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# Digital Modulation Recognition in Noisy Environment Using a Learning Machine

***Abstract***- *This paper proposes a method to identify the type of digitally modulated signals. The modulation classification process is performed using Support Vector Machines (SVMs) with one versus all approach. A multi-class recognition system is required. Consequently, the Radial Basis Function (RBF) kernel is proposed. The system is intended to classify three types of signals: ASK FSK, and PSK. Five features are extracted from amplitude, frequency and phase of each modulated signal to be the input of the SVM classifier. The system is simulated using MATLAB software. The system is tested against Additive White Gaussian Noise (AWGN). The classification rate for all modulated signals is measured at different values of SNR. The overall performance of this classifier is around 83% at -5 dB. Furthermore, to enhance the performance of the classifier further, the data inputs to the SVMs for each modulated signal is reduced by eliminating some key features. These are the standard deviation of the direct value of the centered non-linear component of the instantaneous phase and the standard deviation of the absolute value of the normalized-centered of the instantaneous amplitude. The overall performance after input data reduction is greater than 84% at -5 dB.*

***Keywords***-: *Digital Modulation Recognition, Overall success rate, RBF, Recognition rate, SVMs.*

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## 1. Introduction

Modulation recognition is progressively imperative in an assortment of military applications, and additionally business and non-military personnel purposes. It is utilized for spectrum reconnaissance and administration, source identification, cognitive radio, interference ID et cetera. Therefore, modulation recognition has summoned extraordinary research intrigue. There are two approaches to identify modulation types. These are decision trees (DT) and machine learning (ML). The first approach (DT) requires high SNR for feature extraction. It demands for complex processing to determine the better features. In addition, it is not easy to choose the decision threshold. In ML approach, the conventional neural network algorithm experienced "over learning", "less to learn" that upset its generalization [1].

The statistical learning field has numerous powerful tools, which can be utilized in the modulation classification issue. SVMs provide a process of complex decision-making without a significant part of the requests on SNR and signal segment length.

SVMs offer a proficient method for classification without putting suppositions on signal statistics or on SNRs. The standard binary SVM classifier can be easily stretched out to a multi-class classifier for use for this situation [2].

*I. Characteristics Extraction*

An algorithm based on key feature extraction and multi-class SVM is used in this work as a recognition system to classify various forms of digitally modulated signals under different values of SNR.

This paper is divided into five sections. Different key features and a short review on SVM Classifier is presented in the second section. In third section, the system model is illustrated. The performance evaluation and results are given in fourth section. In spot, five the conclusions derived from this work are stated.

## 2. The Classification System

The SVM modulation recognizer is consisted of two main phases, as shown in Figure 1. The first phase includes preprocessing in which the incoming signal is segmented and the key features are calculated from the signal segments. The second phase includes support vector machine classifier to identify the class of the incoming signals [3].

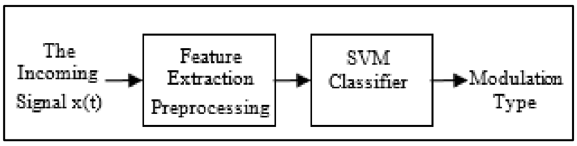


**Figure 1: Modulation recognition scheme**

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To minimize recognition machine computational time, a recognition system is usually fed in by reduced data set. The data set is extracted from original signal and it is usually called signal's key features. The features carry the important characteristic of the signal to be processed. The extracted features technique for modulation recognition and identification was considered in [4, 5]. In this case, the information is covered up in the signal's frequency, phase and instantaneous amplitude. A good feature is independent on SNR, but they should be sensitive to different modulation schemes.

In every available segment, five key characteristics are measured by utilizing traditional signal processing techniques. The five key features are listed below:

**a-** Maximum Value of the Spectral Power Density $\gamma_{max}$ of the normalized-centered instantaneous amplitude$a_{cn}(k)$, [3,4], and it is given:

$$\gamma_{max} = \max\left|FFT(a_{cn}(k))\right|^2 / N_s \quad (1)$$

Where $a_{cn}(k)$ is defined time instants $t = \frac{k}{f_s}$, $(k = 1,2,\ldots,N_s)$, and it is determined by:

$$a_{cn}(k) = a_n(k) - 1, \text{where } a_n(k) = \frac{a(k)}{m_a}, \quad (2)$$

Where $m_a$ average value of instantaneous amplitude is calculated for each segment.

$$m_a = \frac{1}{N_s}\sum_{k=1}^{N_s} a(k), \quad (3)$$

The instantaneous amplitude of the input signal is normalized. So, the channel gain is equalized.

