Identification method for m-ary frequency shift keying signals based on adaptive neural-fuzzy inference system (ANFIS) and discrete wavelet transform

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Abstract. Automatic modulation identification (AMI) is the ability to classify the modulated signals of an arbitrary modulation schemes. The extension of digitally modulated signal applications are continuous to grow which gives the AMI high importance for proper selection of demodulators, interference identification, signal confirmation etc. This paper presents a study of feature extraction and a classifier for M-ary frequency shift keying (MFSK) based on 4^{th}, 6^{th} and 8^{th} order moment of discrete wavelet transform (DWT) as an extracted feature and Adaptive Neural-Fuzzy Inference System (ANFIS) as a classifier. Haar type of DWT are selected, MATLAB program are designed to perform the reduction of number of extracted features as well as classification processes. The M-ary signals are 2FSK, 4FSK, and 8FSK. MFSK signals are generated and the features are extracted for a large set of numerically generated signals. The proposed identification method has a high performance, flexible for identify M-ary FSK signals when the signals are corrupted with additive white Gaussian noise (AWGN) at 0dB, 5dB, and 10 dB signal to noise ratio.

Keywords: M-ary FSK Signals, Adaptive neural fuzzy inference system (ANFIS), Discrete wavelet transform, and high order moment.

1 INTRODUCTION

Automatic modulation identification (AMI) technique identifies the modulated signal type at presence of noise. There are a wide applications of AMI. In military applications, it can utilized for interference recognition, electronic surveillance and monitoring. In civil applications, it can be employed for software defined radio (SDR), spectrum management , signal conformation, and intelligent modems [1]. The existing algorithms for M-ary frequency shift keying (MFSK) identification are mainly classified to decision theoretic (DT), and pattern recognition (PR). DT requires the parameters of modulation formats of MFSK, which is represented by: frequency deviation, carrier frequency, and number of transmitted signal frequencies (M), while PR algorithms need less knowledge of the MFSK parameters of modulation format [2]. Thus higher computation complexity is the major drawback of DT, but PR requires less computational complexity and can be classified to two subsystems, the feature extraction and the classifier [3]. Artificial neural network (ANN) is a good candidate for AMI-PR [4]. but such signal classifiers are suffering from many short comings such as, requiring long signal duration, complex algorithms, big size feature vectors for training, and high computer storage capacity, then the performance of AMI is limited by time and cost, the classifiers are suffering from either over-fitting or under-fitting occasionally, further more there is a degradation in performance of ANN classifier at high signal to noise ratio (SNR), when the training of ANN is performed at low SNR [5][6]. Adaptive neural fuzzy inference system (ANFIS) is proposed as a classifier for MFSK signals identification to overcome some of the shortages of ANN and fuzzy inference system. ANFIS was introduced at 1993 in the first time [7]. ANFIS outperforms ANN in many applications like temperature controller [8], and data rate prediction for cognitive radio (CR) [9]. ANFIS was successfully introduced for digitally modulated signal identification [10]. There are many AMI algorithms are existing to classify MFSK signals. In [11] the standard deviation of the absolute value of the normalized instantaneous frequency is used as a key feature , to discriminate 2FSK, and 4FSK and other digitally modulated signals. The identification is based on ANN and DT and they found that the performance of ANN outperforms DT in this task. The extracted feature is a function of M and the frequency deviation ratio, then the value of the frequency deviation ratio must be known in advance as well as the value of M. In [12] statistical features, high order moments (HOMs) and high order cumulants (HOCs) are used as a feature extraction, ANN as a classifier to classify 2FSK, 4FSK, and 8FSK.and other digitally modulated signals, the drawback of this approach is the statistical features for 2FSK, 4FSK, and 8FSK have the same HOMs and HOCs, especially at low SNR. In [2], fast Fourier transform (FFT) is used to classify 2FSK, 4FSK, 8FSK, 16FSK, and 32FSK, but the drawback is to estimate the value of the symbol constellation size (M), as well as the complexity of FFT algorithm. The proposed approach overcomes some of the problems of the existing identification systems to identify MFSK signals. In this paper the features are extracted using 4^{th}, 6^{th}, 8^{th} order moment for detail coefficient of Haar type discrete wavelet transform (DWT), in order to reduce the complexity of the system when it is compared with FFT. (the complexity of DWT algorithm is less than that FFT algorithm [13]), also the proposed identification process is not require the parameters of MFSK modulation format, like frequency deviation, and number of transmitted signal frequencies (M). This paper is organized as follows: section 2, demonstrates the MFSK signals and mathematical expression, section 3 explains the feature extraction using DWT, and high order moments, section 4 presents a general review of ANFIS, section 5 focuses on the methodology and analysis of simulation, while section 6 presents the conclusion and future work.

