Proposed Simulation of Modulation Identification Based On Wavelet Transform

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Abstract

The Automatic identification of digitally modulated signal is considered as a rapidly evolving field. It has found applications in many areas, including electronic warfare, surveillance and threat analysis. A variety of techniques have been proposed to identify digitally modulated signals such as; quadrature amplitude modulation(QAM) signal, phase shift keying(PSK) signal and frequency shift keying(FSK) signal. One of the important transformations is the Wavelet Transformation (WT). It is well different digitally modulated signals contain different transients in amplitude, frequency or phase. The performance of the identification scheme is investigated through simulations. When CNR is greater than 5 dB, the percentage of correct identification is about 97% with 50 observation symbols. The proposed method was tested via four different case studies.

Keywords

CNR, Identification, Modulation, wavelet transform

1. Introduction

This paper provides the application of wavelet transform to identify a digitally modulated signal . This approach in signal classification based on using the wavelet transform to extract the transient characteristics in a digitally modulation signal, and apply the distinct pattern in wavelet transform domain for simple identification. The relevant statistics for optimum threshold selection are derived under the condition that the input noise is additive white Gaussian. The performance of the identification scheme is investigated through simulations. When CNR is greater than 5 dB, the percentage of correct identification is about 97% with 50 observation symbols.

The WT has capability to extract transient information and thereby allowing simple methods to perform modulation identification [1]. Applied Mallet wavelet to detect the phase changes, and used the likelihood function based on the total number of detected phase changes as a feature to classify M-ary PSK signal. [2], on the other hand, proposed a method to identify PSK and FSK signals using the Haar WT without the need of any communication parameter of a modulated signal. In ideal case, the Haar WT magnitude (|HWT|) of a PSK signal is a constant and that of a FSK signal is a multistep function. Hence the
variance of |HWT| of an input signal is used as a feature to classify the two signals.

2. Theoretical Aspect for Modulation Identification by Wavelet Transform Review Stage

Let the received waveform $r(t), 0 \le 1 \le T$ be described as $r(t) = S(t) + n(t)$, where $n(t)$ is a complex white Gaussian noise. The signal $S(t)$ can be represented in complex form as

$$s(t) = \tilde{s}(t)\,\ell^{\,j(w_c t + \theta_c)} \tag{1}$$

where w_c is the carrier frequency and θ_c is the carrier phase.

For QAM signal,

$$\tilde{s}_{QAM}(t) = \sum_{i=1}^{N} (A_i + jB_i)UT(t - iT)$$
$$A_i, B_i \in \{2m - 1 - M, m = 1,2,...,M\} \tag{2}$$

For PSK signal,

$$\widetilde{s}_{PSK}(t) = \sqrt{s}\sum_{i=1}^{N} e^{j\varphi i} uT(t - iT)$$
$$\varphi i \in \{\frac{2\Pi}{M}(m-1), m = 1,2,...,M\} \quad (3)$$

For FSK signal,

$$\widetilde{s}_{FSK}(t) = \sqrt{s}\sum_{i=1}^{N} e^{j(w_c\tau + \varphi_c)} uT(t - iT)$$
$$\varphi i \in \{w_1, w_2, ...w_m\}, \theta i \in (0,2\Pi) \quad (4)$$

In eq. (1)-(4) S is the signal power, N is the number of observed symbols, T is the symbol duration and υT *(t)* is the standard unit pulse of duration T. In this study, we assume that the three signals have the same symbol duration. It can be seen from eq. (1)-(4) that symbol changes will give rise to transients in the modulated signals. The transients are created independently in the changes of amplitude, phase and frequency respectively. WT can characterize these transients effectively and allowing simple method for identification of the three signals.
The continuous WT of a signal *s(t)* is defined as [1]

$$CWT(a,\tau) = \int s(t)\psi_a^*(t)dt$$
$$= \frac{1}{\sqrt{a}}\int s(t)\psi^*(\frac{t-\tau}{a})dt \quad (5)$$

where a is the scale, τ is the translation and the superscript * denotes complex conjugate. The function $\Psi(t)$ is the mother wavelet and the baby wavelet $\Psi a(t)$ comes from time-scaling and translation of the mother wavelet. The choice of a mother wavelet depends on its application. Some widely used wavelets are Morlet, Haar and Shannon [2]. Due to its simple form and ease of computation, we shall consider the Haar wavelet only. The following analysis derives the Haar WT of QAM, PSK and FSK signals.

