\big[n + M_1\big]\Big) \\ &= arg \quad \min_{\rho \in R} \sum_{i=n-M_1}^{n+M_1} \log[K^2 + (x[i] - \rho)^2] \end{aligned} \tag{3.8}$$

where ρ is the location parameter and K is referred to as linearity parameter. K is adjustable for α-stable distribution and the relation between α and K is given as (Arce, 2005),

$$K = \sqrt{\frac{\alpha}{2 - \alpha}} \tag{3.9}$$

When K has an infinite value, the myriad is transformed into the sample average. When K becomes closer to zero, the myriad has good efficiency on very impulsive noise compared to other filters. Figure 3.7 shows the filter behaviour according to the K parameter and Figure 3.8 shows the K parameter change for α-stable distributions.

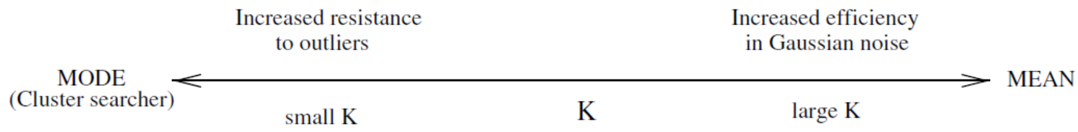

Figure 3.7 Behaviour of myriad filter with respect to the K parameter (Barner & Arce, 2003)

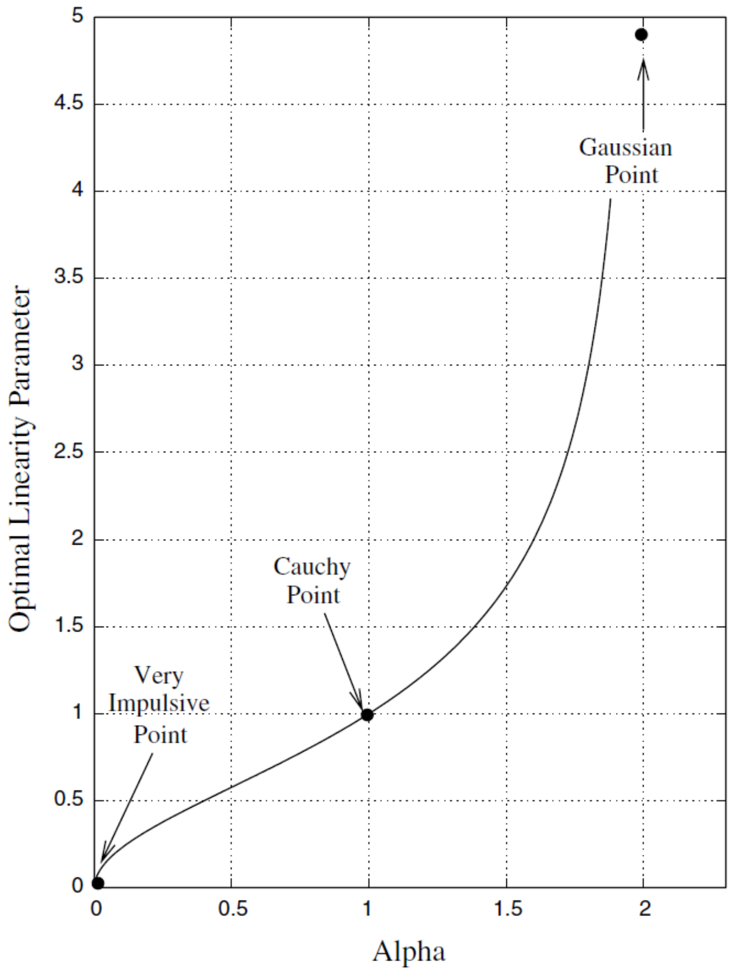

Figure 3.8 Change of K parameter for α-stable distributions (Barner & Arce, 2003)

Figure 3.9 shows the time domain filtered signal. It is observed that the robust estimation techniques such as median filtering, myriad filtering and meridian filtering give a certain noise reduction performance under α-stable distributed noise.

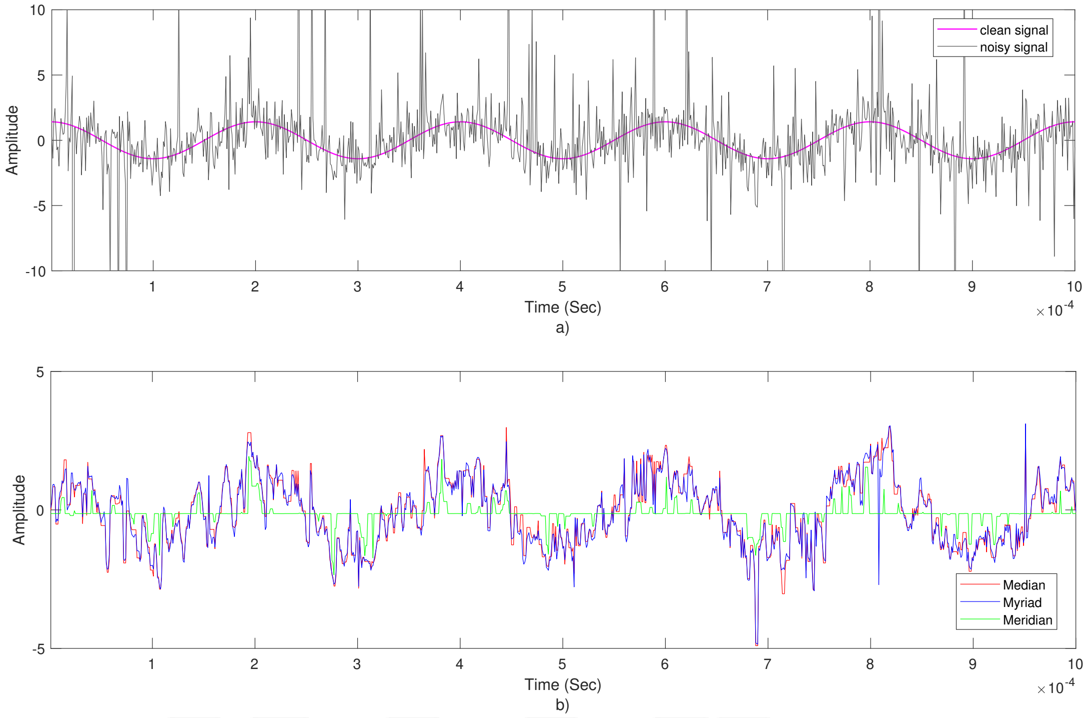

Figure 3.9 Time domain filtered signal under impulsive noise (α = 1.4) a) Clean and noisy signals b) Filtered signals using robust estimators

3.4 Computation of Myriad Value

One of main problems in myriad filter analysis is to reduce the computational effort and achieve the result with minimum divergence from actual value. In this context, most of the algorithms, such as fixed-point search (Kalluri & Arce, 2000), polynomial approximation (Pander, 2010), branch and bound search (Nunez et al., 2008) and fast myriad algorithm (Yue et al., 2013) use the batch processing method to compute the myriad value. The common method for computing sample myriad filter is the fixed-point search algorithm which minimizes the cost function computing fixed points (Goh & Lim, 2012). In fixed-point method, when estimation is performed, delays can occur depending on the input block size and computational complexity increases according to repeated process for each window. Some methods such as sequential myriad algorithm (Goh & Lim, 2012) and exponential myriad smoothing method (Goh et al., 2017) are developed to decrease those types of effects, increase efficiency in computation.

3.4.1 Grid Search Algorithm

In this method no window exist and it is used for single value estimation. This method requires taking more point from input and only returns one value. The window length M equals 1 and length of ρ equals N. The output of the algorithm can be expressed as,

$$\hat{\rho} = \sum_{i=1}^{N} \log[K^2 + (x(i) - \rho(i))^2]. \tag{3.10}$$

After this calculation, the index of minimum value of summation is found and and it is searched in vector ρ to find the output value. It is a basic grid search algorithm to compute the myriad value.