2 M-ARY FREQUENCY SHIFT KEYING AND MATHEMATICAL EXPRESSIONS

Frequency modulation is the process when the baseband signal modulates the carrier frequency of the modulated signal. If the baseband signals are digital signals the process is called Frequency shift keying (FSK). The digital data is mapped through the variations in the carrier signal frequency, while the amplitude and frequency remain constant. In a binary FSK (BFSK), the two symbols (1 and 0) are mapped through two sinusoidal waves different by a fixed amount from each other. To represent the signal of BFSK:

$$S_{K_{BFSK}}(t) = \sqrt{\frac{2E_b}{T_b}}\cos(2\pi f_k t) \qquad 0 \le t \le T_b \tag{1}$$

Where $k = 1,2$

E_b represents the bit energy , $f_k = \frac{nc+k}{T_b}$, T_b is a single bit period

In M-ary FSK, the carrier frequency is changed more than two values, and the transmitted signal can be represented by:

$$S_{K_{MFSK}}(t) = \sqrt{\frac{2E_S}{T_S}} \cos\left[\left(2\pi f_c + \frac{\pi k}{T_S}\right)t\right] \qquad 0 \le t \le T_S \qquad (2)$$

For $k = 1,2, \ldots, M$

E_S represents transmitted symbol energy, The carrier frequency $f_c = \frac{nc}{2T_S}$, $E_S = E_b \log_2 M$, $T_S = T_b \log_2 M$, T_S represents the symbol duration, nc is a fixed integer. The main advantage of FSK system, that it is not susceptible to noise, any voltage spikes introduced by noise affects the amplitude and the frequency is not affected [14]. In the simulation MATLAB program, we assume T_b=1msec,and unity bit energy. Each of MFSK signals have sub carrier frequencies for a certain modulation scheme must be different from other schemes, the fix integer nc is set to 2, 1, 7 in the simulation program for 2FSK, 4FSK and 8FSK signals respectively, to prohibit the sub carrier frequencies to be identical for different MFSK signals.

3 FEATURE EXTRACTION

In typical AMI systems, the dimension of raw data is reduced before the classifier processing. These new reduced data is represented as a feature extraction. In feature extraction the useful information with discriminative characteristics that differentiate between the modulated signals is extracted from the raw data to be pertinent for classification. The performance of the classifiers depends on discriminatory information of the extracted features while some of the extracted features are redundant, overlap, unrelated, and noisy. Negative impact on the identification performance will be took place by irrelevant features. For many pattern recognition algorithms, the increase in the number of feature extraction will increase the training time directly or exponentially [15]. In this paper the extracted feature by DWT are reduced by applying the 4^{th},6^{th}, and 8^{th} order moment, as well as some useful statement in the MATLAB program are introduced like if-statement with "and" and "or" logic statements, to reduce the number of extracted feature to mitigate the impediment of the classifier.

