Karaelmas Fen ve Müh. Derg. 12(2):223-230, 2022

Karaelmas Science and Engineering Journal
Journal home page: https://dergipark.org.tr/tr/pub/karaelmasfen
DOI: 10.7212/karaelmasfen.1098045

Research Article
Received / Geliş tarihi : 04.04.2022
Accepted / Kabul tarihi : 25.04.2022

Pulse Detection Using Sub-Optimal Detectors Under Additive non-Gaussian Noise Having Unknown Level of Impulsiveness

Bilinmeyen Dürtüsellik Seviyesine Sahip Toplamsal Gauss Olmayan Gürültü Altında Alt-Optimal Seziciler Kullanarak Darbe Sezimi

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Abstract

In this study, real time rectangular pulse detection problem is addressed when the channel noise distribution is not known in advance. Since there is no information about the noise parameters, sub-optimal detectors such as soft limiter, sign correlator and the proposed signed power are utilized for real time pulse detection problem using only received noisy samples. Noting that the unknown channel noise is not necessarily to be Gaussian, symmetric α-stable (SαS) distribution is given as non-Gaussian noise model. Since one of the main objectives is to detect the existent pulse within minimum observation interval, detector performances characterized by detection and false alarm probabilities are analyzed with respect to pulse length under both Gaussian and SαS noise. It is shown that not only the given sub-optimal detectors can exhibit performance close to optimal linear detector under Gaussian noise, but also they provide superior performance under SαS distribution. When the channel has strong impulsiveness, it is observed that the sign correlator and signed power detector introduced in this study exhibit better detection performance compared with soft limiter detector. Consequently, these detectors can be practically implemented to determine existence of pulse within a certain observation interval when there is no prior information about channel noise which is most likely non-Gaussian. Among the other sub-optimal detectors, the proposed signed-power detector is observed to exhibit more stable detection performance under channel noise having varying impulsiveness.

Keywords: Binary hypothesis testing, Non-Gaussian noise, Probability of detection, Probability of false alarm, Sign correlator detector, Signed power detector, Soft limiter detector

Öz

Bu çalışmada, kanaldaki gürültünün dağılımı önceden bilinmiyorken gerçek zamanlı dikdörtgensel darbe algılama problemi ele alınmaktadır. Gürültü parametreleri hakkında bilgi olmadığından, sadece alınan gürültülü örnekleri kullanan yumuşak kırpıcı, işaret ilintileyici ve önerilen işaretli güç sezicisi gibi alt-optimal algılayıcılardan gerçek zamanlı darbe sezim problemi için faydalanılır. Bilinmeyen kanal gürültüsünün Gauss olmasının gerekmediğini dikkate alarak, simetrik α-kararlı (SαS) dağılım Gauss olmayan gürültü modeli olarak verilmektedir. Ana amaçlardan birisi mevcut darbenin minimum gözlem aralığında sezilmesi olduğundan, sezim ve yanlış alarm olasılığı ile tanımlanan sezici başarımı Gauss ve dürtüsel davranış gösteren SαS dağılım altında darbe uzunluğuna göre analiz edilmektedir. Verilen alt-optimal sezicilerin, Gauss dağılım altında optimal doğrusal seziciye yakın başarım sergilemekle kalmayıp SαS dağılım altında üstün başarım sağladığı gösterilmektedir. Kanal gürültüsü kuvvetli dürtüselliğe sahip olduğunda işaret ilintileyici ve bu çalışmada tanıtılan işaretli güç sezicisinin yumuşak kırpıcı seziciye kıyasla daha iyi sezim başarımı sergilediği gözlenmektedir. Sonuç olarak, yüksek olasılıkla Gauss olmayan kanal gürültüsü hakkında ön bilgi olmadığında, bu seziciler belirli bir gözlem aralığı içinde darbenin varlığına karar vermek için pratik olarak uygulanabilir. Diğer alt-optimal seziciler arasında, önerilen işaretli güç sezicisinin değişen dürtüsellik sergileyen kanal gürültüsü altında daha kararlı bir sezim başarımı sergilediği gözlenmektedir.

Anahtar Kelimeler: İkili hipotez testi, Gauss olmayan gürültü, Sezim olasılığı, Yanlış alarm olasılığı, İşaret ilinti sezici, İşaretli güç sezicisi, Yumuşak kırpıcı sezici

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1. Introduction

In radar systems, the pulse repetition interval (PRI) is one of the significant parameters to characterize targets in terms of variation of duration between adjacent pulses (Wiley, 2006). Analysis of radar systems containing rectangular pulse is given in detail (Hao et al., 2022). Basic PRI modulation type is defined as a function of difference between times of arrival (TOA) of each pulse (Gencol et al., 2016) for a specified target. However, these radar pulses are observed in noisy environment and detection accuracy of a particular pulse onset directly affects the deviation from exact PRI modulation pattern. The deviation in PRI modulation types is analyzed in (Gao and Tian, 2015). In this context, recent studies concentrate on detecting existence of radar pulse where short time Fourier transform is used in (Liu et al., 2019), alternatively the pulses are detected by edge enhancement (Li et al., 2020), and edge detection is performed by Haar wavelet filter (Ranney et al., 2021). Moreover, moving sum filter is used to detect magnitude change for pulse detection (Ranney et al., 2022).