**b-** Standard deviation of the absolute value of the centered non-linear component of the instantaneous phase [3, 4]

$$\sigma_{ap} = \sqrt{\frac{1}{Ct}\left(\sum_{a_n(k)>a_t} \theta^2{}_{NL}(k)\right) - \left(\frac{1}{Ct}\sum_{a_n(k)>a_t}|\theta_{NL}(k)|\right)^2} \quad (4)$$

Where $\theta_{NL}(k)$ is the value of the centered non-linear component of the instantaneous phase at time instants$t = \frac{k}{f_s}$. And $Ct$ is the number of samples in $\{\theta_{NL}(k)\}$ for which$a_n(k) > a_t$ , and $a_t$ is a threshold for $\{a(k)\}$ below which the assessment of the instantaneous phase is easily affected by noise.

**c-** Standard deviation of the direct value of the $\theta_{NL}(k)$evaluated over the non-weak intervals of a signal segment [4,5]:

$$\sigma_{dp} = \sqrt{\frac{1}{Ct}\left(\sum_{a_n(k)>a_t} \theta^2{}_{NL}(k)\right) - \left(\frac{1}{Ct}\sum_{a_n(k)>a_t} \theta_{NL}(k)\right)^2} \quad (5)$$

**d-** Standard deviation of the absolute value of the $a_{cn}(k)$ of a signal segment [3,4]:

$$\sigma_{aa} = \sqrt{\frac{1}{N_s}\left(\sum_{k=1}^{N_s} a^2{}_{cn}(k)\right) - \left(\frac{1}{N_s}\sum_{k=1}^{N_s}|a_{cn}(k)|\right)^2} \quad (6)$$

**e-** "Standard deviation of the absolute value of the normalized centered instantaneous frequency calculated over the non-delicate period of a signal segment" [3, 4]:

$$\sigma_{af} = \sqrt{\frac{1}{Ct}\left(\sum_{a_n(k)>a_t} f^2{}_N(k)\right) - \left(\frac{1}{Ct}\sum_{a_n(k)>a_t}|f_N(k)|\right)^2} \quad (7)$$

Where

$f_N(k) = \frac{f_m(k)}{r_s}$,

$f_m(k) = f(k) - m_f$

Also $m_f = \frac{1}{N_s}\sum_{k=1}^{N_s} f(k)$ (8)

$r_s$: represents the symbol rate

*II. SVMs Classifier*

SVM is a feed-foreword network, which had been proposed by Professor VAPNIK as indicated by the statistical learning hypothesis. Many studies have been published on SVM and its applications in pattern recognition and regression [6]. In modulation classification, an SVM is utilized in order to identify the class of digital modulation signals, It is supposed that the extracted features are training points $(x_k, y_k)$ where $x_k(k = 1,\ldots,M)$ is m-dimensional training relate to Class 1 or 2 and the affiliated brands (target output) be $y_k$ = 1 for Class 1 and −1 for Class 2.

The training set can be segregated by the

$$w^T x + b = 0 \quad (9)$$

Where w is an m-dimensional weight vector, and $b$ is a bias term (offset constant). If this hyper-plane amplifies the margin, then

$$y_k(w^T x + b) \geq 1 \quad \text{for all x.} \quad (10)$$

By using Lagrange multipliers ($\alpha_k, k = 1, \dots, M$; $\alpha_k \geq 0$), and by some calculation, the optimal decision function is presented by [5,6]:

$$f(x) = \sum_{k \in S} \alpha_k y_k x_k{}^T x_k + b \quad (11)$$

Where S is the support vector indexes set.
Equation (10) is applied for linearly separable data, which is known as hard-margin SVM. When the input signal is affected by a high amount of noise, SVM utilizes soft margins. Theses margins are defined as follows with the presentation of the positive slack variables$\xi_k, k = 1, \dots, M$:

$$y_k(w^T x_k + b) \geq 1 - \xi_k \text{ for} k = 1, \dots, M \quad (12)$$

Optimal separating hyper-plane is achieved by minimizing the

$$Q(w, \xi) = \frac{1}{2} \|w\|^2 + C \sum_{k=1}^{M} \xi_k \quad (13)$$

The margin constant $C$ must be correctly selected so that there is a compromise between the maximization of the margin and the reduction of the classification error. The unique distinction between soft-margin SVMs and hard-margin SVMs is that $\alpha_i$ must be less than $C$.

$$f(x) = \sum_{i \in S} \alpha_i \, y_i x_i{}^T x + b$$
(14)

In the distinguishable cases of nonlinearity, the training points are mapped by SVM in a nonlinear manner to a feature space of high dimensional. This is carried out by utilizing the kernel function K(x,x′), in order to achieve linear separation. Gaussian RBF, abbreviated as GRBF, is one of the common known Kernel functions, which is emphasized on in more depth in [6,7].

$$K(x, x') = \exp\left(-\frac{1}{2\sigma^2} \|x - x'\|^2\right) \quad (15)$$

Where $\sigma$ is the width of the RBF kernel.
At the end of training process, the decision function turns into:

$$f(x) = \sum_{i \in S} \alpha_i y_i K(x_i, x) + b \quad (16)$$

In this paper, the GRBF is used, due to its superior performance as it set against other types of kernels.
Essentially, An SVM classifier is a two states classifier. This implies that it can classify signals of two different classes. Anyhow, SVMs are expanded to multiclass classifiers by regarding N-class classification issue as N two-class issues. This is called one-versus-rest classification. There is another approach called one-versus-one [6,7]. In this work, the modulation recognition is achieved by utilizing five binary classifiers, each one acts as one-versus-all classifier.