3.1 Wavelet transform

Wavelet transform (WT) analyzes the signals into different frequency components, each component can be studied with respect to its scale. WT overcomes traditional Fourier transform when the signal contains sharp spikes and discontinuities. WT outperforms short time Fourier transform (STFT) for analyzing signals because WT applies multi-resolution techniques with different frequencies and resolutions while STFT uses a constant resolution for all frequencies, thus WT is powerful tool for feature extraction with MFSK signals. There are several families of WT, some of them are: Haar, Daubechies, Coiflets, Biorthogonal, Morlet, Meyer, Mexican Hat, Symlets, Reverse Bior and others. DWT is a sampled version of CWT with discrete translation and dilation parameters. DWT can be performed by using a filter bank. High pass (HP) filter and low pass (LP) filter are utilized to decompose the signal, the output gives the approximation coefficients from LP filter and detail coefficients from the HP filter [16]. In this paper detail coefficients of Haar wavelet are used.

3.2 Moments

Statistical moments are the expected value of a random variable raised to the power indicated by the order of the moment.

$$\mu_i = E[(X - E[X])^i] \qquad (3)$$

$$\mu = E[X] \qquad (4)$$

$$\mu_i = \frac{1}{N}\sum_{j=0}^{N-1}(X_j - \mu)^i \qquad (5)$$

N is the size of data length, μ is the mean, and i is the order of moment.

4 ADAPTIVE NEURAL-FUZZY INFERENCE SYSTEM

A fuzzy inference system (FIS) is a process of using the theory of fuzzy sets and fuzzy rules to map a given input to an output. The performance of FIS depends on the identification of membership functions (MFs) and the fuzzy rules tuned to the requested applications. Usually it is difficult or not available to transform human knowledge to a fuzzy rules and MFs tuning in terms of cost and time. ANN was introduced to overcome these limitations by identifying fuzzy rules and tuning the parameters of MFs automatically [17]. ANFIS system is a FIS whose parameters are trained by means of any ANN learning algorithms. ANFIS is a multi-layer feed forward, uses Sugeno type FIS [7]. The equivalent ANFIS architecture as an example is shown in Figure 1, the system is assumed with two inputs and one output. The individual layers of ANFIS are discussed briefly in the following:

Layer 1: Layer 1 is the fuzzification layer. The fuzzification is performed by the neurons in this layer. The nodes in this layer are adaptive with a function.

$$O_{1,i} = \mu_{A_i}(x) \qquad for\ i = 1,2 \qquad (6)$$

$$O_{1,i} = \mu_{B_{i-2}}(y) \qquad for\ i = 3,4 \qquad (7)$$

Where $O_{1,i}$ is the output of layer 1, μ_{A_i} is the MF of the linguistic variable of fuzzy sets A_i, and $\mu_{B_{i-2}}$is the MF of the linguistic variable of fuzzy sets B_{i-2}.

Layer 2: This layer receives inputs from layer 1 in the fuzzification form, the output of each