In (Tsihrintzis and Nikias, 1997), radar clutter is modelled by $\alpha-$stable distribution as an earlier application on radar signal processing. Moreover, it is reported by (Win et al., 2009) network interference on wireless systems can be statistically modelled by symmetrical $\alpha-$stable distributions. The evidence of impulsive noise in applications of communication and radar/sonar signal processing brings a motivation to construct further analysis to extract the information related with the application area. Therefore, it is shown in these studies that the channel noise does not always exhibit Gaussian behaviour. The pulses need to be analyzed in presence of non-Gaussian noise which is modelled by $\alpha-$stable distribution in this study.

An earlier approach based on maximum correntropy is also applied for antipodal signal detection in (Hakimi and Hodtani, 2018). In (Sun et al., 2021), fractional lower moment is evaluated within the observed sliding time interval. Similarly, robust detection of a target is performed by utilizing fractional lower order moments (Huang et al., 2021). Receiver design and detection regions under impulsive noise interference are also investigated in (Clavier et al., 2021). In the literature, it is seen that the noise in the channel is generally assumed to be known. However, the noise distribution may not be known exactly in practice or its parameters may not remain unchanged. Therefore, the optimal maximum likelihood detector and Cauchy detector are not involved in this study since entire noise parameters and noise intensity are respectively required to decide the existence of pulse for these detectors. Consequently, there is a lack in the literature performing real time pulse detection in case of unknown noise. Since the detection performance is assumed to be determined in real time, the length of the time interval is significant to provide reasonable detection probability obtained from short signal length.

The main contribution of this study is not only to implement practical suboptimal detectors used in digital communication systems in order to detect rectangular pulse when the statistical information related with channel noise is unknown, but also a sub-optimal detector called signed power detector based on fractional power of the observed signal is proposed in this study to exhibit robust detection performance under impulsive noise channels with unknown impulsiveness. The paper is organized as follows. In the next section rectangular pulse detection problem and analytical results are derived under Gaussian noise condition. Subsequently, the sub-optimal detectors together with the proposed signed power detector are described. The performances of these detectors are illustrated by computer simulations in Section 3 under Gaussian and symmetric $\alpha-$stable $(S\alpha S)$ distribution having different impulsiveness. In the last section obtained results are concluded.

2. Method

Pulse detection problem within a certain time interval is formulated in terms of binary hypothesis testing and the sub-optimal detectors are described in the following subsection.

2.1. Pulse Detection

In the given signal detection problem under Additive White Gaussian Noise (AWGN), the entire observed signal having N samples including rectangular pulse with known amplitude A having duration N_P samples is modelled as given in Equation 1.

$$\times[n]=\begin{cases} w[n] & ,n=1,2,...,N_0 \\ A+w[n] & ,n=N_0+1,...,N_0+N_P \\ w[n] & ,n=N_0+N_P+1,...,N \end{cases} \qquad (1)$$

where the noise samples are taken from the Gaussian distribution $w[\cdot]\sim\mathcal{N}(0,\sigma^2)$ and the time instant of pulse onset N_0 is assumed to be unknown. In order to perform real time analysis, a running window having length $W<N_P$ is defined in which the existence of pulse is investigated. Evolution of observed signal within the window length involving all possible scenarios is illustrated in Figure 1.

Since the main objective is restricted to online detection of pulse onset, the problem is localized to construct the binary hypothesis testing within the duration $M \leq W < N_P$ where the parameter M is the length of the existing rectangular pulse within the running window. Accordingly, the binary hypothesis test becomes as given in Equation 2.

$$H_0: x[n] = w[n] \quad , n = 1,2,...,W$$
$$H_1: x[n] = \begin{cases} w[n] & , n = 1,2,...,W-M \\ A + w[n] & , n = W-M+1,...,W \end{cases} \quad (2)$$

It is obvious that first $W-M$ samples are common for both hypotheses and act as irrelevant data since any information cannot be provided. Thus, the problem is reduced to detecting existence of pulse only within the length of interval M given in Equation 3.