## 3. System Model

A set of digital pass-band signals (ASK2, ASK4, PSK2, FSK2 and FSK4) corrupted by AWGN is simulated in MATLAB environment. The parameters of the input signal are: the sampling frequency,$f_s$ is set to 1.2MHz , the frequency of the carrier,$f_c$ is 0.15MHz, the and the symbol rate, $r_s$ , of 12.5 kHz [8].
The input signal of L seconds is partitioned into segments. The length of every segment is $N_s = 2048$ samples (each segment duration $t$ is equal to $t = \frac{k}{f_s}$, where $i = 2048$ thus $t = 1.706$ msec.). Thus $M_s = Lf_s/N_s$=400 segments. The five key features are extracted from each segment, which will be utilized in the next step as the inputs to the SVM classifier. The whole keys are taken out from the instantaneous attributes of a signal segment. These characteristics are computed from the analytic signal, which is a complex signal composed of two parts, the real and the imaginary. The Hilbert transform is used with each signal segment to obtain the analytic signal. The key features for each digitally modulated signal are measured without adding noise. Figure 2 displays the values of key features for every modulated signal. Based on Figure 2, the influential key feature for each modulated signal can be determined.
The data inputs of the SVM classifier are the extracted five key features ($\gamma_{max}, \sigma_{aa}, \sigma_{ap}, \sigma_{dp}, \sigma_{af}$) of the received signals. The goal of the SVM training process is to find the optimal weights and biases that represent the hyper-planes or thresholds, for the modulated signal. Due to the noise effect, the data samples of the positive and negative classes are misclassified and the data points are not linearly separable. As a result, SVM utilize soft margin via kernel function and formulate a segregation hyper-plane. This hyper-plane is employed in mapping the training data into higher dimensional space non-linearly. RBF is chosen as a mapping kernel function

$$(K(x, y) = \exp(-\|x - y\|^2 / 2\sigma^2)) \quad (17)$$

where$\sigma = 1$, with regularization parameter $C = 1$ (the value $\sigma$ and $C$ is chosen by the researcher).

RBF has been used due to its soupier performance compared to other kernels.

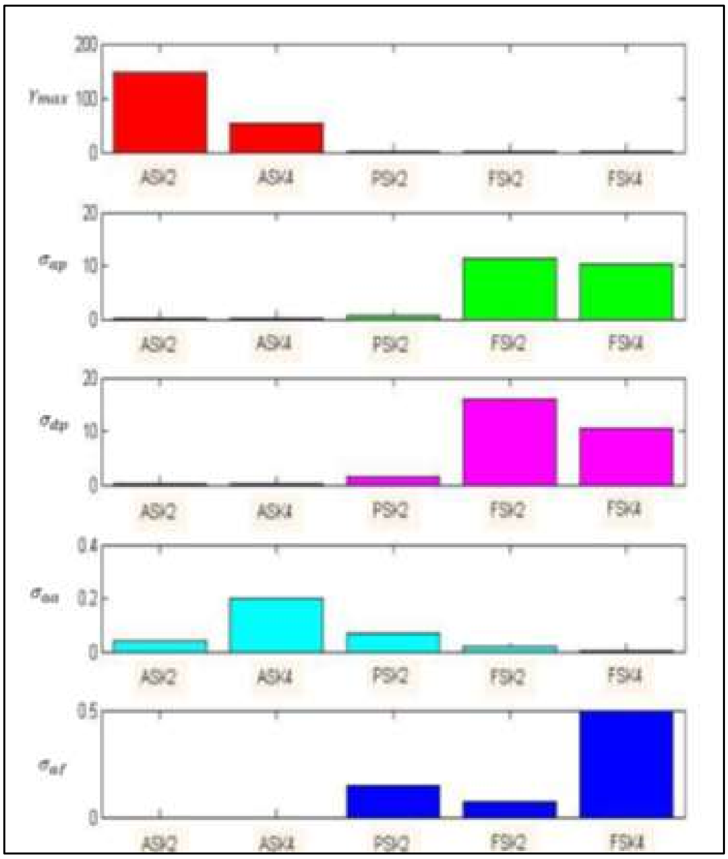


**Figure 2: All Features for all Modulated Signals without Adding Noise**

Figure 3 outlines the block diagram of the proposed method, which is devoted to classify five digitally modulated signals.

