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Research Article

M-PAM Signals Classification Using Modified Gabor Filter Network

Sajjad Ahmed Ghauri[1,2] and Ijaz Mansoor Qureshi[3]

[1] *ISRA University, Islamabad, Pakistan*
[2] *Department of Electronics Engineering, International Islamic University, Islamabad 44000, Pakistan*
[3] *AIR University, Islamabad, Pakistan*

Correspondence should be addressed to Sajjad Ahmed Ghauri; sajjad.ghauri@iiu.edu.pk

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A Modified Gabor Filter (MGF) network based approach is used for feature extraction and classification of M-ary Pulse Amplitude Modulated (M-PAM) signals by adaptively tuning the parameters of MGF network. Modulation classification of M-PAM signals is done under the influence of additive white Gaussian noise (AWGN) and channel effects such as Rayleigh flat fading and Rician flat fading. The MGF network uses the network structure of two layers. First layer which is input layer constitutes the adaptive feature extraction part and second layer constitutes the signal classification part. The Gabor atom parameters are tuned using Delta rule and updating of weights of MGF using Recursive Least Square (RLS) algorithm. The simulation results in the form confusion matrix show that proposed modified modulation classification algorithm has high classification accuracy at low signal to noise ratio (SNR). The performance comparison with state-of-the-art existing techniques shows the significant performance improvement of proposed MGF based classifier.

1. Introduction

Automatic Modulation Classification (AMC) is an approach which classifies the modulation format of the received signal at the receiver side. AMC has found extensive importance in the field of electronic surveillance, military domain, electronic counter measures, civil domain, software defined radios, and lately cognitive radios. For example, in military domains, it may be employed for monitoring and interference recognitions, while in civil domain it includes interference confirmation, spectrum management, and signal confirmation. The most important applications in civil domain are intelligent modems, software defined radios, and cognitive radios. Due to incremental technologies such as cognitive radios, the recent research has been focussed to identify and then classify these types of signal as discussed by Haykin [1].

To accomplish AMC, there are two approaches, decision theoretic approach, which is based upon likelihood function of the received signal, and pattern recognition approach, which is based upon features extraction from the received signal [2]. The likelihood function based decision theoretic approach is optimal, but computationally complex. The classifier based upon decision theoretic approach is proposed in [3]. In [4], author gives survey of the decision theoretic approach and the comparison of proposed classifier performances in the literature. The modulation classification in decision theoretic approach is viewed as multiple hypothesis test or may be sequence of pairwise multiple hypothesis test. Once the likelihood function is set up, average likelihood ratio test (ALRT), generalized likelihood ratio test (GLRT), hybrid likelihood ratio test (HLRT), and combinations of these tests are to be used to determine the modulation format of the received signal [5]. Due to phase errors, channel effects, timing jitter, and frequency offset, the decision theoretic approach is not robust to model mismatch [6]. Maximum likelihood method is used in classification of digital modulations in [7]. The author shows that ML classifier is capable

of classifying any finite set constellations with zero error rate when the number of available data symbols goes to infinity. The modulation classification algorithm proposed for identification of software defined radio modulation schemes without pilot symbols between transmitter and receiver in [8]. The classifier based upon likelihood ratio test loads the values of test function for likelihood ratio test; the proposed algorithm converts unknown signal symbol to the address of lookup table.

The feature extraction based pattern recognition approach (PRA) is robust to model mismatch, but not optimal with less computational complexity as compared to decision theoretic approach. The PRA is divided into two modules. In the first module, distinct features are extracted from the received signal, which undergo channel effects such as fading and also channel noise such as additive white Gaussian noise (AWGN). After the successful extraction of these features, second module is classifier which decides about the modulation format of the received signal [9].

The previous techniques employed in literature for feature extraction based modulation classification are discussed below. In [10], authors considered seven modulation formats for classification using genetic algorithm (GA) based clustering. The features extracted are spectral features from the received signal and reduced set of parameters is derived from these coefficients and input to GA based clustering technique. The modulation classification based upon combination of 2nd, 4th, 6th, and 8th order cumulants and spectral features are proposed in [11]. Hierarchical support vector machine (SVM) is used as classifier. The optimization Bee algorithm is used to improve the overall performance of proposed classifier. Spectral features, statistical features, and wavelet based features are used to classify the modulation formats in [12] and performance is evaluated on AWGN channel. The authors proposed a classifier based upon SVM and optimization of algorithm is done using particle swarm optimization (PSO). The modulation formats are recognized using artificial neural network (ANN) and resilient back propagation in [13]. The GA is used to select the best feature subset from the combined spectral features and statistical features. The classifier based on a SVM is proposed as multiclass classifier in [14]. The features used are higher order statistics and GA is used for selecting the parameters of classifier. The performance is discussed with or without optimization. The modulation classification of M-QAM signals is considered in [15]. The classifier based upon combination of subtractive clustering and PSO is used to extract features. The algorithm gives higher accuracy in the presence of AWGN channel at higher SNRs. Higher order cumulants (HOC) are used as feature set for the classification of several modulation formats in the presence of AWGN channel in [16]. Hybrid classifier which is neural network based is used for classification. The Cramer-Rao lower bound is derived for 4th order cumulants estimator in [17], and the classification accuracy is measured on AWGN channel. The author proposed a classifier which is based upon optimized distribution sampling test (ODST) for classification [18]. GA is used to optimize distance metrics using sampled distribution parameters. The decision is based upon candidate modulation and distance between tested signals. Time frequency distributions are proposed for modulation classification in [19]. The classification accuracy increased using time frequency features and multilayer classifier are used to classify six modulation formats.

From literature review of the feature based modulation classifications approaches, there are some issues which need to be properly addressed for the development of efficient classifier. The main two issues are choice of extraction of features from the received signal which had undergone channel effects and noise and the classifier structure which is used to discriminate the features for desired modulation format.