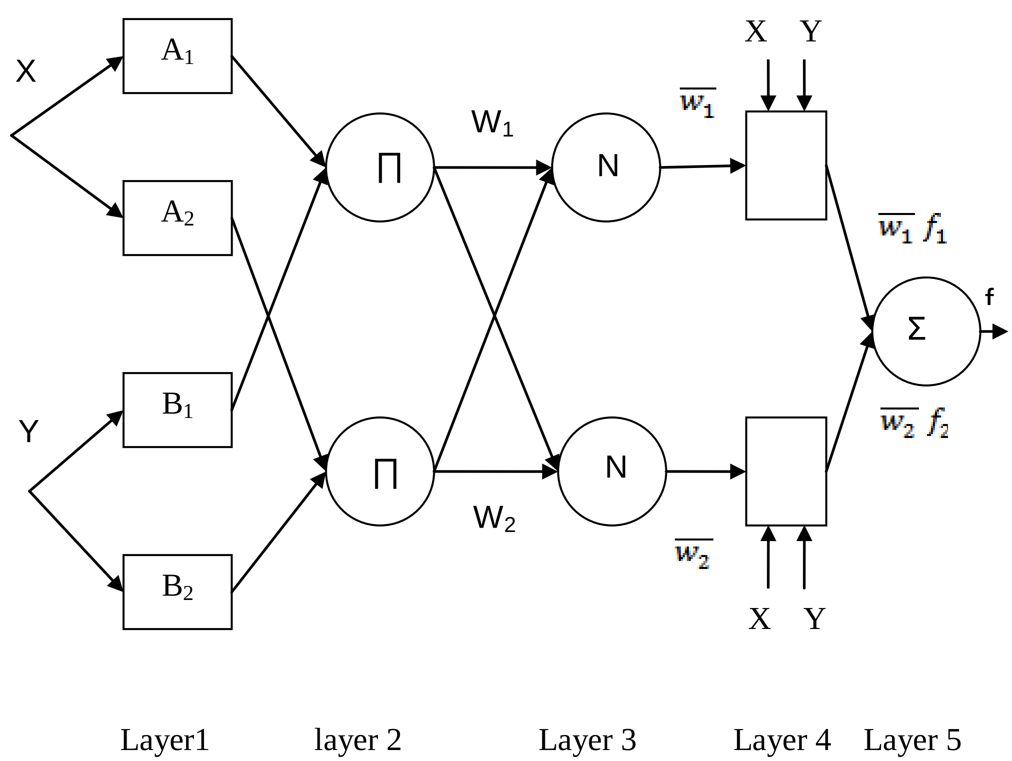

Fig. 1. ANFIS architecture

node is obtained by multiplying the incoming signals. The nodes in this layer for Figure 1 are labeled ∏.

$$O_{2,i} = w_i = \mu_{A_i}(x) * \mu_{B_i}(x) \qquad i = 1,2 \qquad (8)$$

Where $O_{2,i}$ is the output of layer 2.

Layer 3: The nodes in this layer are fixed, each node obtains the normalization, that is calculating the ratio of the firing strength of each rule to the sum of all firing strengths of all rules. The output is given by:

$$O_{3,i} = \overline{w_i} = \frac{w_i}{w_1 + w_2} \qquad for\ i = 1,2 \qquad (9)$$

$O_{3,i}$ is the output of layer 3.

Layer 4: The nodes in this layer are adaptive node and receive the input x, and y, to compute the output of the rule by evaluating the Sugeno type linear approximator f_i multiplied by the normalized firing strength:

$$O_{4,i} = \overline{w_i} f_i = \overline{w_i}(k_{0i} + k_{1i}x + k_{2i}y) \qquad i = 1,2 \qquad (10)$$

Where $O_{4,i}$ is the output of layer 4, k_{0i}, k_{1i}, and k_{2i} are the consequent parameter set. The prescribed four layers represents the equivalent Sugeno fuzzy inference system. The premise part is applied to establish the MFs, which is linguistic variables while the consequent part is represented by a crisp equation .

Layer 5: The layer consists of one fixed node which calculate the system output f on the ANFIS architecture of Figure1, the layer is labeled by Σ, which is the sum of all incoming signals:

$$O_{5,i} = \sum_{i=1}^{2} \overline{w_1} f_i = \frac{\sum_i w_i f_i}{\sum_i w_i} \qquad for\ i = 1,2 \qquad (11)$$

$$= \overline{w_1}\,(k_{01} + k_{11}x + k_{21}y) + \overline{w_2}\,(k_{02} + k_{12}x + k_{22}y)$$

Where $O_{5,i}$ is the output of layer 5. Then the output of ANFIS is determined by the consequent part within the premise parts [18].