In the SVM classifier algorithm, Figure 3, all the features for each modulated signal are regarded all together; consequently, the key features arrangements do not influence the likelihood of the correct modulation classification. Each signal has 400 feature sets; hence, the input feature vector at each SVM stage is of 2000 realization. 1000 realizations are used for training and 1000 realization are used for testing. The technique of using half Ms segments for training and other half for testing is performed by using the cross-validation function (MATLAB code).

The incoming signal samples are tested with all the obtained hyper-plane at each SVM stage. However, each stage has a decision function that gives the maximum value of average probability of correct decisions among all function.

## 4. Performance Evaluation

This section shows the performance evaluation of the technique used in this framework. The classification of digital signals is evaluated without and with data input reduction to the classifier.

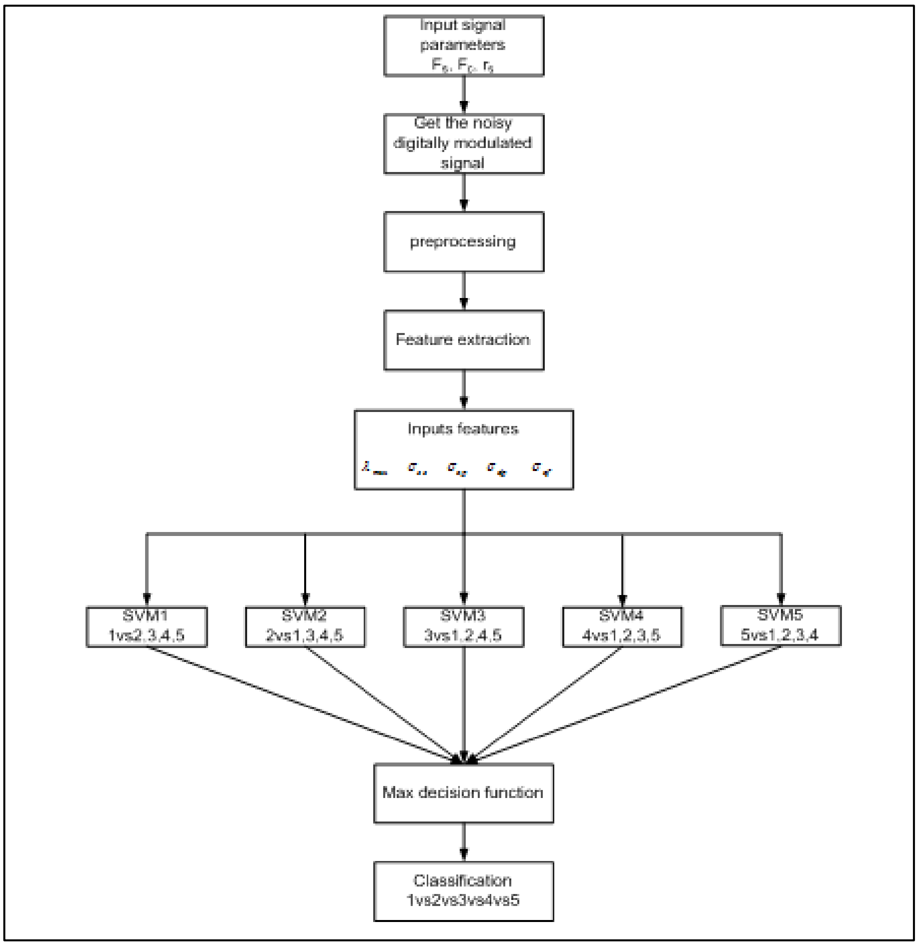


**Figure 3: Block Diagram of the Proposed Algorithm**

*I. Performance without Data Input Reduction*

The performance of the proposed classifier is tested by two simulation experiments. In the first experiment, the five digitally modulated signals are corrupted by AWGN. The classifier is examined at different SNR values. In this test, five key features are utilized to classify the signals. Table 1, demonstrates the recognition rate of the (2ASK, 4ASK, 2FSK, 4FSK, and 2PSK) signals when the SNR is varied from -5dB to 20dB. It is noticed that all of the signals are successfully recognized with a recognition rate higher than 79%. At 20 dB SNR, it is seen that the FSK2 and FSK4 signals are correctly recognized with a recognition rate as high as 98%, while the rest of the signals are perfectly classified. The average recognition rates, at each SNR values, of the digital modulated signals are presented in Table 2, which shows good results at low SNR.

The results reveal that the system performance is very satisfactory even at low SNR values. Principally, because of the following: the key features are selected properly and the classifier based on SVM technique has good ability to recognize the digital modulated signals even at low SNRs.