In this paper, MGF based efficient features are extracted from the received signal which to the best of our knowledge have not been utilized for the problem of modulation classification of M-ary Pulse Amplitude Modulated signals. The features are extracted from the noisy (AWGN) signals plus channel effects (Rayleigh flat fading and Rician flat fading) using MGF network. After successful extraction of the features, weights of adaptive filter are updated using RLS algorithm and classification algorithm efficiently classifies the M-PAM signals. Our previous paper for M-QAM, M-PSK, and M-FSK classification was not at all efficient for M-PAM signals [20]. In this paper, we have made two important changes to make it efficient for M-PAM signals. The classification accuracy of the proposed classifier is also compared with well-known state-of-the-art existing techniques.

The rest of the paper is organized as follows. Section 2 represents the Modified Gabor Filter network and system model and also feature extraction using Gabor filter is presented. In Section 3, Modified Gabor Filter algorithm for training and testing is presented. In Section 4, performance of proposed modified classifier in the presence of AWGN channel, Rician fading channel, and Rayleigh fading channel is presented. Section 5 concludes the paper.

2. Gabor Filter Based System Model

2.1. System Model. The generalized expression for signal received is given by a work of Ghauri et al. [2]:

$$r(n) = s(n) + g(n), \tag{1}$$

where $r(n)$ is complex baseband envelope of received signal and $g(n)$ is the additive white Gaussian noise with zero mean and a variance of σ_g^2. The $s(n)$ is defined as

$$s(n) = Ae^{i(w_o nT+\theta_n)} \sum_{j=-\infty}^{\infty} s(l)\, h\left(n\tau - j\tau + \epsilon_T \tau\right), \tag{2}$$

where $s(l)$ is the input symbol sequence which is drawn from set of M constellations of known symbols and it is not necessary that symbols are equiprobable. A is the amplitude of signal, w_o is angular frequency offset constant, τ is symbol spacing, θ_n is the phase jitter which varies from symbol to symbol, $h(\cdot)$ is the channel effects, and ϵ_T is the timing jitter. The system model for classification of M-PAM signals is shown in Figure 1. The received signal is first preprocessed in which the main part is to remove the noise from the signal

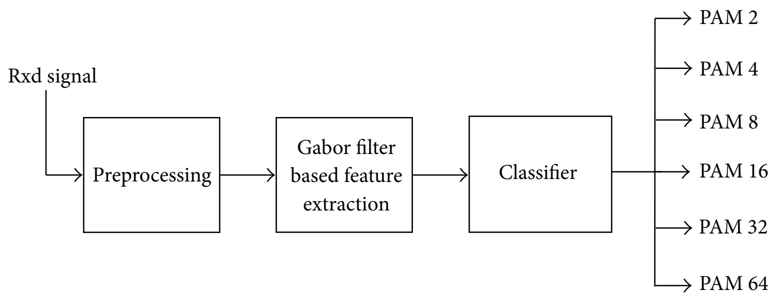

Figure 1: System model for classification of M-PAM signals.

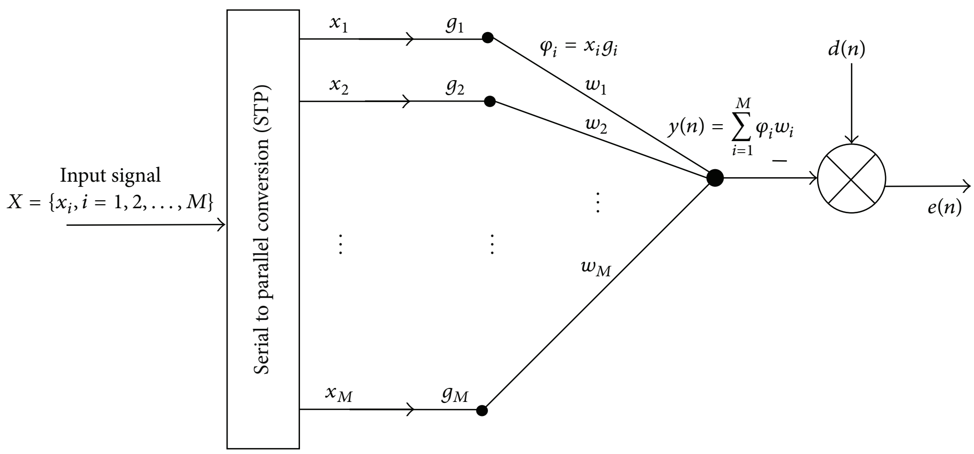

Figure 2: Training of Modified Gabor Filter network for M-PAM signals classification.

or to eliminate the sources of variations. After preprocessing efficient features are extracted using Gabor filter network and these features are used for classification of M-PAM formats among class of M-PAM signals.

2.2. Feature Extraction Using Modified Gabor Filter Network. The Gabor atom is used for the extraction of features and in generalized form it can be written as

$$g_{(c,\sigma,f)}(t) = \frac{1}{\sqrt{\sigma}} g\left(\frac{t-c}{\sigma}\right) e^{jft}, \quad (3)$$

where $g(t) = 2^{1/4} e^{-\pi t^2}$ and c, σ, and f are shift parameter, scale parameter, and modulation parameter, respectively [20]. There are two layer structures for Gabor filter; in first layer, features are extracted adjusting the Gabor atom parameters (c, σ, f) until some cost function is minimized. In second layer, adjustment of adaptive filter weights and the classification process is to be done. As seen from Figure 2, $X = \{x_i, i = 1, 2, \ldots, M\}$ input to the filter is first serial to parallel converted and after that Gabor atom nodes are calculated using the relationship $\varphi_i = |\langle g_i, x_i \rangle|$. The output of the ith Gabor atom node is φ_i corresponding to input signal x_i. Thus, output of Gabor atom is defined as

$$\phi(i) = \left| \int \frac{1}{\sqrt{\sigma_i}} g^* \left(\frac{t-c_i}{\sigma_i}\right) e^{-jf_i t} x_i(t)\, dt \right|. \quad (4)$$