5 METHODOLOGY AND ANALYSIS OF SIMULATION

The identification of M-ary FSK system is shown in Figure 2. The signals for proposed identification processes are 2FSK, 4FSK, and 8FSK, the signals are digitally generated according to equations No. (1), and No. (2), using MATLAB Toolbox. The program is designed, 240 signals are generated, additive white Gaussian noise is added at 0dB, 5dB, and 10dB, the sample numbers of each signal is 1000 samples, the identification system consists of feature extraction and classification layers, the feature extraction plays the key rule of identification processes and improve the performance of the classifier, but not all the extracted feature is important for identification process. The selected features should fewer as far as possible to reduce the complexity of the system. In order to find the appropriate features, computer program are designed to generate the signals 2FSK, 4FSK, and 8FSK, all the signals are corrupted with AWGN, at 0dB, 5dB, and 10dB , 240 signals of 240000 samples are investigated, detail coefficient DWT "Haar Type" is applied to the samples through the period Tb, high numbers of features are extracted , 4th , 6th, and 8th order moments are applied to the detail coefficient of DWT, thus the extracted features are transformed into another reduced features which posses the discrimination facilities of the signals. After investigating the results, we find that the extracted feature magnitude has a slight variation at different symbols for the same modulation scheme, moment order, and SNR. Table 1 shows this variation as an example for 4FSK, which is 4 different symbols namely S1, S2, S3, and S4 at 10dB SNR. From this results Matlab program is extended to limit each group of extracted features for all the symbols of a certain modulation scheme, like $(0.0303 \le moment\ 4th\ order \le 0.0433)$, if statement with logical "OR" and logical "AND" are employed to define each group of features, the groups of features having the discriminating properties are used to train the ANFIS classifier.

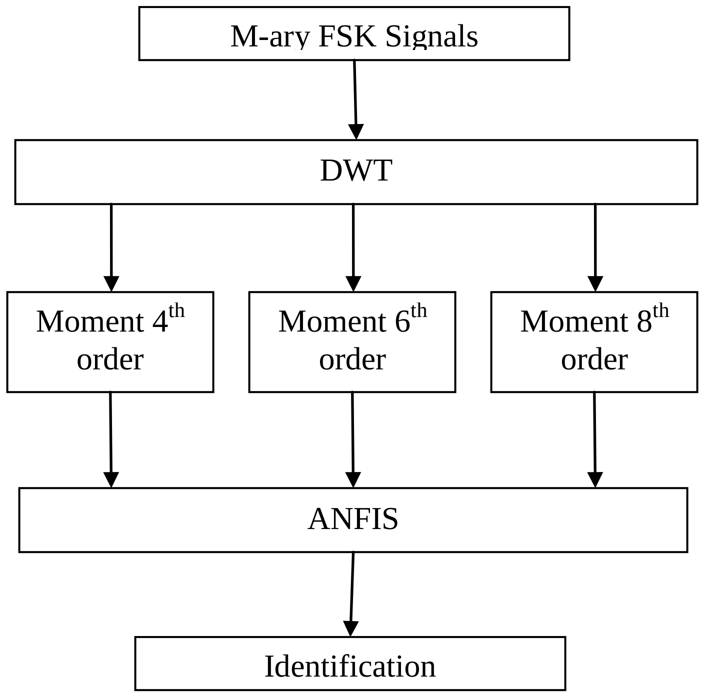

Fig. 2. Identification processes

Table 1. Feature extraction for 4FSK, at different symbols and 10dB SNR.

	S1	S2	S3	S4
Moment 4^{th} order	0.0303	0.0335	0.0364	0.0433
Moment 6^{th} order	0.0173	0.0195	0.0203	0.0244

Moment 8^{th} order	0.0133	0.0151	0.0154	0.0186

This approach is used to reduce the complexity of the system, as well as to reduce the training time of ANFIS. The operation of ANFIS classifier is starting with loading the vectors of the training data as mentioned before, the type of the MFSK modulated schemes are distinguished through the output number, the program represents No. 1 for 2FSK, No. 2 for 4FSK, No. 3 for 8FSK, then generating fuzzy inference system (FIS), input number of membership function (MF)=3, "Generalized Bell" MF is utilized as input membership function, the type of output MF is "linear", hybrid learning algorithm "Least Square and Back propagation" is used. Figure 3 shows the structure of ANFIS using MATLAB.