**Table 1: Recognition rate for each modulation type**

| SNR (dB) | Modulated Signal | | | | |
|---|---|---|---|---|---|
| | ASK2 | FSK2 | PSK2 | ASK4 | FSK4 |
| -5 | 79.80% | 82.70% | 81.30% | 79.00% | 92.80% |
| -1 | 81.10% | 85.70% | 87.80% | 83.20% | 93.10% |
| 0 | 83.10% | 86.90% | 88.80% | 84.70% | 94.30% |
| 5 | 86.90% | 93.10% | 97.70% | 89.00% | 95.10% |
| 10 | 90.50% | 96.40% | 99.40% | 91.60% | 97.00% |
| 15 | 99.90% | 97.70% | 100% | 100% | 97.60% |
| 20 | 100% | 98.70% | 100% | 100% | 99.90% |

**Table 2: Overall recognition rates without data input reduction**

| SNR (dB) | Overall recognition rates |
|---|---|
| -5 | 83.0% |
| -1 | 86.10% |
| 0 | 87.56% |
| 5 | 92.36% |
| 10 | 94.9% |
| 15 | 99.0% |
| 20 | 99.72% |

*II. Performance with data input reduction*

In this subsection, the improvement is considered by trying to reduce the data set inputs to the classifier. This is done first by eliminating one of the five key features every time and then evaluate the performance of the new-trained SVMs.

The probability of correct classification for each modulated signal is depicted through Figures 4-8. When $\gamma_{max}$ is eliminated the classification of ASK2 and ASK4 are degraded as shown in Figures 4 and 5. So, this key feature should not be deleted from the dataset.