$$H_0: x[n] = w[n] \quad , n = 1,2,...,M$$
$$H_1: x[n] = A + w[n] \quad , n = 1,2,...,M \quad (3)$$

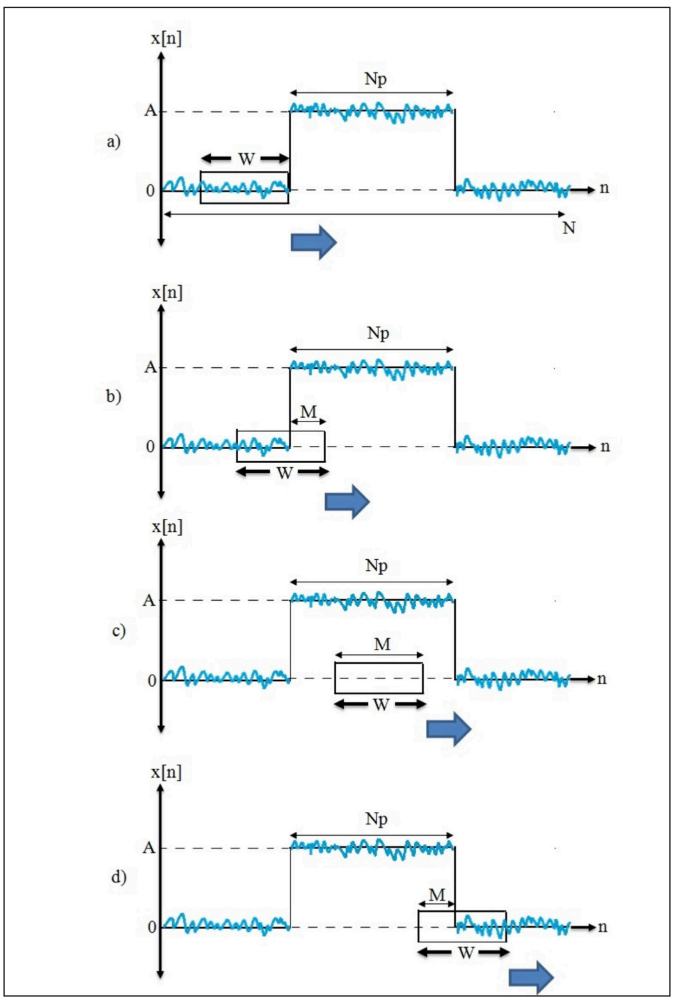

Figure 1. Evolution of real time pulse detection problem based on running window.

Considering the pulse amplitude is reasonably assumed to be known, the observed signal can be modified as $y[n] = x[n] - \frac{A}{2}$ and the binary hypothesis test in (3) is reformulated as in Equation 4.

$$H_0: y[n] = -\frac{A}{2} + w[n], \quad n = 1,2,...,M$$
$$H_1: y[n] = \frac{A}{2} + w[n], \quad n = 1,2,...,M \quad (4)$$

where the problem is converted into antipodal signal detection. The likelihood functions under the Gaussian noise having zero mean and σ^2 variance are given in (5) and (6)

$$p(y[n]; H_0) = \frac{1}{\sqrt{2\pi\sigma^2}} \exp\left(-\frac{(y[n] + \frac{A}{2})^2}{2\sigma^2}\right) \quad (5)$$

and

$$p(y[n]; H_1) = \frac{1}{\sqrt{2\pi\sigma^2}} \exp\left(-\frac{(y[n] - \frac{A}{2})^2}{2\sigma^2}\right) \quad (6)$$

Once the investigation of pulse existence is characterized by samples, Neyman-Pearson test can be applied to determine the likelihood ratio (Kay, 1998) $L(x) = \frac{p(x;H_1)}{p(x;H_0)} > \gamma$ by comparing with threshold γ and is given in (7)

$$L(y) = \frac{\frac{1}{(2\pi\sigma^2)^{\frac{M}{2}}} \exp\left[-\frac{1}{2\sigma^2}\sum_{n=0}^{M-1}(x[n] - \frac{A}{2})^2\right]}{\frac{1}{(2\pi\sigma^2)^{\frac{M}{2}}} \exp\left[-\frac{1}{2\sigma^2}\sum_{n=0}^{M-1}(x[n] + \frac{A}{2})^2\right]} > \gamma \quad (7)$$