3.4.2 Sequential Algorithm

Sequential algorithm is a fast algorithm when compared to other methods. Let a set of n independent observations be given as $x_1, x_2, \ldots, x_n, \ldots, x_n$, output of the sample myriad $\rho[n]$ is found solving the following equation which is the derivative of Eq. (3.8). It is the most conventional method (Goh & Lim, 2012).

$$\sum_{i=1}^{N} \frac{x_i - \rho}{K^2 + (x_i - \rho)^2} = 0 \tag{3.11}$$

Solving the previous equation is not needed for sequential algorithm. The aim of the sequential algorithm is the updating $\hat{\rho}[n]$ to find the next value $\hat{\rho}[n+1]$. Sequential sample myriad includes an iterative approach and the performance of this algorithm is measured with respect to rate of convergence.

Calculation steps of sequential algorithm are given below (Goh & Lim, 2012), Step 1: Calculate the gradient just once which is derived in (Goh & Lim, 2012),

$$\hat{J}[n] = \sum_{i=1}^{n} \frac{-K^2 + (x_i - \hat{\rho}[n-1])^2}{[K^2 + (x_i - \hat{\rho}[n-1])^2]^2}. \tag{3.12}$$

Step 2: Update the gradient $\hat{J}[n+1]$,

$$\hat{J}[n+1] = \hat{J}[n] + \frac{-K^2 + (x_{i+1} - \hat{\rho}[n])^2}{[K^2 + (x_{i+1} - \hat{\rho}[n])^2]^2}. \tag{3.13}$$

Step 3: Find the updated value $\hat{\rho}[n+1]$,

$$\hat{\rho}[n+1] = \hat{\rho}[n] - (\hat{J}[n+1])^{-1} \frac{x_{i+1} - \hat{\rho}[n]}{K^2 + (x_{i+1} - \hat{\rho}[n])^2}. \tag{3.14}$$

The initial value $\hat{\rho}[0]$ can be calculated minimizing the objective function for the input samples (Barner & Arce, 2003). Using this algorithm simulation can be performed. Figure 3.10 shows the convergence of myriad value.

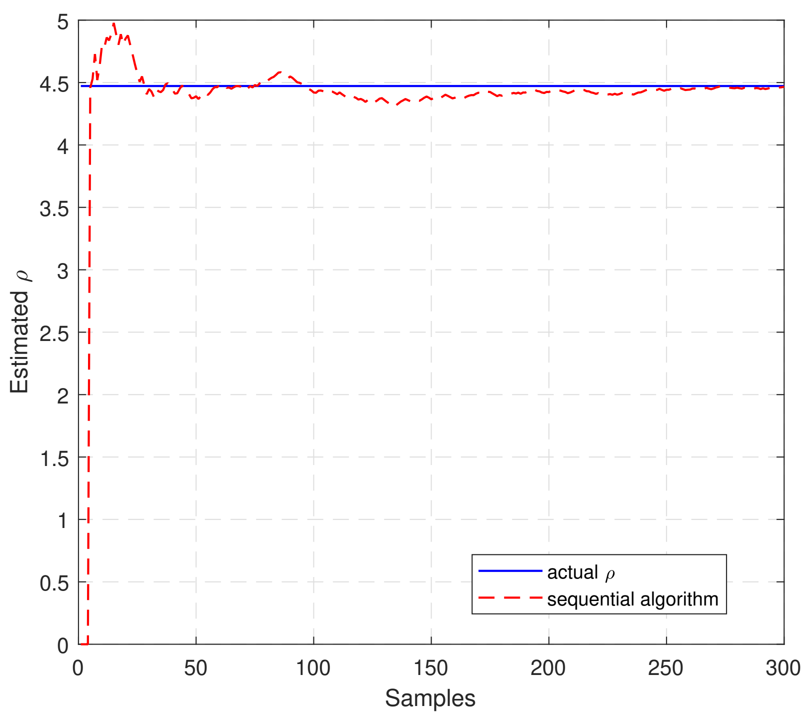

Figure 3.10 Convergence of myriad value according to the sequential algorithm

3.5 Stochastic Resonance in Robust Estimation

Stochastic resonance in skewed alpha stable distributed noise is described in Section 2.4. In this section, intentional noise having the same characteristic exponent with channel noise is added at the receiver input and then robust estimation is applied to reduce the impulsive noise. Main difference is that intentional noise has the opposite skewness compared with channel noise. According to Figure 3.11 lowest BER value is observed to be achieved when the noise is symmetric in absence of intentional noise.

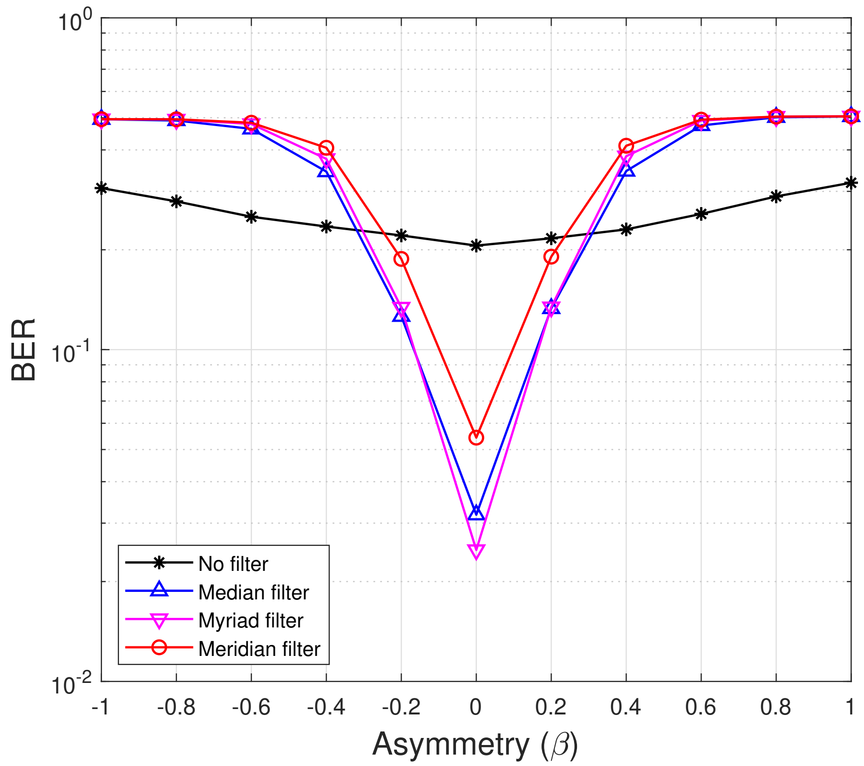

Figure 3.11 BER performance change according to the β parameter (α = 1.4)

Simulations are performed over antipodal signals which corresponds to binary phase shift keying (BPSK) modulated signal. Antipodal signalling is formulated in Section 2.2. This can be considered as indicator of necessity of adding intentional noise to symmetrize the resultant noise distribution. Monte Carlo simulation is performed over 10^4 bits and ensemble averaging of 10 realizations. Sliding window has identical right and left window length and the total window length is taken as N=9 samples for robust filters.

In Figures 3.12, 3.13 and 3.14 sample median, meridian, and myriad filters are used respectively with fixed noise intensity for intentional noise. Bit error rate improvement is shown in 3-D plots depending on the changing asymmetry and GSNR in receiver when the asymmetry value of the intentional noise is in opposite direction to the asymmetry of the noise in the channel. The asymmetry value of skewed α -stable distributed noise is $\beta = 0.5$ and it is expected that the BER performance reaches the best value if asymmetry parameter of intentional noise is equal to $\beta = -0.5$.