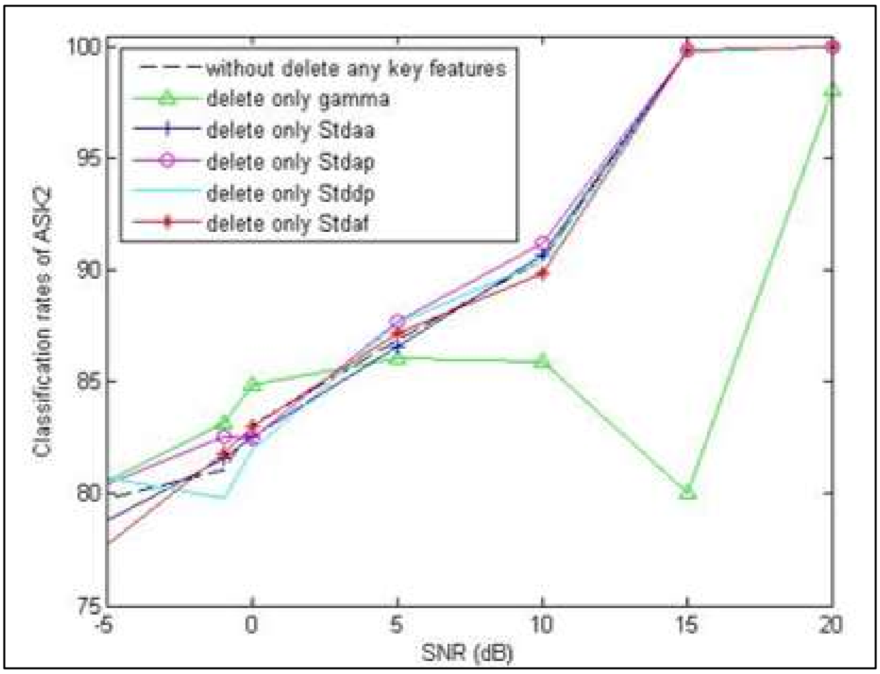


**Figure 4: Classification Rate of ASK2**

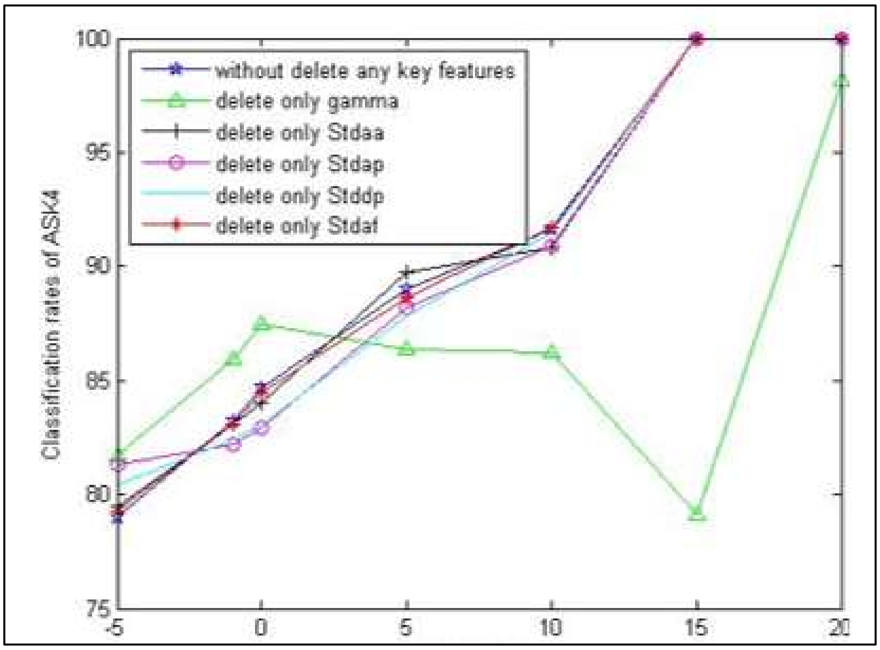


**Figure 5: Classification Rates of ASK4**

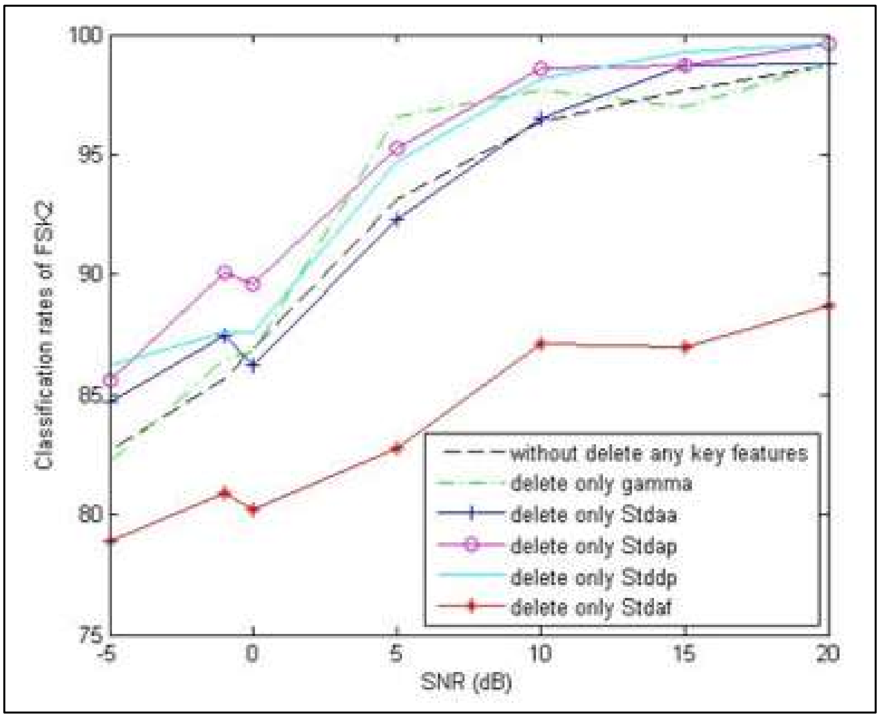


**Figure 6: Classification Rates of FSK2**

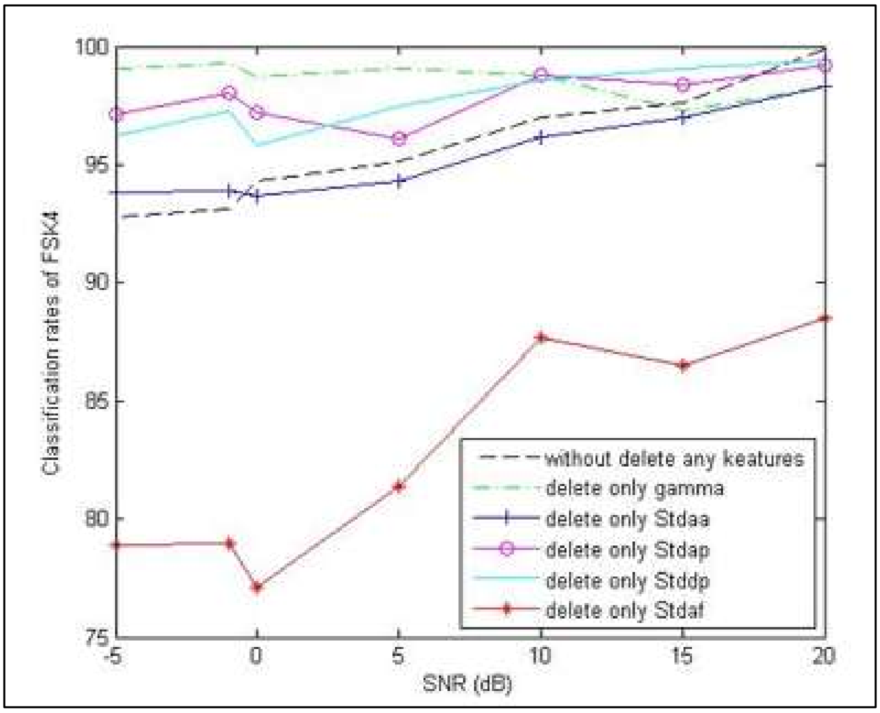


**Figure 7: Classification Rates of FSK4**

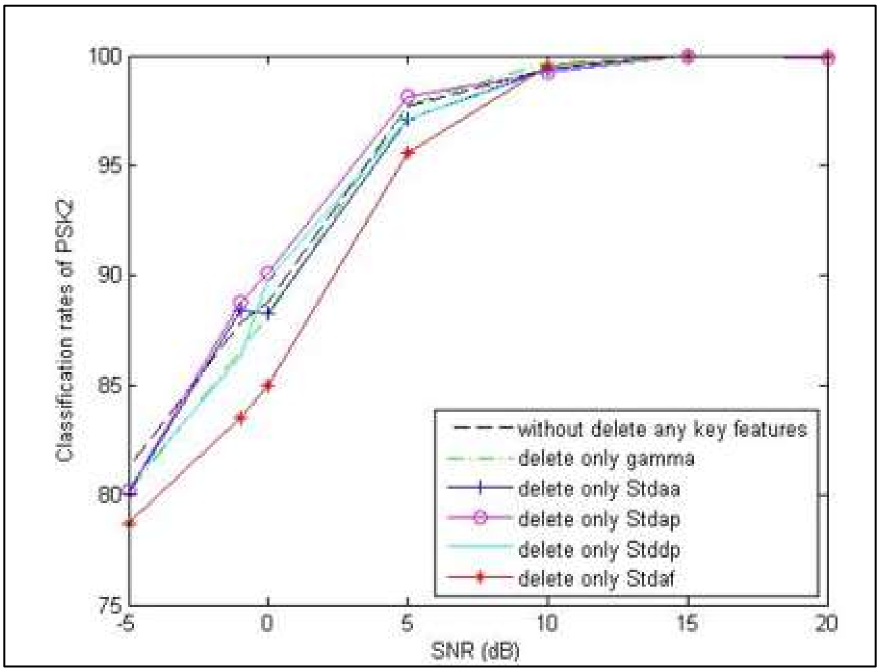


**Figure 8: Classification Rates of PSK2**

While, the performance for classifying ASK2 and ASK4 in Figures (4 and 5) respectively is not affected by deleting another key feature at a time is almost not changed.

The Figures 6 - 8 show the performance of FSK2, FSK4, and PSK2 signals. The classification rate is degraded when $\sigma_{af}$ is eliminated, which is utilized to distinguish between FSK4 and FSK2.

From Figures 4 - 8, $\sigma_{af}$ and $\gamma_{max}$ should not be eliminated. Based on some experiments, the deletion of $\sigma_{aa}$ and $\sigma_{dp}$ from all modulated signal will show improved results.

In the second experiment, we examined the effect of the three key features ($\gamma_{max}, \sigma_{ap}, \sigma_{af}$) on the signal classification. Table 3 displays the recognition rate of the system for the following SNR (-5, -1, 0, 5, 10, 15, and 20) values. It is evident that the enhanced recognizer has higher recognition rate, particularly at small amount of SNRs. Table 4 shows the overall recognition rate of the enhanced classifier at a specific SNRs.