The Gabor atom $\{g_i, i = 1, 2, 3, \ldots, M\}$ is defined as

$$g(i,t) = \frac{1}{\sqrt{\sigma_i}} g\left(\frac{t-c_i}{\sigma_i}\right) e^{jf_i t}. \quad (5)$$

The output of the Gabor atom node φ_i in the input layer is weighted by w_i; that is,

$$y(n) = \sum_{i=1}^{M} \varphi_i w_i, \quad (6)$$

where $n = 1, 2, \ldots, N$. The difference between the desired outputs $d(n)$ and actual output $y(n)$ is defined as

$$e(n) = d(n) - y(n). \quad (7)$$

The cost function is square of error function $e(n)$ which is given by

$$J(n) = [d(n) - y(n)]^2. \quad (8)$$

The four parameters of Gabor filter network and adaptive filter (c, σ, f, w) are adjusted until the $J(n)$ is minimized and approaches to zero.

3. Testing and Training of Proposed Algorithm

To classify the M-PAM signals, the training and testing of the proposed algorithm have to be done. The PAM formats are

spread about axis, and as increasing the M which may vary from 2 to 64, the values of amplitudes are also increasing. The increased values of amplitudes destroy the convergence of the algorithm. To cope up with the problem of divergence, following are the proposed changes in the existing algorithm [20] for classification of PAM formats:

(1) The absolute values of amplitude are taken instead of taking whole input modulated signal; for example, PAM 4 have amplitudes $\{-3, -1, 1, 3\}$ but only take absolute values of amplitudes, that is, $\{3, 1, 1, 3\}$.

(2) The desired responses for each of the considered modulation formats are the average amplitudes

$$a = \sum_{j=1}^{M} \left(\frac{|A_j|}{M} \right), \tag{9}$$

where $\{A_j \varepsilon - 7, -5, -3, -1, 1, 3, 5, 7\}$, for example, for PAM 8, and the desired response for the PAM 8 is 4.

(3) The weights of the adaptive filter are updated using Recursive Least Square (RLS) algorithm instead of using Least Mean Square (LMS) algorithm for the two motives. First, the convergence rate of RLS is sooner than the LMS. Second, the mean square error produced by RLS is lesser than the LMS.

(A) Training of MGF Network. The training of MGF network for PAM 2, PAM 4, PAM 8, PAM 16, PAM 32, and PAM 64 is carried out by adjusting the three parameters of MGF network which are shift, scale, and modulation parameters (c, σ, f) and weights of the adaptive filter (w). Figure 2 shows the training of Gabor filter network by adjusting the three parameters and weights of the adaptive filter by using Delta rule and RLS algorithm, respectively. The training process continues until error function is minimized to some threshold or approaches to zero.

To update (c, σ, f), Delta rule is used to calculate the change in shift parameter c_i, scale parameter σ_i, and modulation parameter f_i:

$$\begin{aligned}
\Delta c_i &= c_i(n+1) - c_i(n), \\
\Delta c_i &= -\frac{\eta_c}{2}\left[\frac{\partial J(n)}{\partial \varphi_i}\frac{\partial \varphi_i}{\partial c_i}\right], \\
\Delta \sigma_i &= \sigma_i(n+1) - \sigma_i(n), \\
\Delta \sigma_i &= -\frac{\eta_\sigma}{2}\left[\frac{\partial J(n)}{\partial \varphi_i}\frac{\partial \varphi_i}{\partial \sigma_i}\right], \\
\Delta f_i &= f_i(n+1) - f_i(n), \\
\Delta f_i &= -\frac{\eta_f}{2}\left[\frac{\partial J(n)}{\partial \varphi_i}\frac{\partial \varphi_i}{\partial f_i}\right].
\end{aligned} \tag{10}$$

To minimize the cost function $J(n)$ for the Gabor filter network parameters (c, σ, f), we take the partial derivatives with respect to shift parameter c_i, scale parameter σ_i, and modulation parameter f_i:

$$\frac{\partial J(n)}{\partial \varphi_i} = -2\left[d(n) - y(n)\right]\frac{\partial}{\partial \varphi_i} y(n). \tag{11}$$

From (6),

$$\frac{\partial}{\partial \varphi_i} y(n) = w_i. \tag{12}$$

Using the above result in (11),

$$\frac{\partial J(n)}{\partial \varphi_i} = -2\left[d(n) - y(n)\right] w_i. \tag{13}$$

From (4),

$$\phi_i = \left| x_i \frac{1}{\sqrt{\sigma_i}} e^{-\pi((t-c_i)/\sigma_i)^2} \cos(f_i t) \right|. \tag{14}$$

The partial derivatives of φ_i with respect to shift parameter c_i, scale parameter σ_i, and modulation parameter f_i are as follows [20]:

$$\begin{aligned}
\frac{\partial \varphi_i}{\partial c_i} &= \frac{\partial}{\partial c_i}(x_i g_i) \\
&= \frac{x_i}{\sqrt[5]{\sigma_i}} \cos(f_i t)\, 2\pi (t - c_i)\, e^{-\pi((t-c_i)/\sigma_i)^2}, \\
\frac{\partial \varphi_i}{\partial \sigma_i} &= \frac{\partial}{\partial \sigma_i}\left[x_i \frac{1}{\sqrt{\sigma_i}} e^{-\pi((t-c_i)/\sigma_i)^2} \cos(f_i t)\right] \\
&= \frac{x_i \cos(f_i t)}{\sqrt{\sigma_i}} e^{-\pi((t-c_i)/\sigma_i)^2} \left[\frac{2\pi (t-c_i)^2}{\sigma_i^3} - \frac{1}{2\sigma_i}\right], \\
\frac{\partial \varphi_i}{\partial f_i} &= \frac{\partial}{\partial f_i}\left[x_i \frac{1}{\sqrt{\sigma_i}} e^{-\pi((t-c_i)/\sigma_i)^2} \cos(f_i t)\right] \\
&= -\frac{t}{\sqrt{\sigma_i}} x_i e^{-\pi((t-c_i)/\sigma_i)^2} \sin(f_i t).
\end{aligned} \tag{15}$$