In ideal case, when the Haar wavelet is within a symbol time, the Haar WT of a QAM signal is:

$$CWT(a,\tau) = \frac{1}{\sqrt{a}}(\int_{-\frac{a}{2}}^{0}(A_i + jB_i)e^{j(w_c(t+\tau)+\theta_c)}dt - \int_{-0}^{\frac{a}{2}}(A_i + jB_i)e^{j(w_c(t+\tau)+\theta_c)}dt)$$
$$= \frac{4\sqrt{s_i}}{j\sqrt{aw_i}}\sin^2(w_c\frac{a}{4})e^{j(w_c\tau+\theta_c+\phi_i)} \quad (6)$$

where $\delta i = \sqrt{\mathrm{A}i + \mathrm{B}i}$ is the amplitude of the *ith* symbol and $\phi = \tan(\mathrm{B}i / \mathrm{A}i)$ is the phase of the *ith* symbol. Taking the magnitude of Eq. (6) to eliminate the unknown
carrier phase gives

$$\left|CWT_{QAM}(a,\tau)\right| = \frac{4\sqrt{s_i}}{j\sqrt{aw_i}}\sin^2(\frac{w_c a}{4}) \quad (7)$$

When the Haar wavelet covers a symbol change, the Haar WT of a QAM signal is

$$CWT(a,\tau) = \frac{1}{\sqrt{a}}(\int_{-\frac{a}{2}}^{d}(A_i + jB_i)e^{j(w_c(t+\tau)+\theta_c)}dt + \int_{d}^{0}(A_{i+1} + jB_{i+1})e^{j(w_c(t+\tau)+\theta_c)}dt)$$
$$-\int_{0}^{\frac{a}{2}}(A_{i+1} + jB_{i+1})e^{j(w_c(t+\tau)+\theta_c)}dt)$$
$$= \frac{1}{j\sqrt{aw_c}}e^{j(w_c\tau+\theta_c+\phi_c)}[S_i(e^{jw_cd} - e^{-jw_c\frac{a}{2}}) + S_{i+1}e^{j\alpha}(2 - e^{jw_cd} - e^{jw_c\frac{a}{2}})] \quad (8)$$

where δi and $\delta i + 1$ are the amplitudes of the *ith* and *(i +1)th* symbols, ϕi and $\delta i + 1$ are the phases of *ith* and *(i +1)th* symbols, $\delta i\alpha = \phi i + 1 - \phi i$ is the phase change
and d is the time instance when the symbol changes relative to the center of the wavelet. It is assumed to be negative in eq. (8).For positive d, we can derive a similar formula as eq. (8).

It is observed from eq. (6), (8) that when the wavelet is within a symbol period, the |HWT| of a QAM signal without noise is constant independent of the translation T . Since the amplitude of the QAM signal Si is variable, the |HWT| pattern of a QAM signal is a multi-step function. There will be distinct peaks in the |HWT| resulted from phase changes at the times where the wavelet covers a symbol change.

The |HWT| of PSK signal and FSK signal have been derived from eq. (8) when the Haar wavelet is within a symbol time:

$$\left|CWT_{PSK}(a,\tau)\right| = \frac{4\sqrt{s}}{\sqrt{aw_c}}\sin^2\left(\frac{w_c a}{4}\right) \tag{9}$$

$$\left|CWT_{FSK}(a,\tau)\right| = \frac{4\sqrt{s}}{\sqrt{a(w_c+w_i)}}\sin^2\left[\frac{(w_c+w_i)a}{4}\right] \tag{10}$$

Note that ωi is fixed within a symbol.

It is clear from eq. (9) and (10) that in ideal case, the |HWT| of PSK signal is a constant, while the |HWT| of FSK signal is a multi-step function since the frequency is a variable. Similar to QAM signal, there will be distinct peaks in the |HWT| of the two signals when the Haar wavelet covers a symbol change. Figure 1 shows the |HWT| of QAM, PSK and FSK signals.