Analytically, the likelihood ratio is obtained as

$$\bar{y} = \frac{1}{M}\sum_{n=0}^{M-1} y[n] > \frac{\sigma^2}{MA} In\,\gamma = \gamma' \quad (8)$$

where $\bar{y}$ denotes sample mean and is considered as the test statistics $T(y) = \bar{y}$. Note that $T(y)$ is statistically characterized by determining mean under each hypothesis as found in (9) and (10)

$$E(T(y); H_0) = E\left[\frac{1}{M}\sum_{n=0}^{M-1}(-\frac{A}{2} + w[n])\right] = -\frac{A}{2} \quad (9)$$

$$E(T(y); H_1) = E\left[\frac{1}{M}\sum_{n=0}^{M-1}(\frac{A}{2} + w[n])\right] = \frac{A}{2} \quad (10)$$

and variance, obtained under both hypotheses as in (11)

$$var(T(y); H_{0,1}) = var\left(\frac{1}{M}\sum_{n=0}^{M-1} \mp\frac{A}{2} + w[n]\right) = \frac{\sigma^2}{M} \quad (11)$$

Finally, the test statistic for this antipodal signal detection problem is expressed in (12)

$$T(y) \sim \begin{cases} \mathcal{N}(-\frac{A}{2}, \frac{\sigma^2}{M}) \ under\ H_0 \\ \mathcal{N}(+\frac{A}{2}, \frac{\sigma^2}{M}) \ under\ H_1 \end{cases} \tag{12}$$

The probability of detection and probability of false alarm are determined in (13) and (14), respectively,

$$P_{FA} = \Pr\{T(y) > \gamma'; H_0\} = Q\left(\frac{\gamma' + \frac{A}{2}}{\sqrt{\frac{\sigma^2}{M}}}\right) \tag{13}$$

$$P_D = \Pr\{T(y) > \gamma'; H_1\} = Q\left(\frac{\gamma' - \frac{A}{2}}{\sqrt{\frac{\sigma^2}{M}}}\right) \tag{14}$$

where $Q(x)$ is the right tail probability and is given as $Q(x) = \int_x^\infty \frac{1}{\sqrt{2\pi}} e^{\left(-\frac{t^2}{2}\right)} dt$. Relation between detection probability and signal strength is characterized by signal to noise ratio (in (15)

$$SNR(dB) = 10 \log \frac{A^2}{\sigma^2} \tag{15}$$

Since the observed waveform model is converted to exhibit antipodal behaviour, the decision boundary can be set $\gamma' = 0$ and the theoretical results for false alarm and detection probabilities are respectively evaluated as

$$P_{FA} = Q\left(\frac{A/2}{\sqrt{\frac{\sigma^2}{M}}}\right) \tag{16}$$

$$P_D = Q\left(-\frac{A/2}{\sqrt{\frac{\sigma^2}{M}}}\right) = 1 - P_{FA} \tag{18}$$

which results in $P_D + P_{FA} = 1$. Consider that $P_D = P_{FA}$ may occur as the worst case and hence the lower bound for detection probability can be given as $P_D = 0.5$. In the sequel, the practical suboptimal detectors are described for pulse detection problem.

2.2. Sub-Optimal Detectors for Pulse Detection

Conventional linear detector which is reported to be optimal under Gaussian noise (Johnson, 1996) and (Sureka and Kiasaleh, 2013) determines existence of pulse according to the rule given in (18)

Linear detector (Sureka and Kiasaleh, 2013):

$$\sum_{n=1}^{M} y[n] \underset{H_0}{\overset{H_1}{\gtrless}} 0 \tag{18}$$

The soft limiter (SL) detectors clips the observed signal depending on the predefined threshold $\varkappa > 0$ as formulated in (19)

Soft Limiter (SL) Detector (Sureka and Kiasaleh, 2013):

$$\sum_{n=1}^{M} g(y[n]) \underset{H_0}{\overset{H_1}{\gtrless}} 0 \tag{19}$$

where

$$g(z) = \begin{cases} -\mathcal{K} & z \le -\mathcal{K} \\ z & |z| < \mathcal{K} \\ \mathcal{K} & z \ge \mathcal{K} \end{cases} \tag{20}$$

An alternative detector is defined to be the sign correlator (SC) detector which converts the observed noisy signal into binary form and determines the existence of a pulse according to operation in (21)

Sign Correlator (SC) Detector (Saleh et al., 2012):

$$\sum_{n=1}^{M} sgn(y[n]) \underset{H_0}{\overset{H_1}{\gtrless}} 0 \tag{21}$$

where $sgn(z) = \begin{cases} 1, z \ge 0 \\ -1, z < 0 \end{cases}$. The Non-Gaussian channel noise exhibiting impulsive and infinite variance behaviour is modelled by distribution which is expressed by its characteristic function as given in (22) (Nikias and Shao, 1995)

$$\varphi(\theta) = e^{-\sigma^\alpha |\theta|^\alpha + j\delta\theta} \tag{22}$$