The updated Gabor filter parameters are as follows [20]:

$$\begin{aligned}
c_i(n+1) &= c_i(n) + \left[\eta_c \{d(n) - y(n)\} w_i\right] \\
&\quad \cdot \left[\frac{x_i}{\sqrt[5]{\sigma_i}} \cos(f_i t)\, 2\pi (t - c_i)\, e^{-\pi((t-c_i)/\sigma_i)^2}\right], \\
\sigma_i(n+1) &= \sigma_i(n) + \left[\eta_\sigma \{d(n) - y(n)\} w_i\right] \\
&\quad \cdot \left\{\frac{x_i \cos(f_i t)}{\sqrt{\sigma_i}} e^{-\pi((t-c_i)/\sigma_i)^2} \left[\frac{2\pi (t-c_i)^2}{\sigma_i^3} - \frac{1}{2\sigma_i}\right]\right\}, \\
f_i(n+1) &= f_i(n) + \left[\eta_f \{d(n) - y(n)\} w_i\right] \\
&\quad \cdot \left\{-\frac{t}{\sqrt{\sigma_i}} x_i e^{-\pi((t-c_i)/\sigma_i)^2} \sin(f_i t)\right\}.
\end{aligned} \tag{16}$$

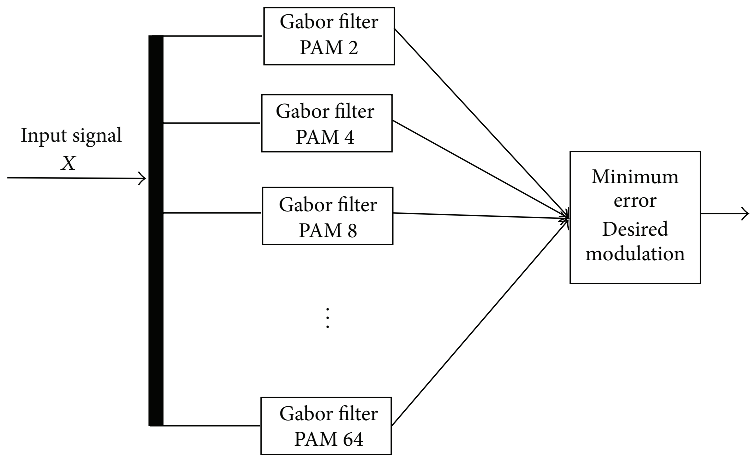

FIGURE 3: Testing of Modified Gabor Filter network for M-PAM signals classification.

The weights of adaptive filter are updated using RLS algorithm as follows:

$$\begin{aligned} k(n) &= \frac{K(n-1)\varphi(n)}{\lambda+\varphi^T(n)K(n-1)\varphi(n)}, \\ e(n) &= d(n)-y(n)=d(n)-\sum_{i=1}^{M}\varphi_i w_i, \\ w(n) &= w(n-1)+k(n)e(n), \\ K(n) &= \lambda^{(-1)}K(n-1)-\lambda^{(-1)}k(n)\varphi^T(n)K(n-1). \end{aligned} \tag{17}$$

To initialize the algorithm, weights are initialized as $w(0) = [1, 1, \ldots, 1]$ and the K is referred to as inverse correlation matrix. The $\varphi(n)$ is the input vector and λ is forgetting factor.

Algorithm 1 (training of Modified Gabor Filter network for modulation classification).

Step 1. Initialize Gabor atom parameters.

Step 2. Compute all Gabor atom nodes using (14).

Step 3. Adjust adaptive filter using RLS (17).

Step 4. After adjusting the weights, calculate error form (7).

Step 5. If error is less than chosen threshold, then training of algorithm is stopped and save Gabor atom parameters (c_i, σ_i, f_i) and Gabor filter weights w_i.

Step 6. If error is not less than threshold, repeat step (3) by using the error calculated in step (4).

Step 7. Tune the Gabor atom parameters (c_i, σ_i, f_i) using (16).

(B) Testing of MGF Network. Figure 3 shows the testing of MGF network by computing the error function of each Gabor filter network. The minimum error corresponds to the desired modulation format among class of M-PAM signals.

The algorithm for testing of MGF network for classification of M-PAM signals is as shown below.

Algorithm 2 (testing of Modified Gabor Filter network for modulation classification).

Step 1. Input digital modulated signal which may be PAM 2 to 64 modulated.

Step 2. Compute the output of each Gabor filter network by using the relation

$$y = \sum_{i=1}^{M}\varphi_i w_i. \tag{18}$$

Step 3. Compute the error function of each Gabor filter network.

Step 4. Minimum error corresponds to the desired modulation format of the input signal.

4. Simulation Results

The simulation results are divided into two modules; in the first module, training of Gabor filter network is evaluated for the M-PAM signal classification in tabular form and also curves for mean square error versus number of iterations and signal to noise ratio are evaluated. The considered modulation formats are trained accordingly in the class of M-PAM signals. The received signal is also corrupted form AWGN and efficient features are calculated and used for training of Gabor filter network. At the end of training, the three parameters of Gabor filter network (shift, scale, and modulation parameters) and adaptive filter weights are saved for minimum mean square error. In the second module, the testing of Gabor filter network is carried out by finding the error function of each Gabor filter network and minimum error corresponds to desired modulation format. The simulation results in testing module are in the form of probability of correctness curve versus SNR under the effects of AWGN and channel effects.