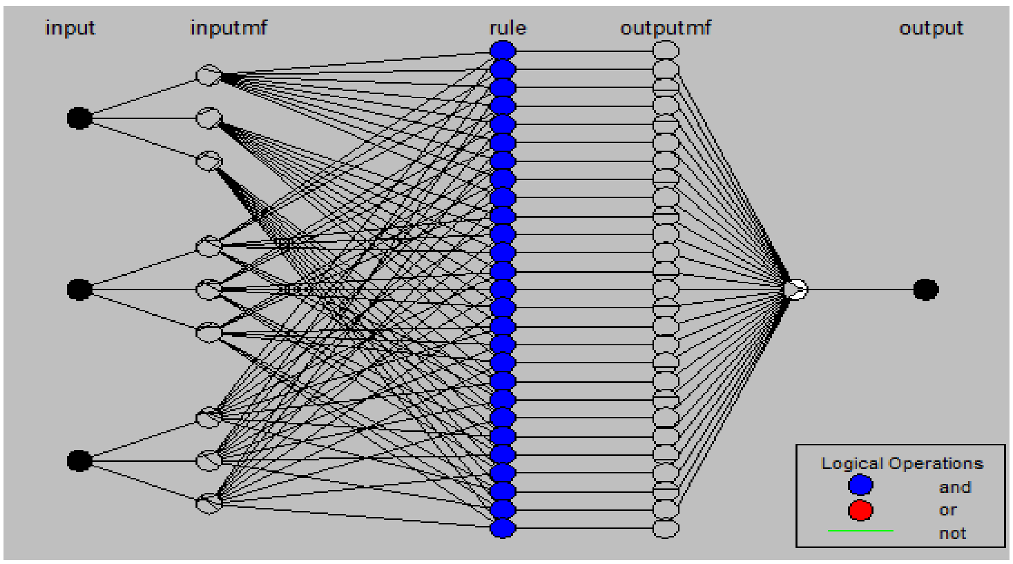

Fig. 3. ANFIS Structure

After the proposed number of epochs through the training period which is equal to 25 epochs is reached, the error minimizing graph shows that the error is $2.7048*10^{-7}$, as shown in Figure. 4.

The surface graphs for MFSK identification are shown in Figures 5, 6, and 7, for 2FSK, 4FSK, 8FSK. respectively. From the graphs it is clearly shown that the output with No. 1 of Figure 5 represents the correct identification of 2FSK, No. (2) of Figure 6 represents the correct

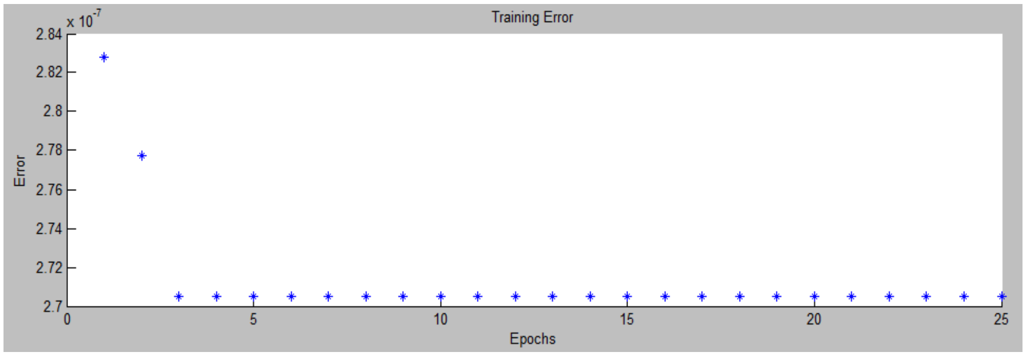

Fig. 4. error minimizing graph

identification of 4FSK, and No. (3) of Figure 7 represents the identification of 8FSK signals, while the inputs are the group of extracted features representation. The identification approach is tested using different signals of 2FSK, 4FSK, 8FSK, the percentages of correct identification is 92.9% for 0dB SNR, and 100% at 5dB, and 10dB SNR.