where the parameters $\alpha \in (0,2]$ is the characteristic exponent tuning the impulsiveness of the noise, is the shift parameter adjusting the location. The impulsive noise is symmetrical around the origin when $\delta = 0$ and correspondingly the location parameter δ is assumed to be $\delta = 0$ in this study. The scale parameter σ arranges the intensity of the noise. When $\alpha = 2$, it can be considered as identical with the standard deviation of Gaussian noise. Note that pdf of $S\alpha S$ noise cannot be analytically expressed except for special cases where Gaussian noise is obtained for characteristic exponent $\alpha = 2$ and Cauchy noise is obtained for $\alpha = 1$ which is frequently used to characterize the impulsive noise. In the presence of such an impulsive noise with infinite variance for $\alpha < 2$, the term generalized signal to noise ratio $(GSNR)$ needs to be defined alternative to SNR (Sureka and Kiasaleh, 2013)

$$GSNR(dB) = 10 \log \frac{A^2}{\sigma^\alpha} \tag{23}$$

2.3. Signed Power Detector

One of the distinctive properties of $\alpha-$stable random variable X is described in terms of its moments. Note that a random variable X having alpha-stable distribution for $0 < \alpha < 2$ is given to have finite moments according to the satisfaction of the condition in (24) (Nikias and Shao, 1995), (Samorodnitsky and Taqqu, 1994)

$$E[|X|^p] < \infty \quad if\ 0 < p < \alpha$$
$$E[|X|^p] = \infty \quad if \qquad p \geq \alpha \tag{24}$$

According to (24), one can conclude only the fractional lower order moments (FLOM) satisfying $p < \alpha$ is finite, otherwise they are said to be infinite. This property is utilized in density parameter estimation from the set of observations having length to determine the signed fractional moment (Kuruoglu, 2001) given in (25)

$$S_p = \frac{1}{L}\sum_{k=1}^{L} X_k^{<p>} \tag{25}$$

where X_k are taken from $S\alpha S$ distribution and the pth signed power of a number z is described as (Kuruoglu, 2001)

$$z^{<p>} = sign(z)|z|^p \tag{26}$$

One of the challenging problems is the selection of moment order which is comprehensively discussed in different studies (Ma and Nikias, 1995), (Tsihrintzis and Nikias, 1996), (Kuruoglu, 2001) and (Bibalan et al., 2017). Utilizing the feedback from the studies in the literature, the moment order in this study is set constant $p = 0.01$ where the characteristic exponent of the channel is assumed to be $\alpha > 0.01$ although it is declared to be unknown. Under $S\alpha S$ noise, the signed power (SP) detector is defined as

$$\sum_{n=1}^{M} sgn(y[n])|y[n]|^p \underset{H_0}{\overset{H_1}{\gtrless}} 0 \tag{27}$$

satisfying the condition $p < \alpha$. Performances of these detectors are shown in simulation results in the next section.

3. Simulation Results and Discussion

The experimental results are obtained by Monte Carlo simulations using Matlab software as a result of ensemble averaging of 10^4 realizations. The threshold for soft limiter and the signed power detector are taken as $\varkappa = 4A$ consistent with (Sureka, and Kiasaleh, 2013) and $p = 0.01$, respectively. For sake of simplicity, the noise intensity for both Gaussian and $S\alpha S$ noise is set $\sigma = 1$ and the pulse amplitude is tuned according to the specified SNR or $GSNR$ value.

3.1. Effect of Channel Impulsiveness

The simulation results reflecting the effect of impulsiveness on detection probability of rectangular pulse is shown in Figure 2 as a function of characteristic exponent α according to fixed observed pulse length M and $GSNR$ values. The characteristic exponent range lies between $\alpha = 2$ (Gaussian noise) and $\alpha = 0.6$ corresponding to strongly impulsive noise. Although the optimal linear detector given in (Johnson, 1996) is seen to yield the best detection performance under Gaussian noise as expected, when the channel noise becomes impulsive as decreases, the linear detector performance get worse dramatically compared with other detectors. This result indicates the necessity of other suboptimal detectors in case the noise exhibits non-Gaussian behaviour. Moreover, the suboptimal detector performances need to be analyzed in two regions according to results in Figure 2 where the soft limiter in (Sureka and Kiasaleh, 2013) exhibits superior detection probability compared with sign correlator in (Saleh at al., 2012) and proposed signed power detector as it is observed to be $\alpha > 1.2$. However, when the noise samples have extreme outliers, especially for $\alpha \leq 1$, the signed correlator and signed power detector performances become apparently better than soft limiter detector.