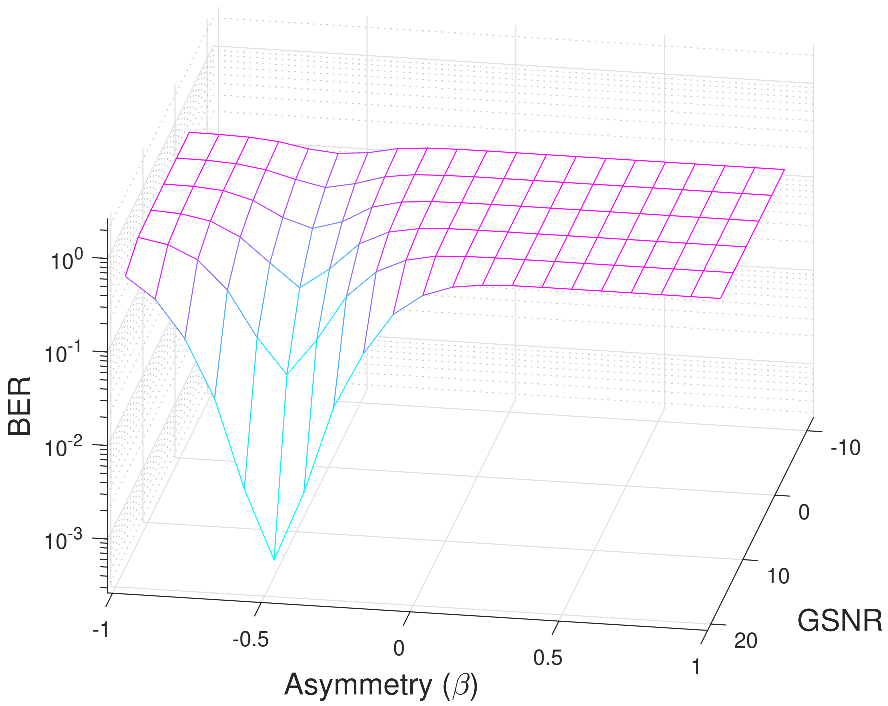

Figure 3.12 BER performance with respect to the parameters β - GSNR using median filter (α = 1.2)

As shown in Figures 3.12 through 3.14, there is a valley corresponding to the opposite skewness of the channel noise when the intentional noise having this opposite skewness is added. Therefore this performance enhancement due to noise addition is the contribution of stochastic resonance. The point to be noted is that as the total intensity of the intentional noise and channel noise increase, the resonance is weakened due to the GSNR value. Although the resonance is observed more clearly under high impulsiveness, the bit error rate performance becomes worse.

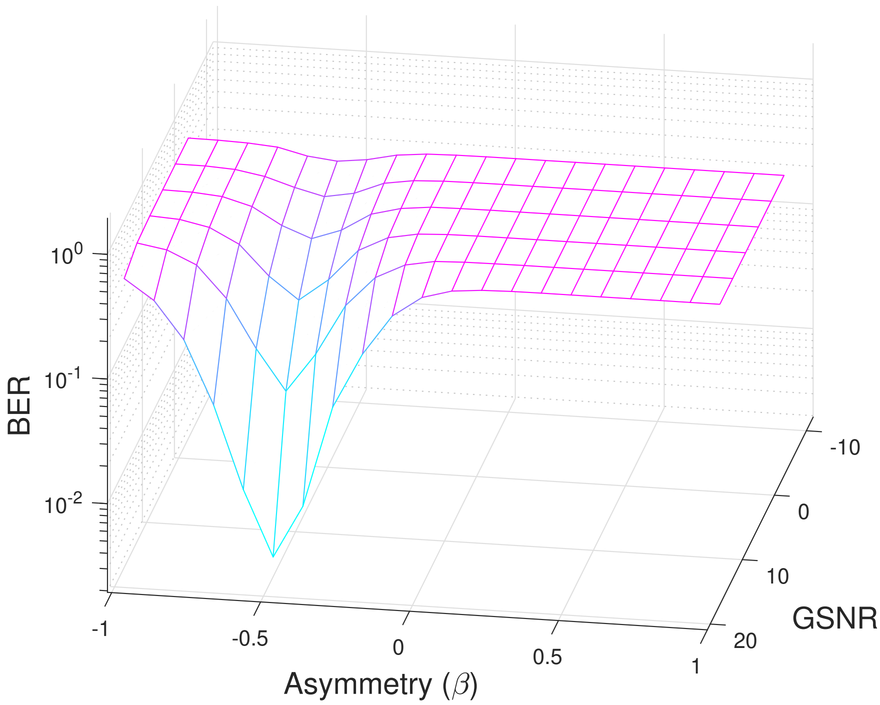

Figure 3.13 BER performance with respect to the parameters β - GSNR using meridian filter (α = 1.2)

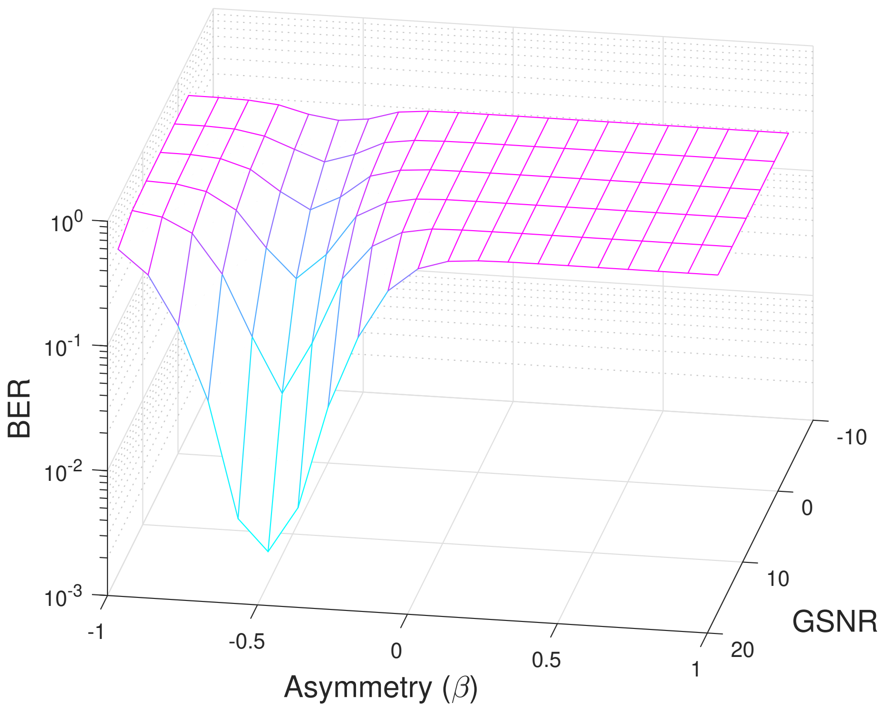

Figure 3.14 BER performance with respect to the parameters β - GSNR using myriad filter (α = 1.2)

3.6 Signal Estimation in Baseband Communication System

The differentially encoded baseband transmitter, carrying binary message $\{-1,+1\}$, can be expressed as in Eq. (3.15),

$$s[n] = \begin{cases} A, & n = 1,\cdots,N/2 \\ b.A, & n = N/2+1,\cdots,N \end{cases} \tag{3.15}$$

where A is the signal amplitude and $A > 0$, N is the symbol duration. The received signal under AWGN at time instant n is given as,

$$r[n] = s[n] + w[n]. \tag{3.16}$$

Message bits are estimated by non-coherent conventional correlator receiver under Gaussian noise as in Eq. (3.17),

$$\hat{b} = sgn\left(\sum_{n=1}^{N/2} r[n]r[n+N/2]\right) \tag{3.17}$$

where

$$sgn = \begin{cases} 1, & x \geq 0 \\ -1, & x < 0 \end{cases} \tag{3.18}$$

and the formulation of proposed robust estimation for baseband system is given below.