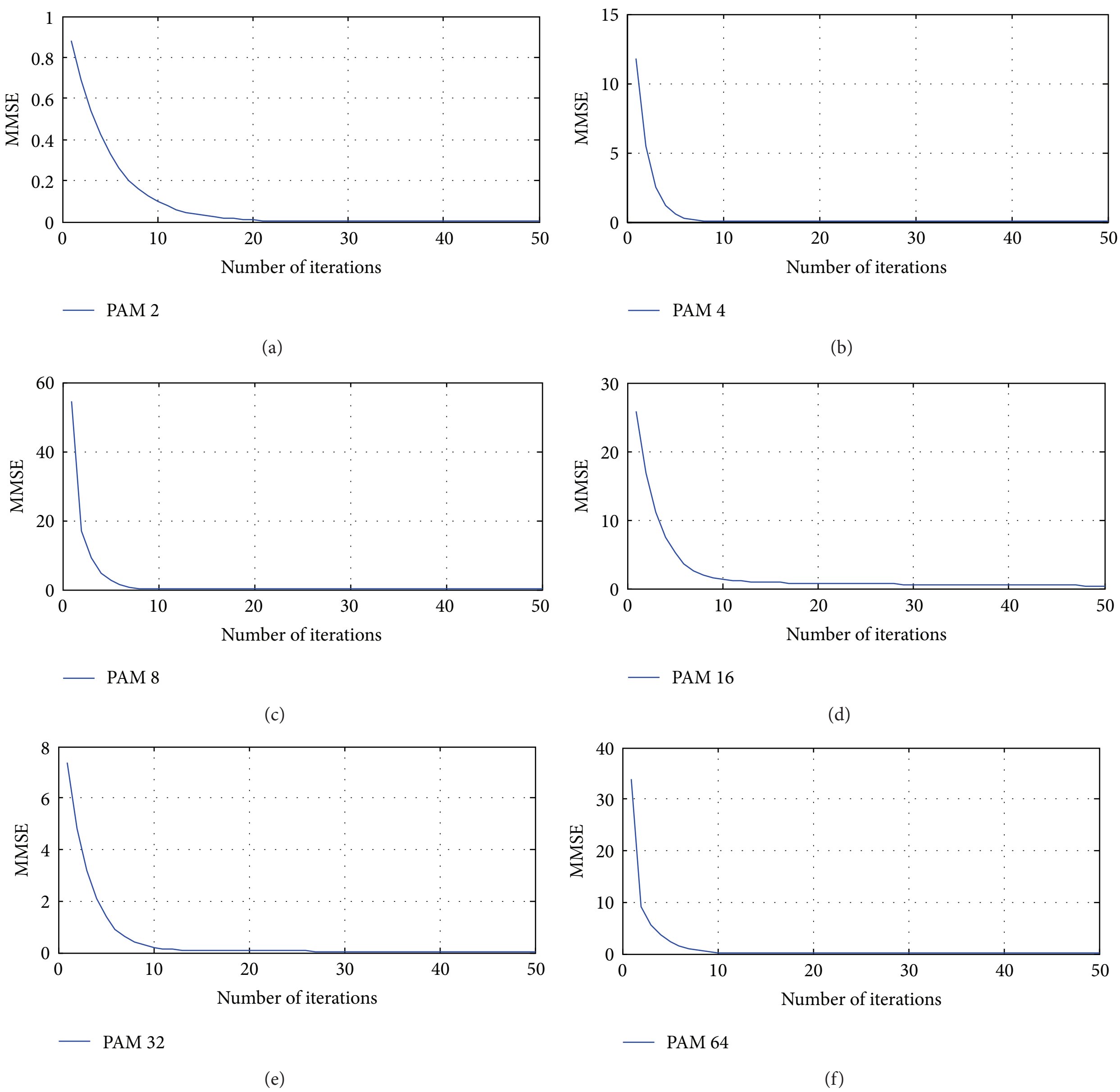

Figure 4: Training of Gabor filter network for the M-PAM formats under no noise.

4.1. Training of Modified Gabor Filter Network. Figure 4 shows the training of Gabor filter network under no noise conditions. From Figure 4, it is clear that the minimum means square error (MMSE) is approaching to zero as the number of iterations increases for all considered modulation formats. The training of network is stopped when MMSE reaches some threshold or zero and the features are stored.

Figure 5 shows the training of Gabor filter network under the influence of AWGN channel with fixed number of iterations. The MMSE is approaching to zero as SNR increases from −10 to 20 dB for the considered modulation formats as shown in Figure 5.

Table 1 shows the training performance of Gabor filter network in the form of diagonal matrix or accuracy matrix for the classification of considered modulation formats (PAM 2, PAM 4, PAM 8, PAM 16, PAM 32, and PAM 64). The training performance is approximately 100% under no noise considerations.

Table 1: Training performance of Gabor filter network of M-PAM signal classification without noise.