We define amplitude normalization of a signal $\tilde{s}(t)$ as follows:

$$\tilde{s}(t) = \frac{\tilde{s}(t)}{\left|\tilde{s}(t)\right|} \tag{11}$$

From eq. (2)-(4), we have the amplitude normalized modulation signals:

$$\tilde{s}_{QAM}(t) = \sum_{i=1}^{N} e^{j\arctan\frac{B_i}{A_i}} uT(t-iT) \tag{12}$$

$$\tilde{s}_{PSK}(t) = \sum_{i=1}^{N} e^{j\varphi_i} uT(t-iT) \tag{13}$$

$$\tilde{s}_{FSK}(t) = \sum_{i=1}^{N} e^{j(w_i t+\theta_i)} uT(t-iT) \tag{14}$$

Amplitude normalization does not affect the modulation type of the PSK signal and FSK signal since they are constant amplitude modulation. On the other hand, the amplitude variations in QAM signal disappear after amplitude normalization. $\tilde{s}\Phi\mathrm{AM}(t)$ has the same form as $\tilde{s}\mathrm{PSK}(t)$. As a result, a QAM signal with amplitude normalization will have a constant |HWT| with peaks due to phase change. However, the characteristics of the |HWT| of amplitude normalized PSK signal and FSK signal will remain the same. Figure 1 shows the |HWT| of the three signals after amplitude normalization.

To differentiate QAM, PSK and FSK signals, we must find a common feature and select a criterion based on differences.

If we ignore the peaks, comparing Figure 1 and Figure 2 reveals that the |HWT| of a QAM signal is a multistep function. It becomes a dc when amplitude normalization is applied to the signal. Again, ignoring the peaks the |HWT| of a PSK signal is a constant and that of a FSK signal is multi-step function, no matter their amplitudes are normalized to unity or not. The variance of a constant is zero while that of a multi-step function is larger than zero. Hence we can distinguish QAM signal, PSK signal and FSK signal by computing the variances of the |HWT| with and without amplitude normalization, after removing the peaks by median filtering.

Figure 3 is the WT modulation identifier for QAM, PSK and FSK signals. The identifier consists of two branches and a decision block. One branch is without amplitude normalization and the other is with amplitude normalization. The identifier first finds the |HWT| of an input signal. After removing the peaks of |HWT| by a median filter, the identifier computes the variance of the median filter outputs. The decision block compares the two variances with two thresholds to decide the modulation type of an input signal. If the variance produced by the branch without amplitude normalization is larger than the threshold while the other variance is smaller than the threshold, the input is classified as a QAM signal. If both variances are lower than the thresholds, the input is classified as a PSK signal. If both variances are higher than the thresholds, the input is classified as a FSK signal.

Under the condition that the input noise is white Gaussian, the relevant statistics for optimum threshold selection can be evaluated. First, we analyze the theoretical variance of |HWT| of the branch without amplitude normalization.

Denote a random variable *r* as the |HWT| and assume the noise power is 2σ. It can be shown that the Haar WT of a white Gaussian noise is normal distributed with the same mean and variance as the white Gaussian noise since WT is a linear transform. Hence the probability density function (pdf) of r is [12]:

$$fR(r) = \frac{r}{\sigma_n{}^2}\exp\left\{-\frac{r^2+A^2}{2\sigma_n{}^2}\right\} Io\left(\frac{Ar}{\sigma_n{}^2}\right) \tag{15}$$

where A is the true |HWT| without noise. $Io(.)$ is the modified Bessel function of the first kind and zero order. The pdf reduces to a Gaussian at high CNR.

If the input is a PSK signal, the theoretical variance of the median filter output can be calculated because the output is a constant with random noise added to it. On the other hand, if the input is QAM signal or FSK signal, the theoretical variance of the median filter output is unknown because it depends on the unknown modulation parameters such as symbol rate, amplitude and carrier frequency.

When the median filter input is the |HWT| of a PSK signal and when the CNR is high, the pdf of the median filter output can be approximated by a Gaussian [13], with the mean $\bar{\nu}$ equals to the theoretical median and variance equals to

$$\sigma_{\nu}^{2} = \frac{1}{4\{L\nu - 1 + [4 f_R^{2}(\bar{\nu})\sigma_n^{2}]\} f_R^{2}(\bar{\nu})} \qquad (16)$$

where $fR(\bar{\nu})$ is the pdf value in eq. (4) evaluated at $r = \bar{\nu}.L\nu$ is the length of the median filter. It can be arbitrary as long as it is greater than 3. $\bar{\nu}$ Can be approximated by averaging the median filter output. Hence under the hypothesis that the input is a PSK signal, the sample variance of the median filter output can be evaluated and it has a Chi-square distribution.
At high CNR, the theoretical variance of |HWT| in the branch with amplitude normalization can be evaluated using the same method as before. It can be shown that the sample variance of the median filter output, under the hypothesis that the input is a PSK signal, is also a Chi-square distribution. Because of amplitude normalization, the noise power in eq. (4) should be replaced by $2\sigma_n^{2} = \frac{2\sigma_n^{2}}{E[|r(t)|^{2}]}$, where $|r(t)|$ is the amplitude of an input signal.