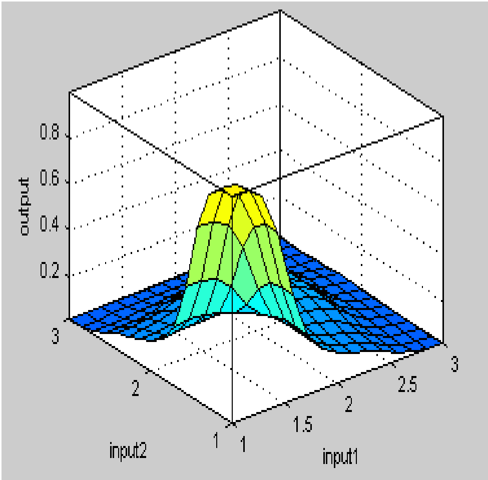

Fig. 5. Surface graph of 2FSK

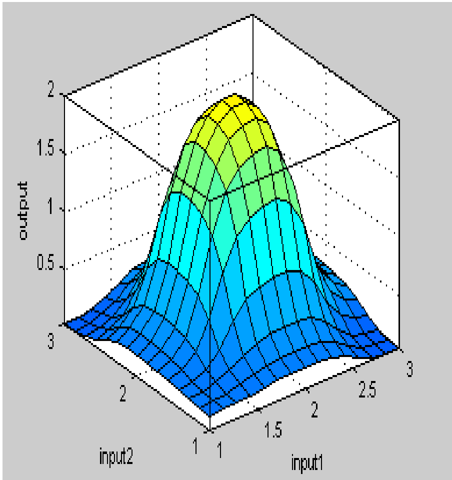

Fig. 6. Surface graph of 4FSK

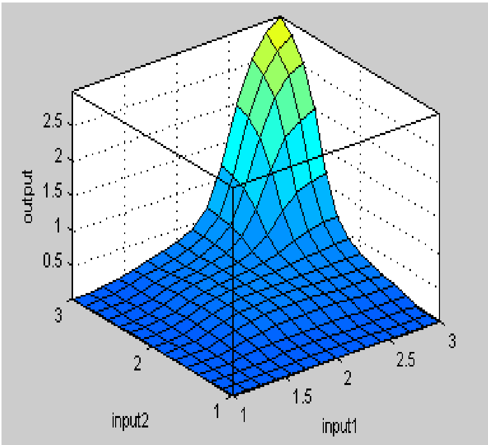

Fig. 7. Surface graph of 8FSK

6 CONCLUSION AND FUTURE WORK

The feature extraction of identification process is based on detail coefficients of DWT, and high order moments. ANFIS is the classifier. Detail coefficients of DWT, Haar type of 2FSK, 4FSK, and 8FSK signals are obtained, moments 4^{th} order, 6^{th}order,and 8^{th} order are applied to the detail coefficient of DWT, the feature extraction parameters are minimized by extending Matlab program to include if statement and logical "OR" and logical "AND", the identification system is simulated at AWGN with 0dB, 5dB, and 10dB SNR, the system exhibits high identification performance, the percentages of correct identification were about 92.9% when SNR is 0dB, and 100% when SNR are 5, and 10 dB. The main advantage of this method is to reduce the training time and reduce the complexity of the classifier. The method has been specified is flexible and can be used as a future work for modulation identification of either MFSK signals or any SNR that are not covered with this paper. This approach could be modified and extended to identify other types of digital modulation like M-ary phase shift keying (MPSK), and Quadratic amplitude modulation (QAM) signals. Another types of DWT could be utilized instead of Haar type and evaluating the performance of the identification.

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