**Table 3: The Recognition Rates for Each Modulation Type with Improvement**

| SNR (dB) | Modulated Signal | | | | |
|---|---|---|---|---|---|
| | ASK2 | FSK2 | PSK2 | ASK4 | FSK4 |
| -5 | 80.50% | 85.70% | 79.60% | 80.60% | 94.30% |
| -1 | 82.30% | 87.80% | 86.00% | 82.40% | 95.70% |
| 0 | 84.10% | 87.80% | 88.90% | 84.80% | 95.90% |
| 5 | 88.10% | 95.50% | 97.00% | 90.00% | 96.50% |
| 10 | 92.30% | 97.00% | 99.30% | 92.60% | 98.50% |
| 15 | 99.70% | 99.50% | 100% | 100% | 99.50% |
| 20 | 100% | 99.70% | 100% | 100% | 99.70% |

**Table 4: Overall Recognition Rates of Improved Technique**

| SNR (dB) | Overall recognition rates |
|---|---|
| -5 | 84.14% |
| -1 | 86.74% |
| 0 | 88.3% |
| 5 | 93.42% |
| 10 | 95.84% |
| 15 | 99.74% |
| 20 | 99.88% |

In order to make a comparison between the two classifiers, the results of Table 2 and Table 4 are plotted against SNR variation. Figure 9 compares between the performances of the non-reduced data and reduced data approach. It is obvious that the elimination of $\sigma_{aa}$ and $\sigma_{dp}$ key features enhances the performance of the classifier for all SNRs.