If the probability of misclassification of PSK signal is given, we can determine the optimum thresholds for the two branches of the identifier.

3. The computer Algorithm to Implement the Proposed Identification

We developed 10 different computer algorithms that are necessary to implement the developed tasks of the modulation identification for the signals (FSK, PSK, QAM, and QASK). The main programming effect were depend on the use if the MATLAB high level programming language due to it; high facilities large mathematical resources that are suitable for signal processing tasks.

3.1Case Study

a. The FSK Digitally Modulated Signal

For developing algorithm with FSK signals, we tested such signal, and measure the output signals according to a specified points marked on the Figure 3, i.e. (point a,b,c,and d). These different outputs will be shown as follow:

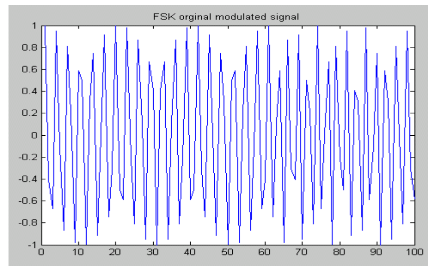
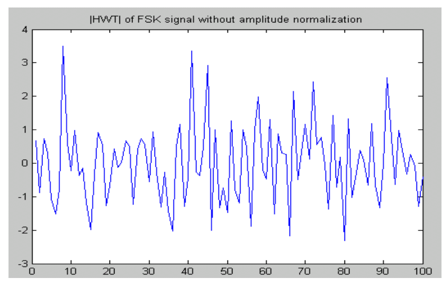
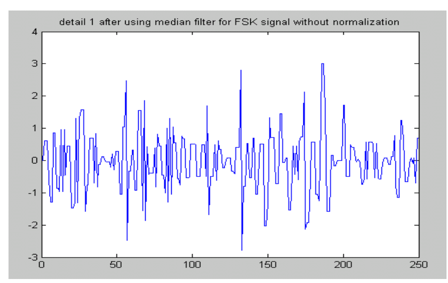


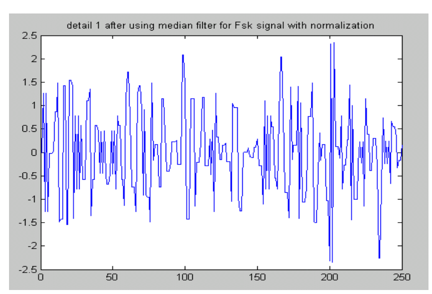
Figure 3 ,a) FSK original modulation signal



b) [HWI] of FSK signal without amplitude normalization



c) Detail after using median filter for FSK signal without normalization



d) Detail after using median filter for FSK signal with normalization

B. The PSK Digitally Modulated Signal

For developing algorithm with FSK signals, we tested such signal, and measure the output signals according to a specified points marked on the Figure 4, i.e. (point a,b,c,and d,). These different outputs will be shown as follow:

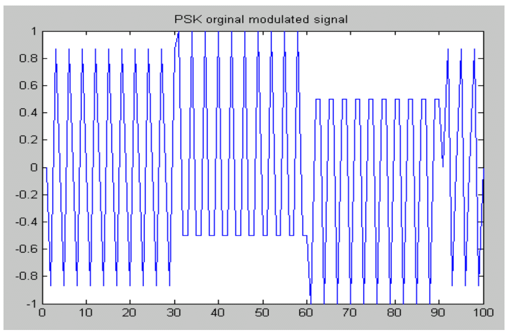
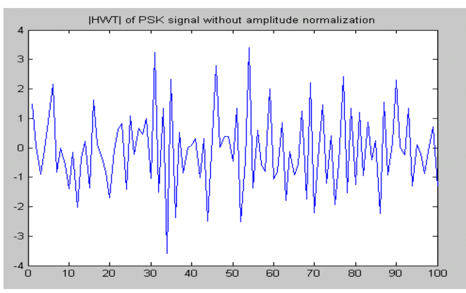
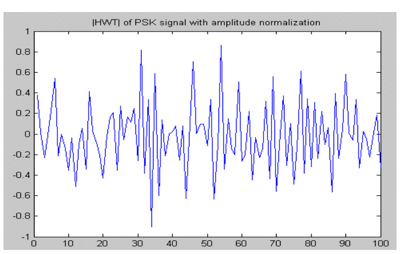