The reference signal s_{ref} in proposed transmitter is defined as,

$$s_{ref}[n] = \begin{cases} A, & n = 1,\cdots,N/4 \\ -A, & n = N/4+1,\cdots,N/2 \end{cases} \tag{3.19}$$

and the proposed transmitted signal $s_p[n]$ is given as in Eq. (3.20),

$$s_p[n] = \begin{cases} s_{ref}[n], & n = 1, \cdots, N/2 \\ b.s_{ref}[n - \frac{N}{2}], & n = N/2+1, \cdots, N. \end{cases} \tag{3.20}$$

Received signal $r_p[n]$ under α-stable distributed noise $w_s[n]$ is obtained as in Eq. (3.21),

$$r_p[n] = s_p[n] + w_s[n]. \tag{3.21}$$

According to the skewness property of stable random variables, noise samples $-w_s[n]$ have the probability density $S(x;\alpha,-\beta,\sigma,\mu)$, i.e., multiplying by -1 provides opposite skewness (Samoradnitsky & Taqqu, 1994). Using this property, the received signal $r_p[n]$ is modified to result in a signal $\hat{r}[n]$ as given in Eq. (3.22) whose resultant skewness is estimated to be $\beta = 0$ between intervals $1 \le n \le N/2$ and $N/2+1 \le n \le N$,

$$\hat{r}[n] = \begin{cases} r_p[n] = A + w_s[n], & n = 1, \cdots, \frac{N}{4} \\ -r_p[n] = A - w_s[n], & n = \frac{N}{4}+1, \cdots, \frac{N}{2} \\ r_p[n] = b.A + w_s[n], & n = \frac{N}{2}+1, \cdots, \frac{3N}{4} \\ -r_p[n] = b.A - w_s[n], & n = \frac{3N}{4}+1, \cdots, N. \end{cases} \tag{3.22}$$

A sample realization of skewed stable noise whose pdf parameters are tuned to be $\alpha = 1.5, \beta = 1$, $\sigma = 1$ for the first 10^4 samples and $\alpha = 1.5, \beta = -1$, $\sigma = 1$ for the second 10^4 samples is illustrated in Figure 3.15a to exhibit the opposite skewed behaviour of the noise in time domain ($A = 0$). The estimated pdf from the data according to the method given in (Koutrouvelis, 1981) is shown in Figure 3.15b for the first half, second half and the whole data, respectively. It is clearly seen that the resultant pdf is almost symmetric.

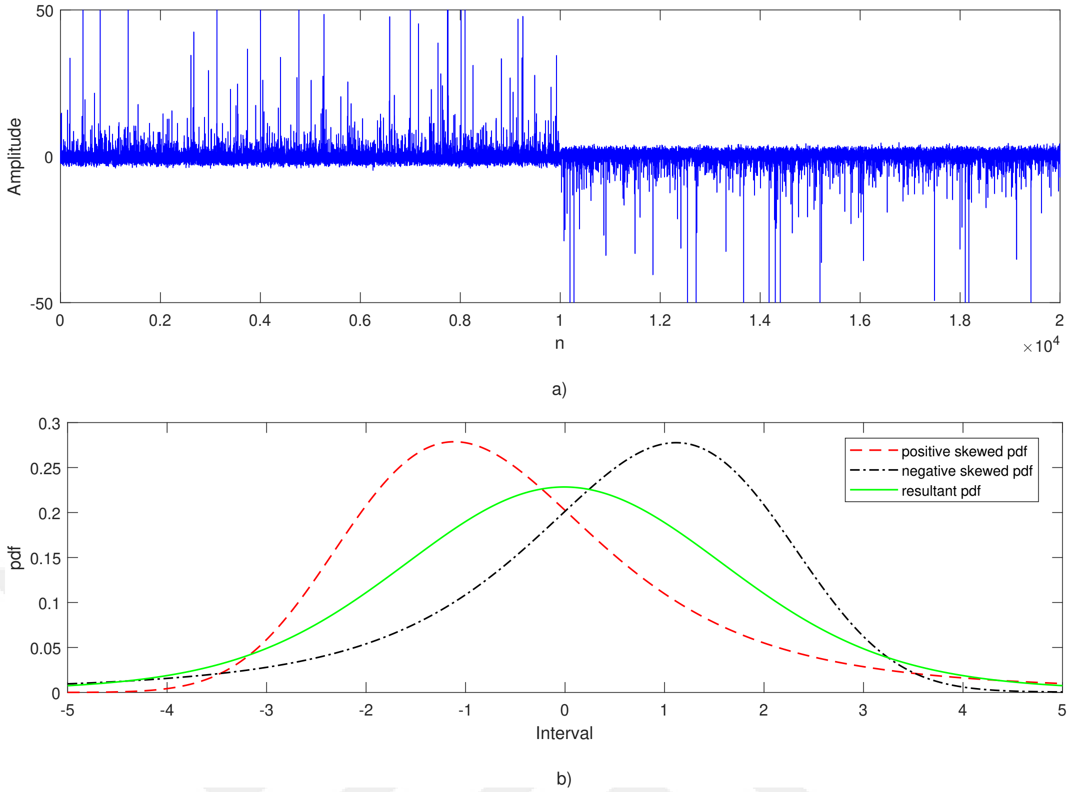

Figure 3.15 a) The first half part of the received signal in Eq. (3.22) b) Estimated positive and negative skewed noise together with resultant pdf

The median filter is separately applied to the first and the second half of $\hat{r}[n]$ to estimate the reference and information bearing components $\hat{A}_{med}$ and $b\hat{A}_{med}$ as given in Eq. (3.23) and Eq. (3.24), respectively.

$$\hat{A}_{med} = MEDIAN(\tilde{r}[n]; n = 1, \cdots, \frac{N}{2}) \tag{3.23}$$

$$b\hat{A}_{med} = MEDIAN(\tilde{r}[n]; n = \frac{N}{2} + 1, \cdots, N) \tag{3.24}$$

Similarly, myriad filter is applied to find the reference and the information bearing part of the baseband signal as given in Eq. (3.25) and Eq. (3.26)

$$\hat{A}_{myr} = MYRIAD(\tilde{r}[n], K; n = 1, \cdots, \frac{N}{2}) \tag{3.25}$$

$$b\hat{A}_{myr} = MYRIAD(\tilde{r}[n], K; n = \frac{N}{2} + 1, \cdots, N). \tag{3.26}$$

The median and myriad estimated message bits $\hat{b}_{med}$ and $\hat{b}_{myr}$ are determined from the filter outputs as given in Eq. (3.27) and Eq. (3.28)

$$\hat{b}_{med} = sgn(\hat{A}_{med}.\hat{bA}_{med}) \tag{3.27}$$

$$\hat{b}_{myr} = sgn(\hat{A}_{myr}.\hat{bA}_{myr}). \tag{3.28}$$

Once the received signal is modified to obtain $\hat{r}[n]$ in Eq. (3.22), robust filters can be applied to the first half and the second half of the data holding reference and information signals, respectively.

3.7 Signal Estimation in Bandpass Communication System

Modified DBPSK modulated signal is used for both baseband and bandpass systems and robust estimation is applied for both systems in this thesis. For the bandpass domain, $s[n]$ is the constant envelope discrete time sinusoidal carrier which has sampling interval T_s and bit duration T_b as given below

$$s[n] = Acos(2\pi f_c \frac{n}{T_s}) \tag{3.29}$$

where $n = 1, \cdots, \frac{T_b}{T_s} = N$, A is the signal amplitude and f_c is the carrier frequency. Transmitted signal s_T for message bit $b \in \{-1, +1\}$ is formulated as,

$$s_T[n] = \begin{cases} s[n], & n = 1, \cdots, N/2 \\ s_b[n], & n = N/2+1, \cdots, N \end{cases} \tag{3.30}$$

where $s_b[n]$ is equal to $b.s[n]$ and the first half of the carrier signal refers to reference signal and contains the first $N/2$ number of samples. The second half of the carrier signal refers to the information bearing signal i.e., binary encoded message. Previously, alpha stable distributed noise was defined and represented by

$w[.] \sim S(.,\alpha,\beta,\sigma,0)$. Received signal under additive non-Gaussian noise at time instant n is given as,

$$r[n] = s_T[n] + w[n]. \tag{3.31}$$

Using conventional correlator receiver, the message bit is estimated at the receiver side and the estimated message bit $\hat{b}$ is given as,

$$\hat{b} = sgn\left(\sum_{n=1}^{N/2} r[n]r[n+N/2]\right). \tag{3.32}$$

The formulation of the proposed robust estimation for bandpass system is given below.