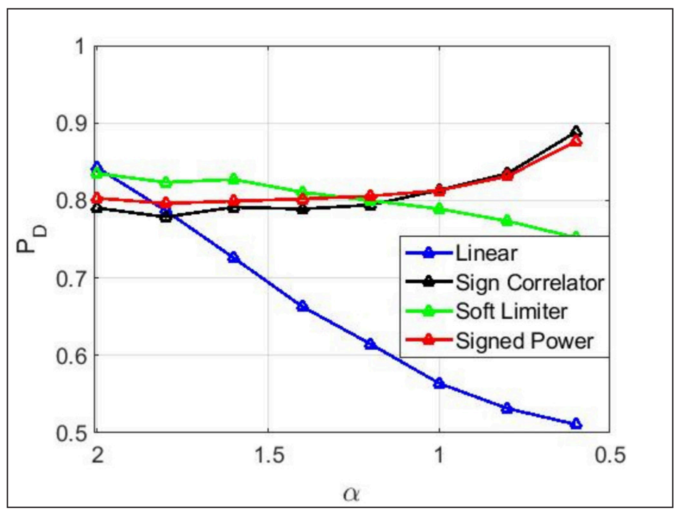

Figure 2. Variation of P_D with respect to stable noise impulsiveness parameter $\alpha; M = 50, GSNR = -8\,dB$.

Therefore, the remaining analyses investigating the effect of observed pulse length M and SNR are explained under Gaussian noise and $\alpha-$stable noise simulated at two different characteristic exponent, separately. As an overall assessment considering entire characteristic exponent range, the proposed signed power detector is seen to exhibit more stable behaviour compared with the other sub optimal detectors sign correlator given in (Saleh et al., 2012) and soft limiter detector given in (Sureka and Kiasaleh, 2013). This finding is put forward by evaluating the mean detection probability and its standard deviation given in Table 1 obtained from the entire range of characteristic exponents.

Table 1. Mean Detection Performance and its standard deviation in the range.

Method	Mean Value of P_D	Std. Dev. of P_D
Gaussian	0.65	0.1234
Soft Limiter	0.80	0.0296
Sign Correlator	0.81	0.0349
Signed Power	0.82	0.0269

As it can be clearly seen, the best detection performance with lowest standard deviation can be achieved by the proposed signed power detector.

3.2. Effect of *SNR*

The detection probability with respect to signal to noise ratio is illustrated in Figure 3 under Gaussian noise and in Figure 4 under $S\alpha S$ noise, respectively. It is seen in Figure 3 that, linear detector has the best detection probability compared with other detectors. However, when the channel noise becomes impulsive as the results shown in Figure 4A, especially for lower value i.e. increased impulsiveness as the detector performances shown in Figure 4B, the distinctive degradation on detection performance of linear detector is apparent although it is optimal under Gaussian case.

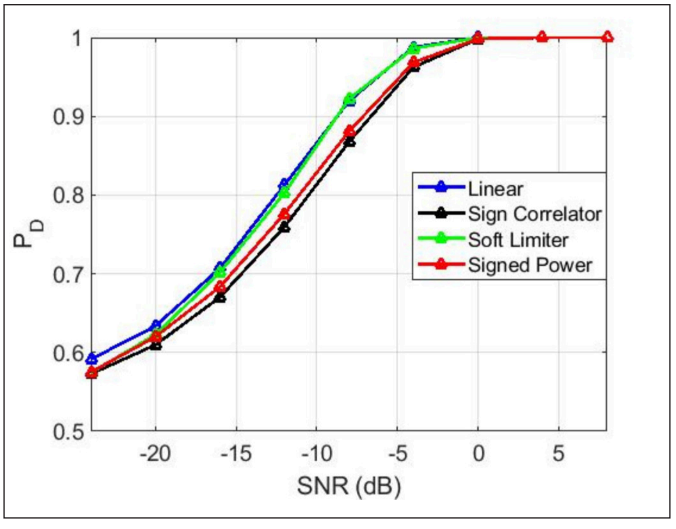

Figure 3. Detection probabilities with respect to SNR under Gaussian noise.

On the other hand, soft limiter detector can be said to exhibit better detection probability according to Figure 4a compared with other sub-optimal detectors such as signed correlator and signed power detector when noise slightly deviates from Gaussian behaviour and soft limiter detector given in (Sureka and Kiasaleh, 2013) may be a reasonable selection rather than other detectors under moderate impulsiveness. However, if the channel exhibits strongly impulsive characteristic, the sign correlator (Saleh et al., 2012) and the proposed signed power detector performances are observed to be apparently superior to both linear (Johnson, 1996) and soft limiter (Sureka, Kiasaleh, 2013) detectors as shown in Figure 4B.