	PAM 2	PAM 4	PAM 8	PAM 16	PAM 32	PAM 64
PAM 2	100%					
PAM 4		100%				
PAM 8			100%			
PAM 16				99.2%		
PAM 32					99.6%	
PAM 64						100%

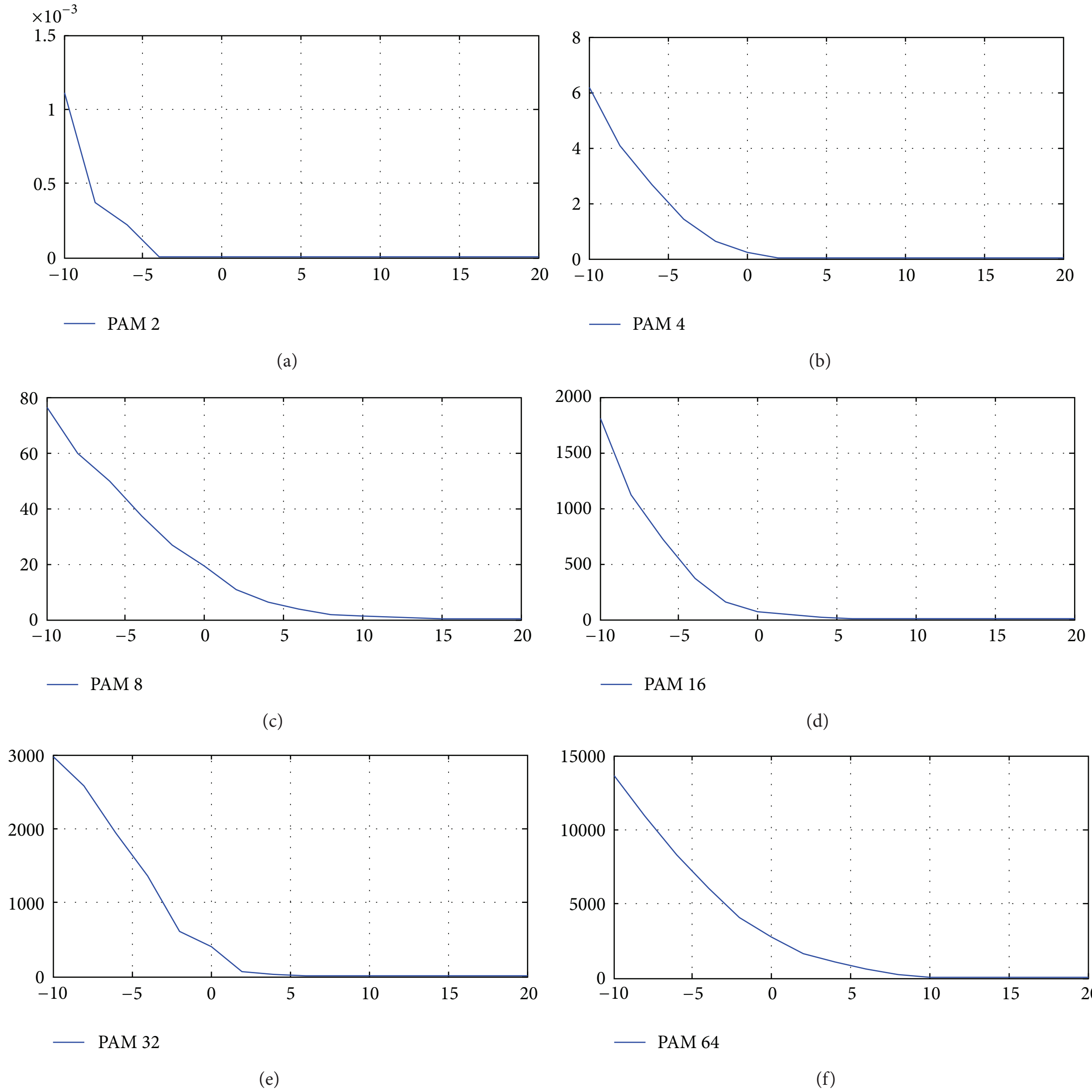

Figure 5: Training of Gabor filter network for the M-PAM formats on AWGN channel.

Table 2: Training performance of Gabor filter network of M-PAM signal classification on AWGN channel.

	PAM 2	PAM 4	PAM 8	PAM 16	PAM 32	PAM 64
PAM 2	100%					
PAM 4		99.9%				
PAM 8			100%			
PAM 16				98.4%		
PAM 32					99.2%	
PAM 64						99.3%

Table 2 shows the training performance of Gabor filter network in the form of diagonal matrix or accuracy matrix for the classification of M-PAM signals under the influence of additive white Gaussian noise. The training of Gabor filter network is done at SNR of 5 dB and accuracy is approximately 99.5% for considered modulation formats.

4.2. Testing of Modified Gabor Filter Network. Table 3 shows the testing performance of Gabor filter network in the form of diagonal matrix for the M-PAM signal classification. The performance is evaluated at SNR of 5 dB and it is shown from the table that percentage accuracy for classifying the modulation formats is much better at low SNRs.

Table 4 shows the testing performance of Gabor filter network in the form of diagonal matrix for the M-PAM signal classification at SNR of 10 dB and it is shown from the table that percentage accuracy for classifying the modulation

Table 3: Testing performance of Gabor filter network of M-PAM signal classification at SNR = 5 dB on AWGN channel.

	PAM 2	PAM 4	PAM 8	PAM 16	PAM 32	PAM 64
PAM 2	98.6%					
PAM 4		97.8%				
PAM 8			96.6%			
PAM 16				96.1%		
PAM 32					98.1%	
PAM 64						97.6%

Table 4: Testing performance of Gabor filter network for M-PAM signal classification at SNR = 10 dB on AWGN channel.

	PAM 2	PAM 4	PAM 8	PAM 16	PAM 32	PAM 64
PAM 2	99.5%					
PAM 4		98.9%				
PAM 8			99.9%			
PAM 16				98.3%		
PAM 32					98.5%	
PAM 64						98.9%

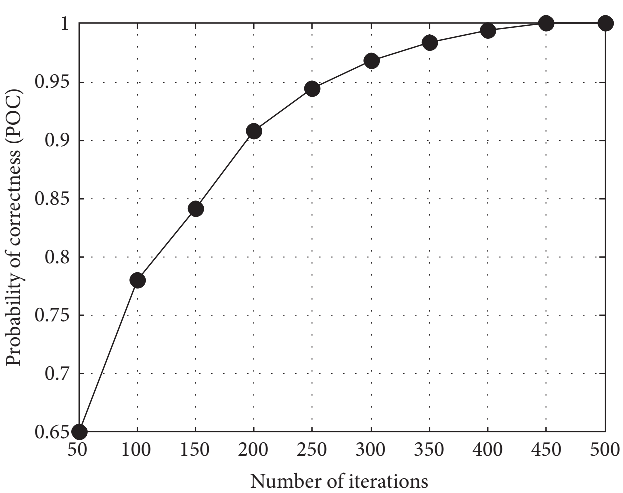

Figure 6: Probability of correctness curve for the example of PAM 16.