The carrier signal which has length $K = \frac{T_c}{T_s}$ samples for each $T_c = \frac{1}{f_c}$ period. Let L be the number of sinusoids in the reference signal which is the first half of the carrier signal having duration $\frac{T_b}{2}$ with $\frac{N}{2} = L.K$ samples. The receiver structure which is proposed to generate the new signal $\tilde{s}[n]$ by modifying the transmitted sinusoidal signal $s[n]$ is given as,

$$\tilde{s}[n] = \begin{cases} s[n], & (l-1).K + 1 \le n < \left(l - \frac{1}{2}\right).K \\ -s[n], & \left(l - \frac{1}{2}\right).K + 1 \le n < l.K \end{cases} \tag{3.33}$$

where $l = 1, \cdots, L$. In the same way, the information bearing signal which is the second half of the transmitted signal $s_b[n]$ is modified to obtain $\tilde{s}_b[n]$ as given in Eq. (3.34),

$$\tilde{s}_b[n] = \begin{cases} s_b[n], & \frac{N}{2} + (l-1).K + 1 \le n < \left(l - \frac{1}{2}\right).K + \frac{N}{2} \\ -s_b[n], & \frac{N}{2} + \left(l - \frac{1}{2}\right).K + 1 \le n < l.K + \frac{N}{2}. \end{cases} \tag{3.34}$$

The transmitted signal has two parts as reference signal and information bearing signal. The received signal $r[n]$ also contains the same parts $r_{ref}[n]$ and $r_b[n]$, respectively, and is given as,

$$r[n] = \begin{cases} r_{ref}[n], & n = 1, \cdots, N/2 \\ r_b[n], & n = N/2+1, \cdots, N. \end{cases} \tag{3.35}$$

The transmitted signal is corrupted by additive alpha stable distributed noise and the modified received signal $\tilde{r}[n]$ is obtained by applying Eq. (3.33), Eq. (3.34) to Eq. (3.35). Thus, $\tilde{r}[n]$ is represented as,

$$\tilde{r}[n] = \begin{cases} \tilde{r}_{ref}[n], & n = 1, \cdots, N/2 \\ \tilde{r}_b[n], & n = N/2+1, \cdots, N. \end{cases} \tag{3.36}$$

The chosen points having the same amplitude of time-varying sinusoidal signal are used as input points of robust estimators which are median and myriad estimators used as location estimators. Output of the median filter can be expressed by,

$$\begin{aligned} \tilde{y}^{med}[\tilde{n}(m)] &= MEDIAN(\tilde{r}_{ref}[\tilde{n}(m)]) \\ \tilde{y}_b^{med}[\tilde{n}(m)] &= MEDIAN(\tilde{r}_b[\tilde{n}(m)]). \end{aligned} \tag{3.37}$$

In the same way, the outputs of the myriad filter can be expressed as,

$$\begin{aligned} \tilde{y}^{myr}[\tilde{n}(m)] &= MYRIAD(K; \tilde{r}_{ref}[\tilde{n}(m)]) \\ \tilde{y}_b^{myr}[\tilde{n}(m)] &= MYRIAD(K; \tilde{r}_b[\tilde{n}(m)]) \end{aligned} \tag{3.38}$$

where

$$\tilde{n}(m) = \begin{cases} (l-1)K+m \\ (l-\frac{1}{2})K-m \\ (l-\frac{1}{2})K+m \\ lK-m \end{cases} \tag{3.39}$$

and $l = 1, \cdots, L, \quad m = 1, \cdots, \frac{K}{4}$.

The input points of the robust estimator are shown in Figure 3.16. This figure illustrates estimator inputs which are obtained from reference signal $\tilde{s}[n]$ having the same amplitude within a bit duration.

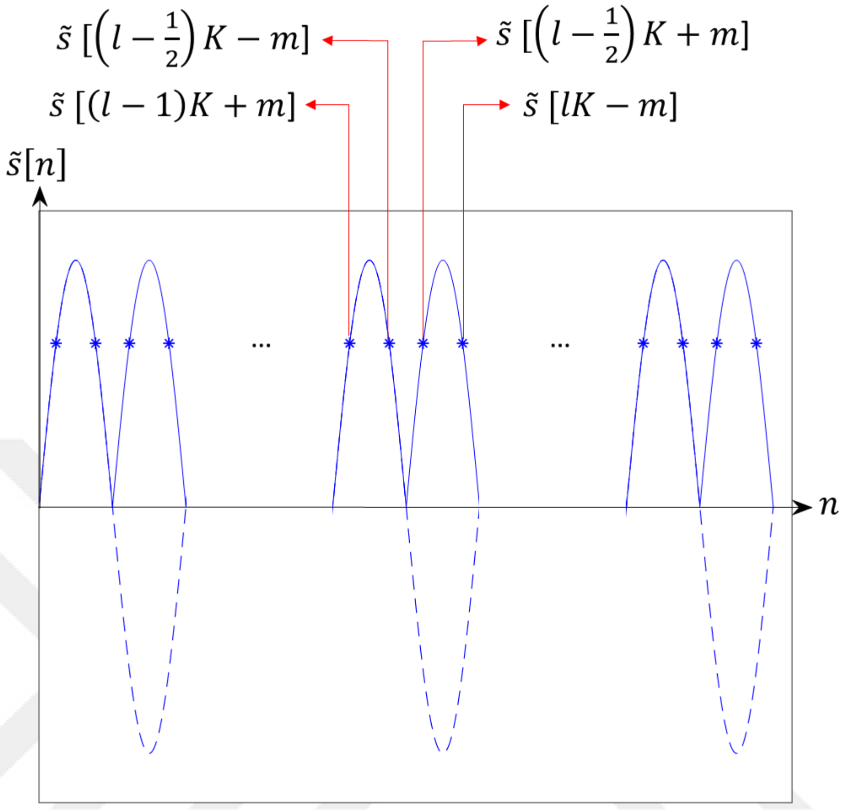

Figure 3.16 Selected input points for the location estimator (noise-free case)

CHAPTER FOUR
SIMULATION RESULTS

Bit error rate (BER) results are achieved by Monte Carlo simulations performed over 10^4 bits of binary data and ensemble averaging of 100 realizations for baseband domain. The data length per bit is taken as $N = 20$. Simulations are performed under α-stable distributed noise using median and myriad filters for proposed baseband system which is described in Section 3.6.

Under symmetric α-stable distributed noise, proposed method using with median filter and the median detector applied with conventional signalling yields the identical BER performance shown in Figure 4.1 ($\beta = 0$). Under skewed α-stable distributed noise, the ability of noise suppression of the proposed method can be seen in Figure 4.2 compared with other detectors.