*III. Performance Comparison*

In order to compare the performance of the proposed classifier with similar works, [3,9,10,11,12]. The overall success rate is considered as an assessing parameter. In this paper five digitally modulated signals are adopted, which are 2ASK, 4ASK, 2FSK, 4FSK, and 2PSK. The overall success rate for the mentioned papers are calculated based on the signals used in this paper, only the signals similar to those used in this work are taken into account. For example, the following signals 2ASK, 4ASK, 2FSK, 4FSK, 2PSK, 4PSK, and 16QAM are chosen by ref. [9], thus the first five signals are considered and the 4PSK and 16QAM signals are neglected. Table 5, displays the overall success rate for modulation recognition of the proposed classifier and the simulation results of reference five papers which covers the period between (2004 to 2015). At SNR of 15dB, it is clear that the proposed system outperforms the technique used in ref. [9] and slightly better than the others. At SNR of 10dB, the proposed system outperforms the classifier in ref. [9], but the classifier of ref. [10] performs better than our classifier by 3.21%. For SNR between (1dB to 8dB) it is evidence that the classifier used in ref. [12] achieves better overall recognition rates than the others. However, for low SNR values between (-5dB to 0dB) the proposed classifier achieves overall recognition rate between (84.14% to 88.3%), which are considered good values.

## 5. Conclusions

An SVM has been used to classify five digital modulated signals. The machine depends on five key features taken out from the instantaneous attributes of the input signal.

The performance evaluation was performed for the 400 feature sets (feature vectors) of each digitally modulated signal at each SNR value (-5, -1, 0, 5, 10, 15, and 20) dB. It is shown that the proposed classifier can achieve recognition of 83% at the SNR of -5dB.

Not all the features are important in classification. For examples, eliminating $\sigma_{aa}$ *and* $\sigma_{dp}$ enhances the classifier performance by around 1%, especially at low SNRs. Besides, reducing the number of the key features will simplifies the implementation of the proposed classifier.

However, the classifier based on SVM technique has good ability to recognize the digital modulated signals even at low SNRs. Finally, the shortcoming of the SVM algorithm is that it requires a very long time for training.

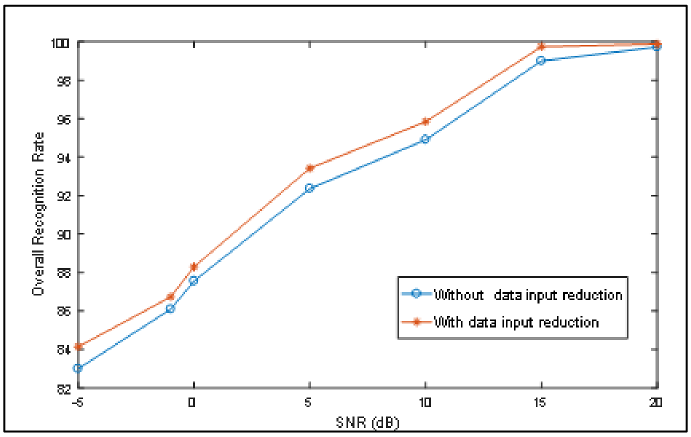


**Figure 9: Overall Recognition Rate for Non-Reduced Data and Reduced Data Classifiers at Different SNR Values**

**Table 5: Overall Recognition Rates of the Current and Similar Works**

| SNR | Ref [9] | Ref [3] | Ref [10] | Ref [11] | Ref [12] | Current work |
|---|---|---|---|---|---|---|
| -5 | - | - | - | - | - | 84.14% |
| -1 | - | - | - | - | - | 86.74% |
| 0 | - | - | - | - | - | 88.3% |
| 1 | - | - | - | 96.85% | - | 89% |
| 5 | - | 94.4% | - | - | - | 93.42% |
| 7 | - | - | - | - | 97.8% | 94.38% |
| 8 | - | - | 97.1% | - | - | 94.87% |
| 10 | 71.6% | - | 99.05% | - | - | 95.84% |
| 15 | 93.8% | - | 99.6% | 99.5% | - | 99.74% |
| 20 | - | - | - | - | - | 99.88% |

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Mohammed Ahmed Shakir, was born in Mosul, Iraq in 1974. He received B.Sc. degree in Electrical Engineering and M.Sc. degree in Electronic & Communication Engineering from university of Mosul, Mosul, Iraq in 1997 and 2000 respectively. In 2007, he received Ph.D. Degree in Computer Engineering from university of Mosul, Mosul, Iraq.
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