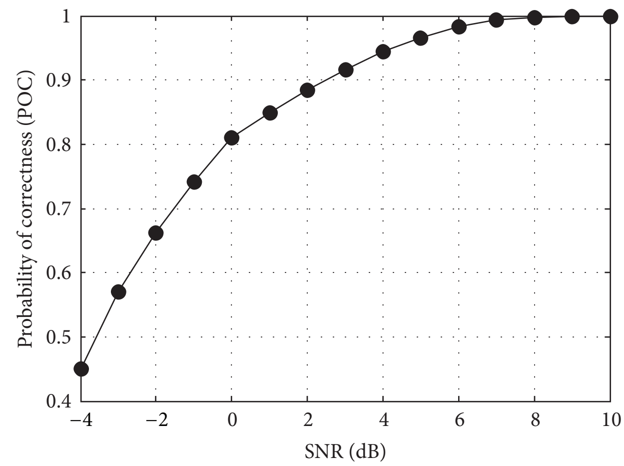

Figure 7: Probability of correctness curve under AWGN channel for the example of PAM 16.

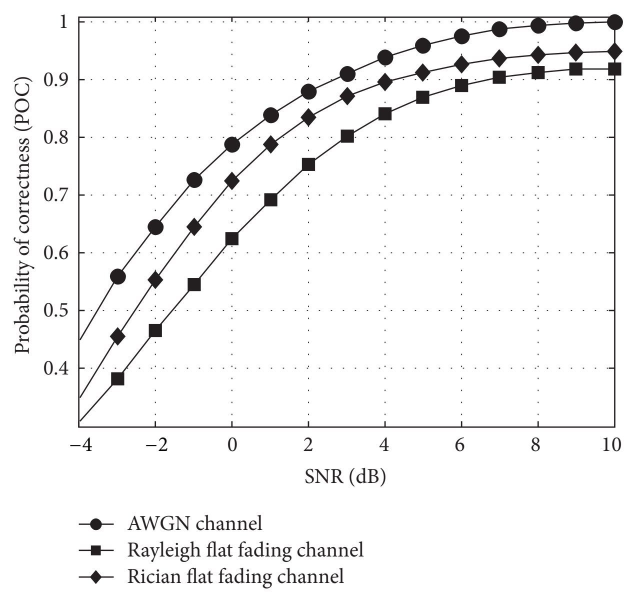

Figure 8: Performance comparison under the effect of AWGN and faded channel for the example of PAM 8.

formats is 98.7%. The testing performance is better due to two facts: first choice of efficient features from the Gabor filter network and second the classifier.

Figure 6 shows the probability of correctness (POC) plotted against number of iterations and from Figure 6, it is clear that POC is approximately 1 when number of iterations increased up to 500. The example considered in Figure 6 is PAM 16 among class of M-PAM signals which are classified correctly.

Figure 7 shows the probability of correctness (POC) plotted against signal to noise (SNR) for fixed number of iterations and from Figure 7 it is clear that POC is approximately 1 when SNR is increased up to 10. The example considered in Figure 7 is PAM 16 and classification accuracy is approximately 90% at SNR greater than 3 dB.

The classification performance of PAM 8 considered example among the M-PAM signals is evaluated in Figure 8. Figure 8 also shows the performance comparison under the effect of AWGN channel, Rician flat fading channel, and Rayleigh flat fading channel. The classification accuracy is much better for the considered example on considered channels.

Table 5 shows the performance comparison of percentage classification on the AWGN channel, Rician flat fading channel, and Rayleigh flat fading channel for the example of 8-PAM among class of M-PAM signals. The classifier performance is evaluated for SNR −4 to 10 dB on fading channel plus AWGN. The classifier performance is approximately 100% on AWGN channel, 95% on Rician flat fading channel, and 92% for the Rayleigh flat fading channel at SNR of 10 dB.

Table 5: Testing performance comparison of Gabor filter network on AWGN and fading channels for the example of 8-PAM format.

SNR in dB	AWGN channel	Rician flat fading channel	Rayleigh flat fading channel
−4	45.0%	35.1%	31.0%
−3	57.0%	45.6%	37.0%
−2	66.2%	55.44%	46.8%
−1	74.2%	64.64%	54.9%
0	81.0%	72.64%	63.4%
1	85.2%	78.84%	70.8%
2	88.4%	83.36%	76.8%
3	91.6%	87.16%	81.0%
4	94.4%	89.6%	85.1%
5	96.6%	91.4%	87.8%
6	98.4%	92.76%	89.8%
7	99.4%	93.76%	91.2%
8	99.91%	94.36%	91.8%
9	100%	94.87%	92.0%
10	100%	95%	92.0%

Table 6: Performance comparison with existing techniques.