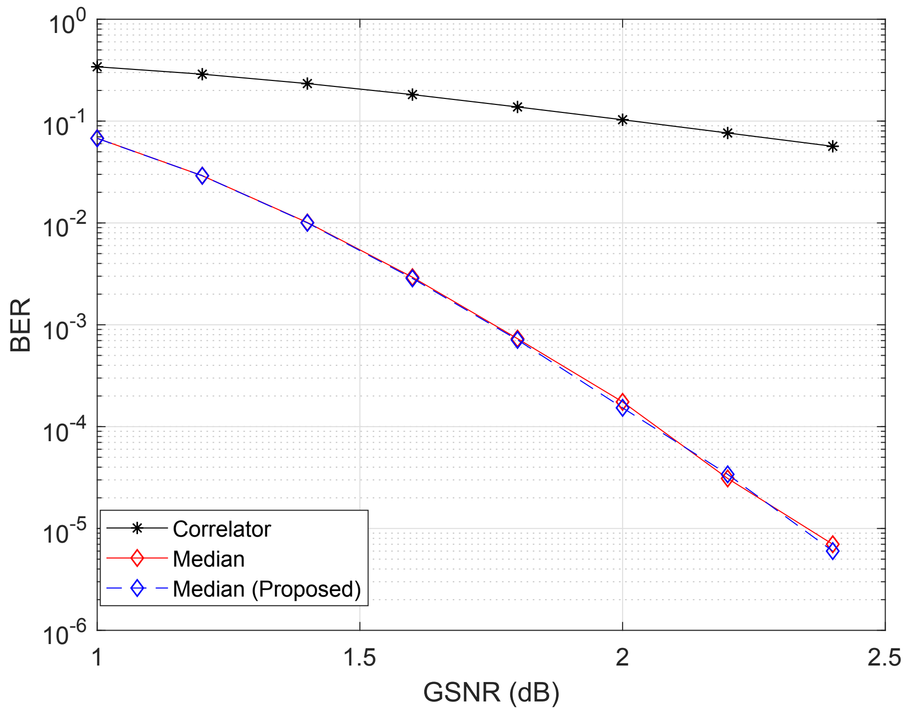

Figure 4.1 BER performance of median filter based baseband communication system with respect to GSNR ($\alpha = 1.2, \beta = 0$)

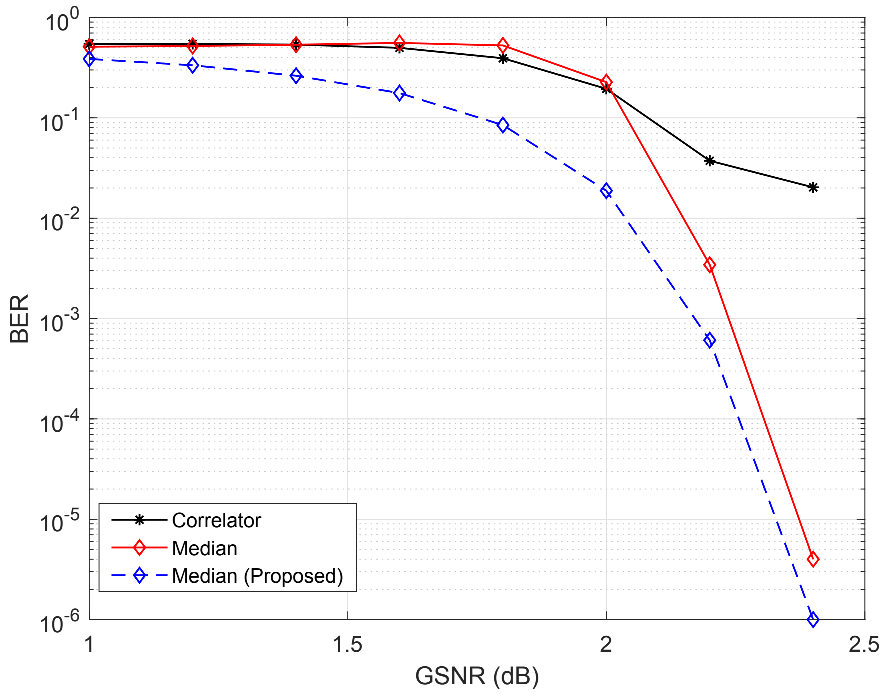

Figure 4.2 BER performance of median filter based baseband communication system with respect to GSNR ($\alpha = 1.2, \beta = 1$)

Similarly, the proposed method is tested on myriad filter based detector together with conventional approach. The BER results are shown in Figure 4.3 and Figure 4.4, having symmetric and skewed α-stable channel noise, respectively. BER improvement is obviously seen if the noise has skewed α-stable distribution whereas an identical BER performance is achieved if the channel noise is symmetric.

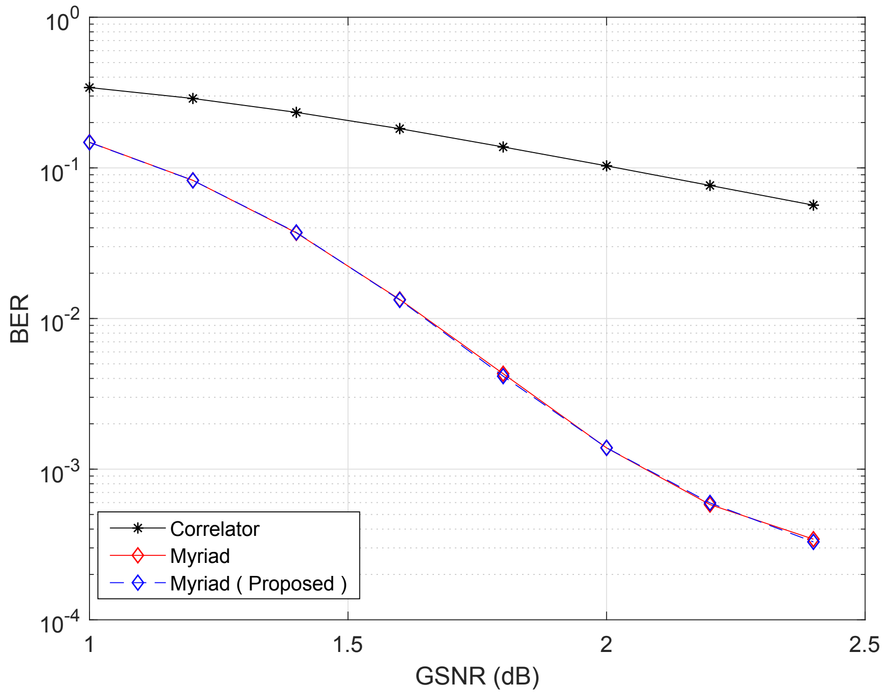

Figure 4.3 BER performance of myriad filter based baseband communication system with respect to GSNR ($\alpha = 1.2, \beta = 0$)

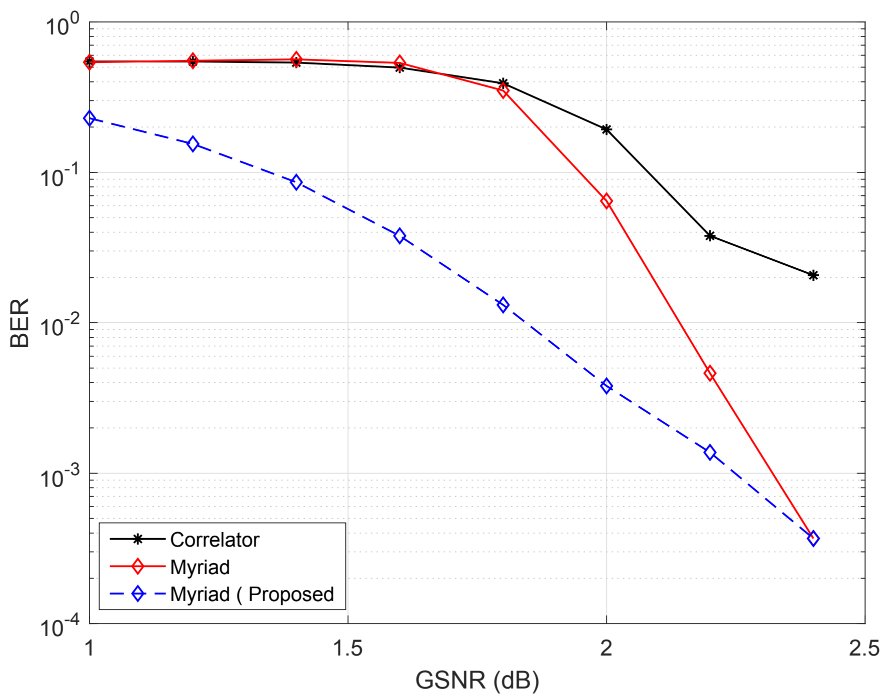

Figure 4.4 BER performance of myriad filter based baseband communication system with respect to GSNR ($\alpha = 1.2, \beta = 1$)

Simulations are performed under α-stable distributed noise using median and myriad filters for proposed bandpass system which is described in Section 3.7. Bit error rate (BER) results are achieved by Monte Carlo simulation is performed and ensemble averaging of 50 realizations for bandpass domain. L is the number of sinusoids in the reference signal and two values of L are chosen for simulations as L=10 and L=50. Since the the noise in the channel has infinite variance, the signal to noise ratio is defined in terms of generalized signal to noise ratio (GSNR) as defined in Section 2.2.