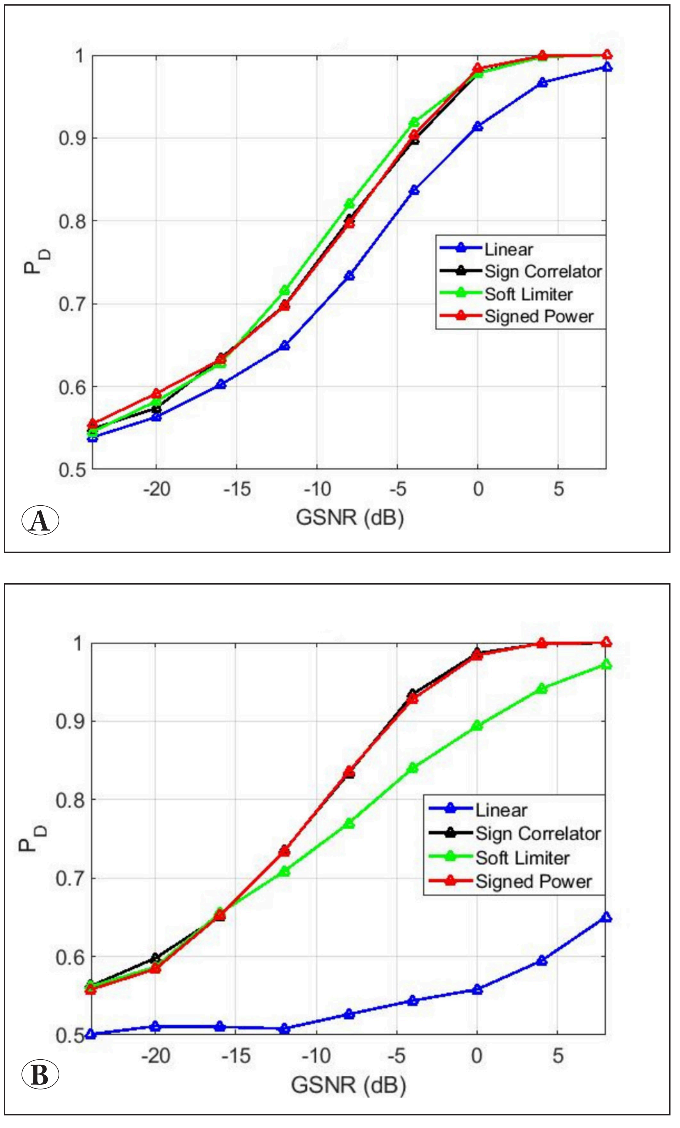

Figure 4. Detection probabilities with respect to $GSNR$ under $S\alpha S$ noise; **A)** ($\alpha = 1.6$), **B)** ($\alpha = 0.8$).

3.3. Effect of *M*

It is seen that the sub-optimal detectors soft limiter and sign correlator together with signed power detector are not critically affected from variation of noise distribution whereas the linear detector performance degrades dramatically when the noise distribution becomes impulsive. Rather than the method in the literature (Li et al., 2020) which processes entire data, it is concentrated on instant detection within the observation length much smaller than pulse length. Since the observed data length is one of the parameters to compare detection performance within short time length, the time-frequency techniques as given in (Liu et al, 2019) are not considered since the spectral resolution becomes poor to yield satisfactory result for the signal within short time interval. Sensitivity of the sub-optimal detectors to the length of observed pulse length M are shown in terms of P_D and P_{FA} in Figure 5 and Figure 6 under Gaussian and $S\alpha S$ noise, respectively. It is clear that the linear detector achieves the theoretical result and exhibits the best $P_D - P_{FA}$ characteristic among the other detectors as shown in Figure 5 under Gaussian case. As the channel impulsiveness increases, the linear detector yields the lowest detection performance for specified M as illustrated in Figure 6A and 6B, respectively.

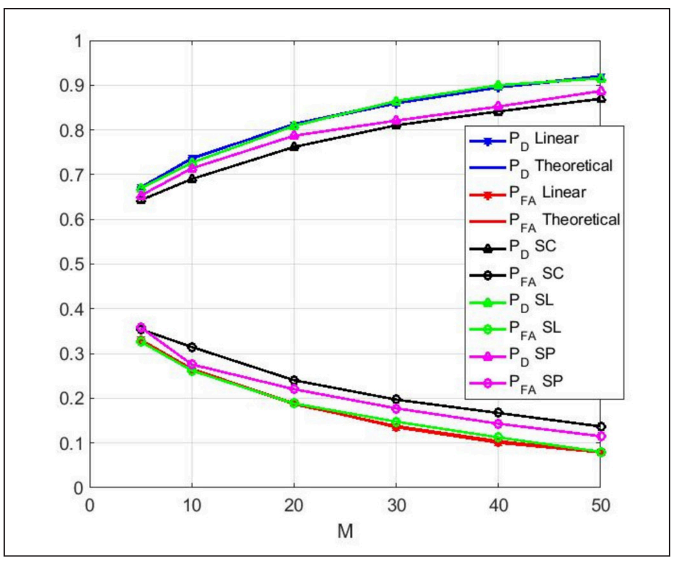

Figure 5. $P_D - P_{FA}$ of detectors as a function of M samples under Gaussian noise. ($SNR = -8\,dB$).