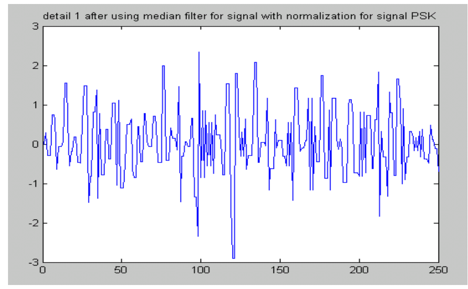
Figure 4, a) PSK original modulation signal



b) [HWI] of PSK signal without amplitude normalization



c) [HWI] of PSK signal with amplitude normalization



d) Detail after using median filter for PSK signal with normalization

C. The QAM Digitally Modulated Signal.

For developing algorithm with FSK signals, we tested such signal, and measure the output signals according to a specified points marked on the Fig.ure 5, i.e. (point a,b,and c). These different outputs will be shown as follow:

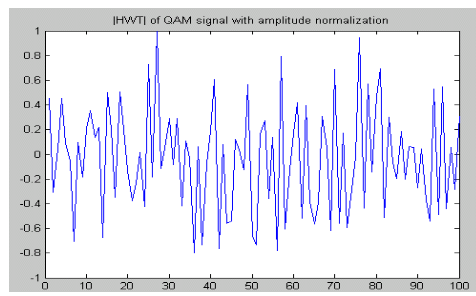
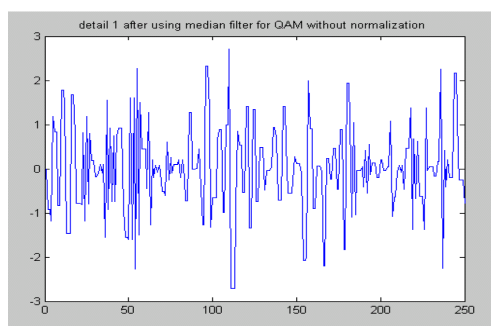
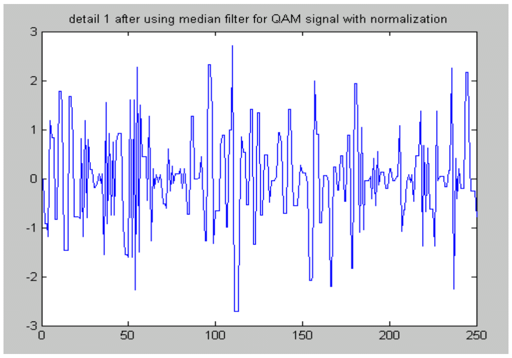


Figure 5, a) [HWI] of QAM signal with amplitude normalization



b) Detail after using median filter for QAM signal without normalization



c) Detail after using median filter for QAM signal with normalization

D. The QASK Digitally Modulated Signal.

For developing algorithm with FSK signals, we tested such signal, and measure the output signals according to a specified points marked on the Fig. (6), i.e. (point a,b,c,and d). These different outputs will be shown as follow:

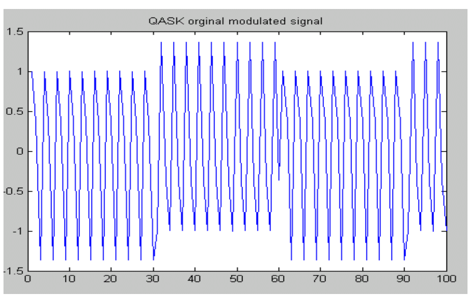
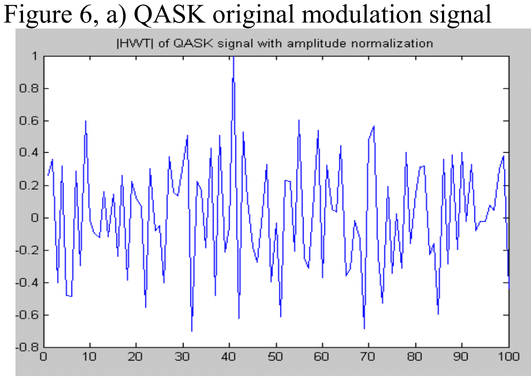
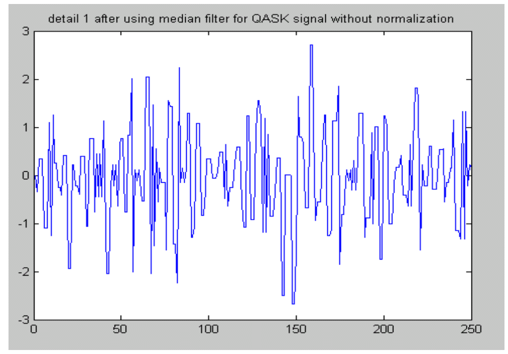


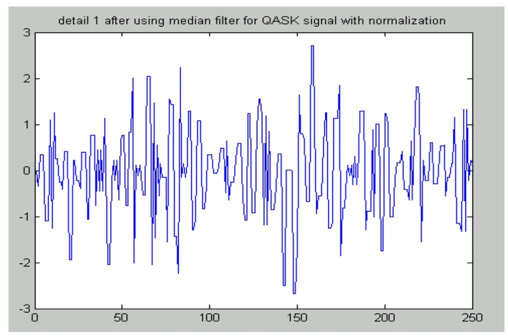
Figure 6, a) QASK original modulation signal



b) [HWI] of QASK signal with amplitude normalization



c) Detail after using median filter for QASK signal without normalization



d) Detail after using median filter for QASK signal with normalization

4. Conclusion

The proposed method was tested via four different case studies. Each one take into consideration a different type of digitally modulated signal, and we have followed the shape of the resulted signal at each points marked on the main proposed system. We tried to investigate the affect of different parameters of the digital signal on the performance of the identification. In the following section we will conclude the result of the changed parameters that showing the variable parameters and the constant parameters for different digitally modulated signal.

1- Changing the digital Data Signal Frequency (FD) the value (1) indicates the correct identification, while values (0) indicate incorrect identification. Note that the SNR per bit in this case was a low value = 5 db.
2- Investigating the effect of changing sampling the sampling frequencies with a constant Fd=4, and M=4, and Fc= and the SNR per bit= 5db. Also the values (1) inside showing the correct decision, while the values (0) showing the incorrect decision, The effect of changing (M), the level of the signal.

3- The effect of changing the SNR per bit 5 db to 25 db.
4- The effect of the change of the interval of the thresholding. From 20 up to 80.

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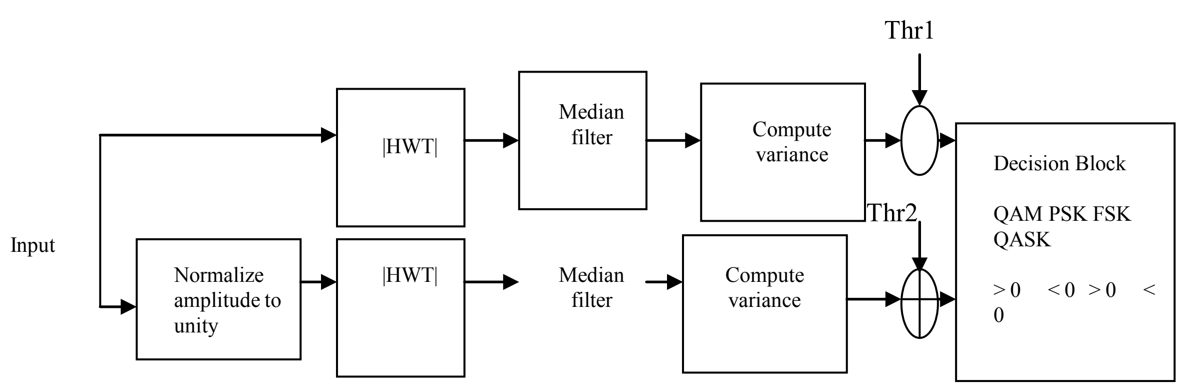

Figure 1. Block diagram of the digital modulation identifier.