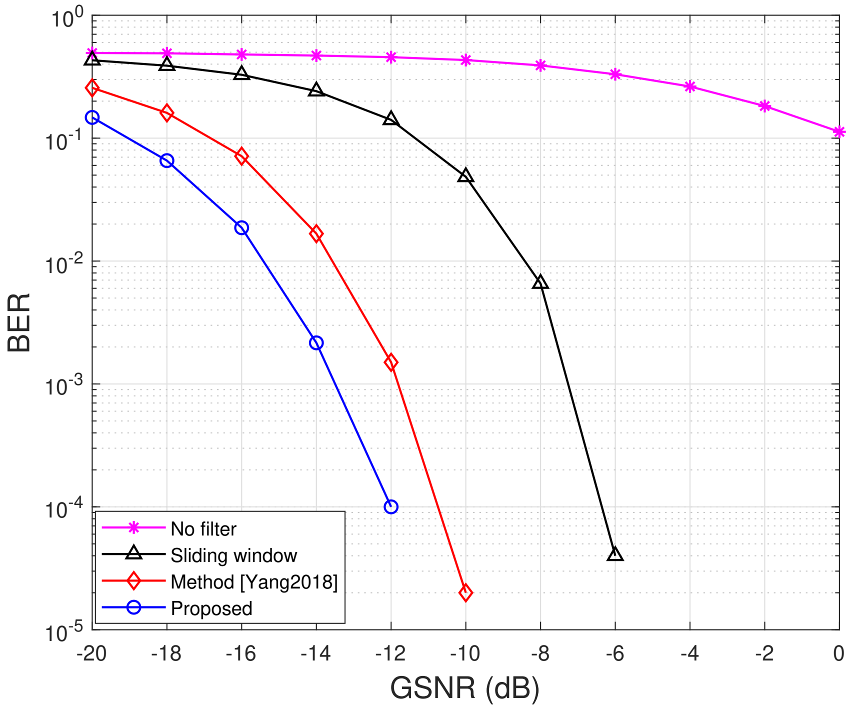

Figure 4.5 BER performance of median filter based bandpass communication system with respect to GSNR ($\alpha = 1.4, \beta = 0, L = 50$)

The error performance of the communication system is shown with respect to different methods for fixed impulsiveness $\alpha = 1.4$. The proposed method gives a better error performance compared to others. When the period of the bit duration increases, the parameter L also increases proportionally and filter processes more data. However, this also corresponds to decreased bit rate and there is a trade-off between the data transmission rate and bit error rate improvement. Even the BER performance changes with respect to L, proposed method always gives a better result for median filter based detector. To show this result, simulations performed for L=10, $\alpha = 1.4$ are given in Figure 4.6.

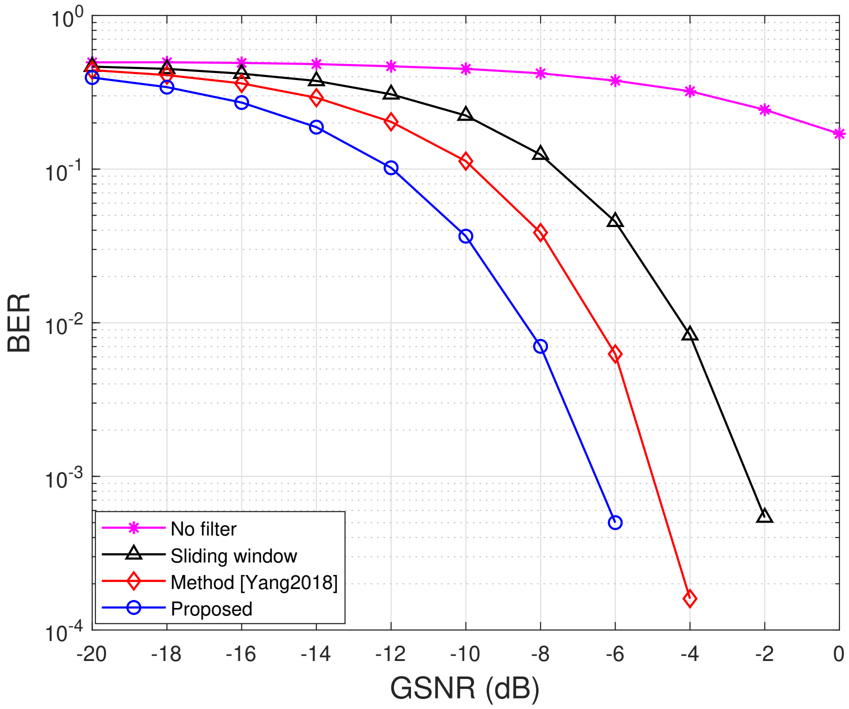

Figure 4.6 BER performance of median filter based bandpass communication system with respect to GSNR ($\alpha = 1.4, \beta = 0, L = 10$)

Similarly, the proposed waveform is applied on myriad filter based detector. The BER performances under $S\alpha S$ using myriad filter are shown in Figure 4.7 and Figure 4.8 with the same simulation parameters and with respect to different methods for fixed impulsiveness $\alpha = 1.4$. As with the median filter, proposed method gives better error performance compared to others and changing of L affects the data transmission rate and bit error rate improvement but proposed method gives a better result for both L values.

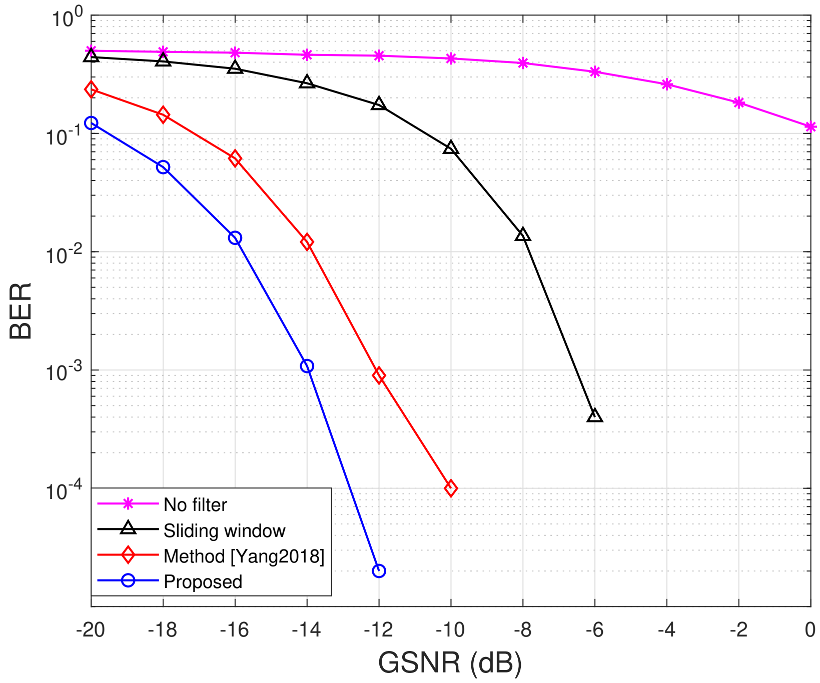

Figure 4.7 BER performance of myriad filter based bandpass communication system with respect to GSNR ($\alpha = 1.4, \beta = 0, L = 50$)