Method year, and reference	Features used	Classification accuracy at 10 dB of SNR
Zero Crossing (1995) [21]	PDF of cross related variables	98% 15 dB of SNR
Hierarchical Architecture (1990) [22]	Spectral features	90%
Multilayer Perceptron, Hierarchical SVM + Bees Algorithm for Optimization (2012) [11]	Spectral features HOM	97.45% (w/o optimization) 99.83% (optimization)
SVM + PSO (2012) [12]	Spectral features Statistical features Wavelets features	98.8%
Artificial Neural Network (2003) [23]	Spectral features	93% 8 dB of SNR
Genetic Algorithm based Clustering (2011) [10]	Spectral features	98.32% (GA) 98.12% (K-mean)
Hierarchical Architecture (2000) [24]	HOC & HOM	96%
Fuzzy based Classifier (2000) [25]	Kurtosis phase histogram	90% 5 dB of SNR
Multilayer Perceptron Neural Network Recognizer (2004) [13]	Spectral features cumulants	99.94%
Binary SVM, Multi SVM GA for Optimization (2010) [14]	HOM & HOC	98.5% (w/o optimization) 99.36% (optimization)
PSO-SVM based Intelligent Classifier (2013) [17]	HOC	96%
Gabor Filter (2014) [20]	Shift, scale, and modulation parameters	100%
Proposed MGF Network based classifier	Shift, scale, modulation, and weights	100% (8 dB of SNR)

The efficient features extraction from the Gabor filter network easily classifies the considered modulation formats with very low probability of error.

Table 6 shows the classification performance comparison with well-known existing techniques. The classification performance of proposed MGF network based classifier is much better at lower SNRs. The proposed classifier is also capable of classifying M-PSK, M-QAM, and M-FSK [20]. The three features are used to classify M-PAM signals.

5. Conclusion

On the basis of simulations, it can be concluded that proposed MGF network efficiently classifies the M-PAM signals on

AWGN channel as well as Rician flat fading channel and Rayleigh flat fading channel. The training and testing of proposed MGF network algorithm are done using Delta rule and RLS algorithm which shows the 100% classification accuracy at 8 dB of SNR. The classification accuracy is much better when compared with state-of-the-art well-known techniques. In our future work, we intend to use other biologically inspired computational intelligence algorithms for optimizing the results and higher classification accuracy.

Conflict of Interests

The authors declare that there is no conflict of interests regarding the publication of this paper.

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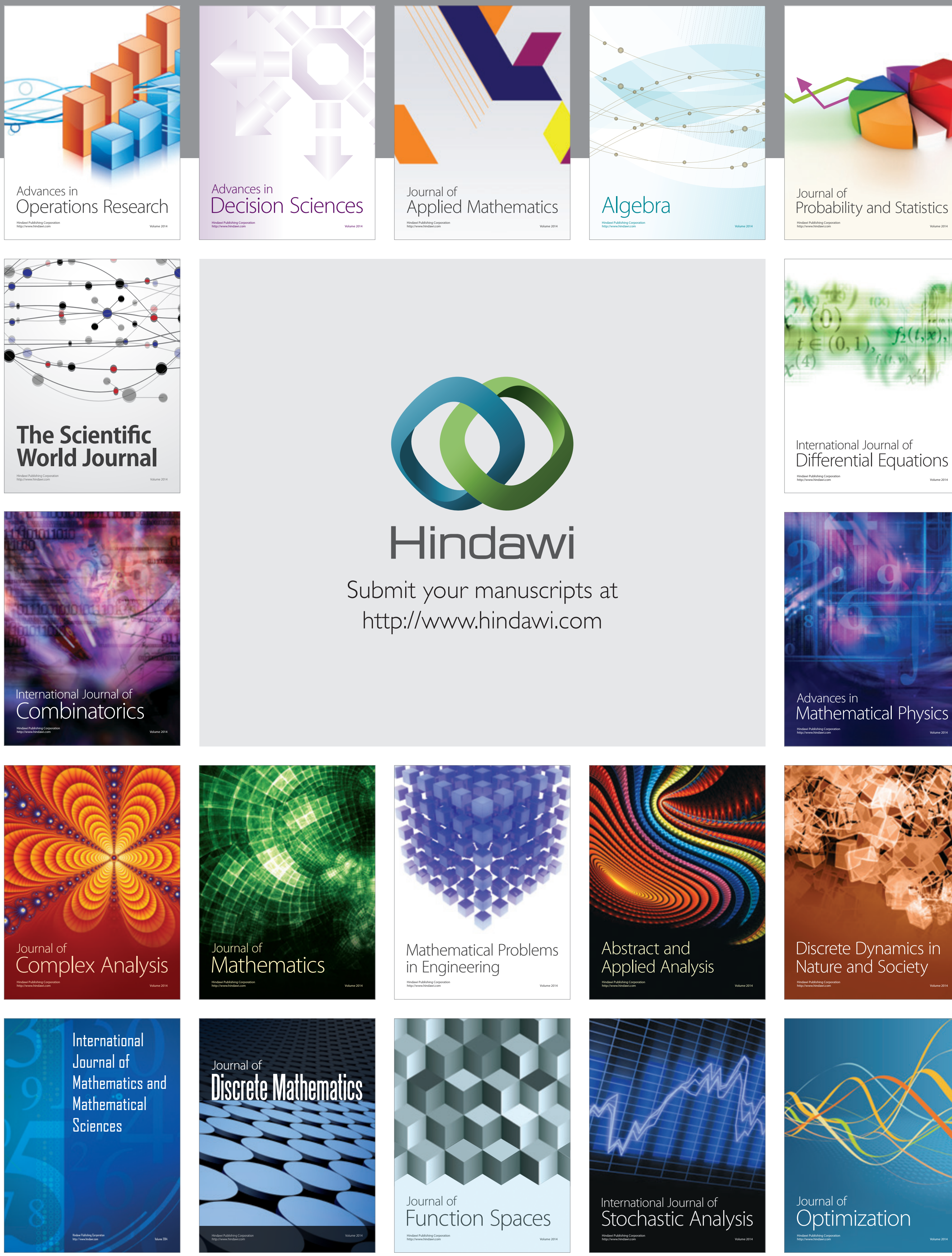
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