According to the results in Figure 6A, soft limiter has more sensitivity to the observed pulse length under $S\alpha S$ noise whereas its performance gets worse than other suboptimal detectors under stronger impulsive noise condition as shown in Figure 6B. Additionally, $P_D - P_{FA}$ performances of sign correlator and the proposed signed power detectors are close to that of soft limiter detector as given in Figure 6A under weak impulsiveness condition and better results are observed under strong impulsive channel as shown in Figure 6B.

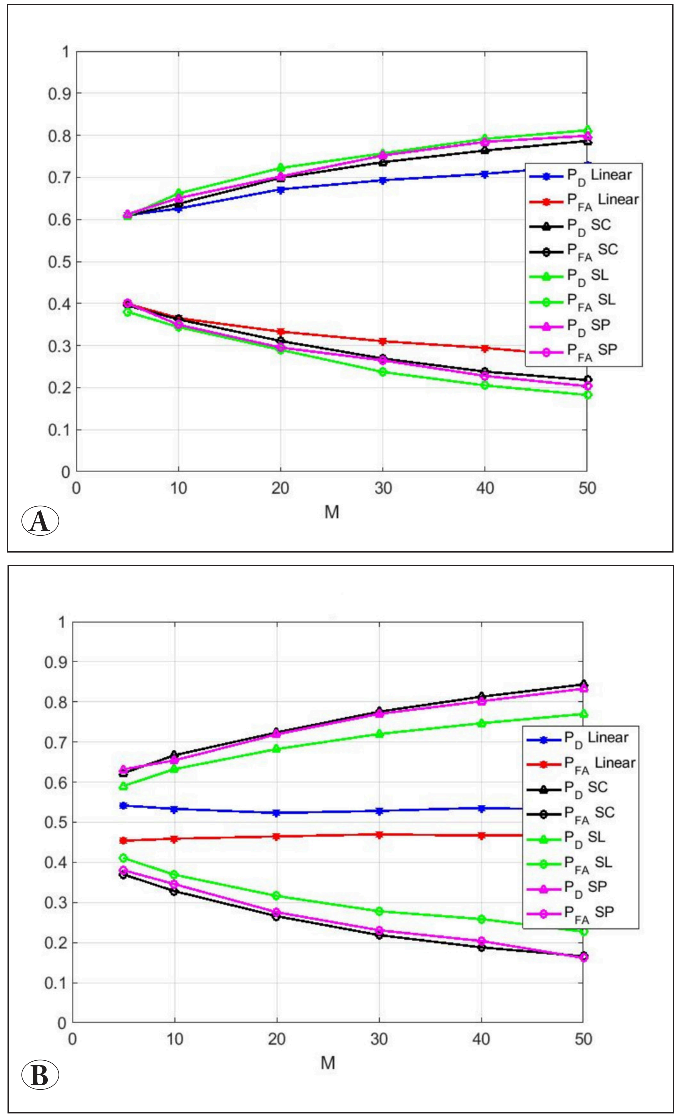

Figure 6. $P_D - P_{FA}$ of detectors as a function of M samples under $S\alpha S$ noise, $(GSNR = -8\,dB)$; **A)** $(\alpha = 1.6)$, **B)** $(\alpha = 0.8)$.

Nevertheless, one can generally conclude that the given sub optimal detectors yield notable robust behaviour against the variation of noise impulsiveness and it can be said that improved detection performance can be achieved for the fixed observed pulse length.

4. Conclusions

This paper proposes utilization of the sub-optimal detectors in detection problem of rectangular pulse in real time within a limited observation interval when the channel noise is assumed to be unknown in advance. The proposed approach is shown to provide a detection mechanism independent of the noise distribution parameters and can be designed to exhibit robust performance against the outlier components in channel noise. It should be noted that the soft limiter detector yields a reasonable pulse detection performance unless the channel exhibits strongly impulsive characteristic. The sign correlator and the proposed signed power detectors come forward if the impulsive outlier samples become dominant in observed data. In terms of different channel noise distribution conditions, the proposed detector can be said to exhibit better detection performance with smaller fluctuation, i.e., more robust stability in detection probability and this can be considered as superiority compared with other sub-optimal detectors.

5. Acknowledgements

Authors would like to thank Tuğçe Toprak for her technical support in preparation of graphical tools in this paper.

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