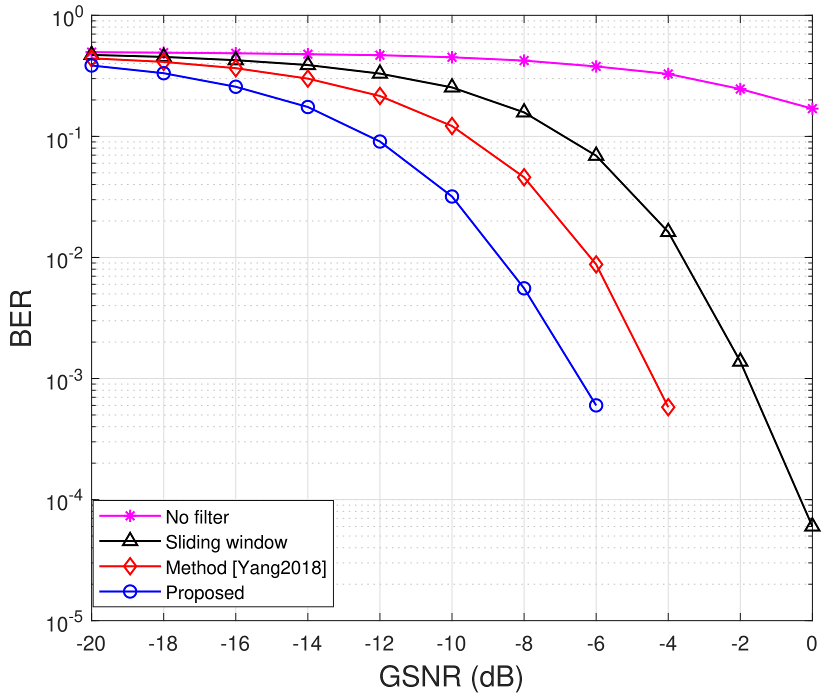

Figure 4.8 BER performance of myriad filter based bandpass communication system with respect to GSNR ($\alpha = 1.4, \beta = 0, L = 10$)

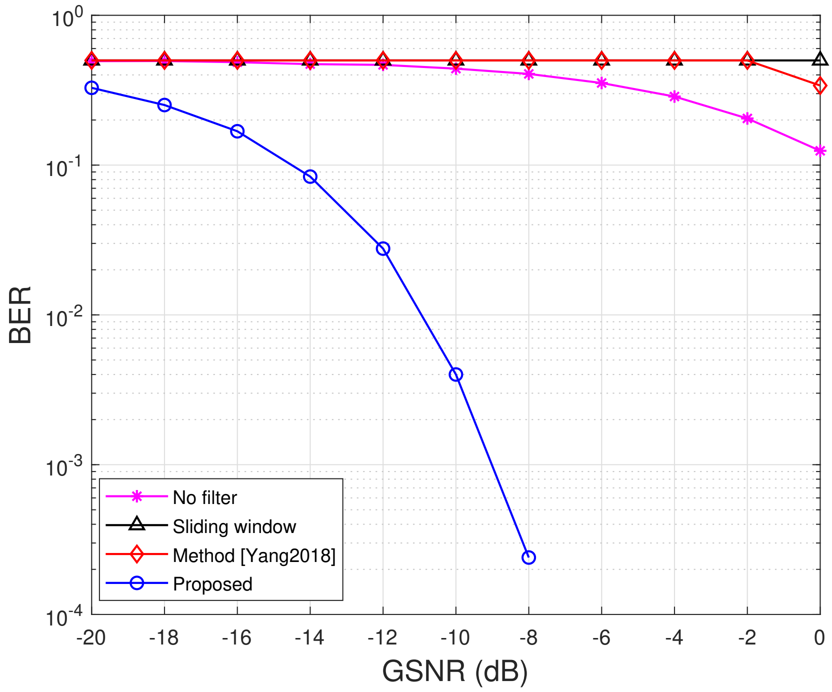

Figure 4.9 BER performance of median filter based bandpass communication system with respect to GSNR ($\alpha = 1.4$, $\beta = 1$)

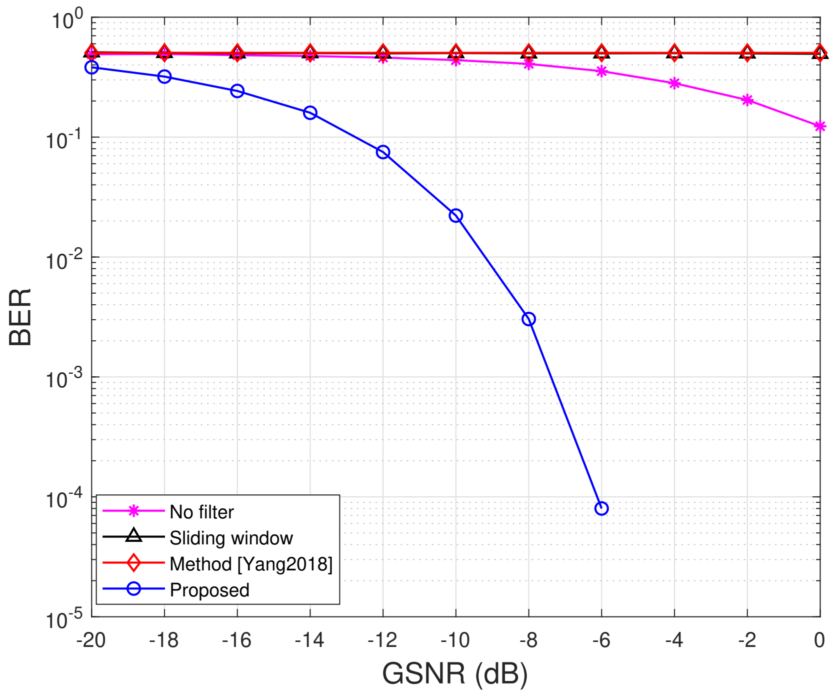

Figure 4.10 BER performance of myriad filter based bandpass communication system with respect to GSNR ($\alpha = 1.4$, $\beta = 1$)

The simulations are performed with the same simulation parameters under skewed-α stable distributed noise ($\beta = 1$) using median and myriad based detector. BER performance of median and myriad filters under skewed-αS noise for different methods are given in Figures 4.9 and 4.10.

As a result of the simulations, the skewed noise suppression ability of the proposed signalling at the output of median and myriad filter is obviously seen and the proposed signalling exhibits a certain superior performance compared with others.

CHAPTER FIVE
CONCLUSION

In this thesis, a digital communication system under skewed alpha-stable noise is analyzed. Since the major aim is to discover the effect of skewness of the channel noise, the communication system is chosen as baseband BPSK in which the receiver performs antipodal signal detection within a certain bit duration. It is shown that the communication system performance decreases when the channel noise becomes more skewed.

In order to neutralize the asymmetry in channel noise, two attempts are proposed as the novel contribution. In the first approach, an intentional noise is added to the received signal which results in symmetrical alpha stable noise, if the characteristic exponent of the channel is known in advance. In order to put forward the improvement due to stochastic resonance, the robust estimators are utilized. It is shown that, when the intentional noise has the same characteristic exponent but opposite skewness compared with channel noise, there is certain bit error rate improvement. However, the assumption of the noise pdf to be known by the receiver may not be satisfied in real life, therefore an alternative waveform design method combined with robust estimators is proposed even if the channel exhibits symmetric and asymmetrical behaviour and pdf is not known in advance. The waveform design technique is primarily based on antipodalization of the signal or expressing the signal as the combination of antipodal components. This provides the reconstruction of the received signal to provide robust estimator to perform location estimation even if the signal may have time varying nature. The only requirement for band-pass signals is the frequency of the sinusoidal carrier be known. If the signal is considered to be a baseband signal, then it is converted into antipodal form before transmitting and the same operation is undone at the receiver. This causes the channel noise to be combined as the positive and negative skewed noise data which results in symmetrical noise. If the information increases, i.e., bit duration increases, the error eliminating performance also increases.

This method gives not only an insight to filter skewed alpha-stable noise but also it is applicable to any non-Gaussian noise having symmetrical and/or asymmetrical structure.

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