A Proposed Identification Method for Multi-user Chirp Spread Spectrum Signals Based on Adaptive Neural-Fuzzy Inference System (ANFIS)

Sattar B. Sadkhan-SMIEEE[1]
university of Babylon
drengsattar@ieee.org

Ashwaq Q. Hameed[2]
University of Technology
AshwaqQHameed@uotechnology

Hadi A. Hamed[3]
Al-Furat Al-Awsat Technical university
[1,3]Babylon, [2]Baghdad ,Iraq
hady.athab@gmail.com

Abstract— **Automatic identification of digitally modulated signal has to be able to identify the digitally modulated signal correctly and accurately. Importance of automatic identification of digitally modulated signals are rising increasingly. In this paper an advanced technique is presented, that automatically identifies the multi-user chirp modulated signals in Additive White Gaussian Noise (AWGN) channel. The proposed technique is implementing high order moments (fourth, sixth, and eighth) of detail coefficients of discrete wavelet transform (DWT) as a feature extraction set. Adaptive Neural-Fuzzy Inference System (ANFIS) is proposed as a classifier. The proposed identification procedure is capable of identifying multi-user chirp modulated signals with high accuracy at 0dB, 5dB, and 10dB Signal to Noise Ratio (SNR), over AWGN channel.**

***Index Terms*-Chirp spread spectrum signals, digitally modulated signal identification, Adaptive neural fuzzy inference system (ANFIS), High order moments, and Discrete wavelet transform.**

I. INTRODUCTION

The Modulation Identification (MI) of digitally modulated signals is to identify the modulation types when the signals are corrupted with noise [1]. MI is rapidly evolving area in research. It covers both civilian and military domain applications like signal monitoring, spectrum management, software defined Radio (SDR), Cognitive Radio (CR), military threat detection, etc. In [2] different algorithms and applications for MI are demonstrated. MI can be classified as Decision Theoretic (DT) approach and Pattern Recognition (PR) approach [3]. DT depends on likelihood functions, zero crossing, signal envelope characteristics and statistical parameters. PR includes features extraction and the identifier. Artificial neural network (ANN) is a good candidate as an identifier for PR. In [4] different features extraction , approaches, algorithms, and training of ANN as PR-identifiers. The disadvantage of ANN, that its performance is degraded at high signal to noise ratio (SNR) when it is trained at low SNR. In 1993 the architecture and learning procedure of Adaptive Neural-Fuzzy Inference System (ANFIS) was presented [5]. ANFIS outperforms ANN in the design applied to temperature controller [6], and data rate prediction for CR [7]. It is successfully introduced for digitally modulated signal identification [8]. In this paper ANFIS is proposed as an identifier for multi-user chirp spread spectrum (CSS) signals. CSS signal was introduced in 1992 [9], the signal is low power consumption, high processing gain, and low cost [10]. In [11] chirp modulated signal is employed in the HF band. In [12] chirp modulation spread spectrum for efficient and flexible multiple access was introduced . In [13] identification of multi-user chirp modulated signals is introduced using different classifiers: maximum likelihood (ML), the support vector machine (SVM), K-nearest neighbor (KNN), and neural network (NN).

This paper proposes a reliable approach to identify the multi-user chirp SS modulated signals with high accuracy using fourth, sixth, and eighth order moments for detail coefficients of discrete Wavelet Transform (DWT) of signals as a features extraction, and ANFIS as a classifier. The reset of the paper is as follow: Section II, presents the CSS signals. Section III, demonstrate the feature extraction, and section IV, presents an overview of ANFIS. Section V presents the implementation and results, while section VI presents conclusion and future work.

II. CHIRP SPREAD SPECTRUM SIGNALS

Chirp Spread Spectrum (CSS) signals are used for different applications, some of them are Beacons, communication systems, Radar, Sonar, under water communication, etc. In general chirp signal is defined as a signal with variable frequency over time continuously [14]. When the frequency is changing from a lower to higher (up chirp) or down chirp in reverse. CSS signal is specified mathematically in [15]:

$$f(t) = A\cos\left(\omega_c t + \frac{1}{2}\mu t^2\right) \quad (1)$$

Where A is [14]:

$$A = (2E/T)^{\frac{1}{2}} \tag{2}$$

μ=dω/dt (frequency sweep rate), ω_c is the angular carrier frequency ($2\pi f_c$), E is the energy of one chirp period, T is chirp period. CSS signals combat multipath interference, high robustness, lower power consumption, and resistance against Doppler effect, which makes CSS interesting for communication purposes, but it sacrifices in signal bit rate for a certain wide bandwidth, then CSS can be introduce multi-users into the same wide bandwidth [16]. CSS can combine with binary orthogonal keying (BOK). Equation (1) can be extended to represents single user CSS-BOK for $0 \le t \le T$:

$$c_1(t) = A\cos(2\pi f_c t + \pi\alpha t^2) \tag{3}$$

$$c_2(t) = A\cos(2\pi f_c t - \pi\alpha t^2) \tag{4}$$

Where α is the chirp rate Hz/sec, equation (3) represents CSS for up chirp, while equation (4) for down chirp. Up chirp represents binary (1), and down-chirp represents binary (0). For multi-user chirp systems with M users sharing the same band width, the users have the same scheme but different in the chirp rate, during the up-chirp and down-chirp [17]. In this paper 5 users as multi-users CSS signals namely (S1, S2, S3, S4, and S5) are simulated and implemented for identification. Figure 1 and 2 show the time-frequency domains for up chirp and down chirp respectively for 5 users, using Matlab, time-bandwidth BT=6000, chirp period T= 1 sec, f_c=1000 Hz .

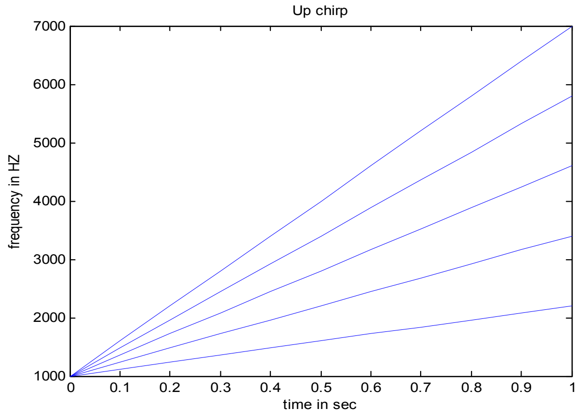

Figure 1 Time-frequency domain for up chirp

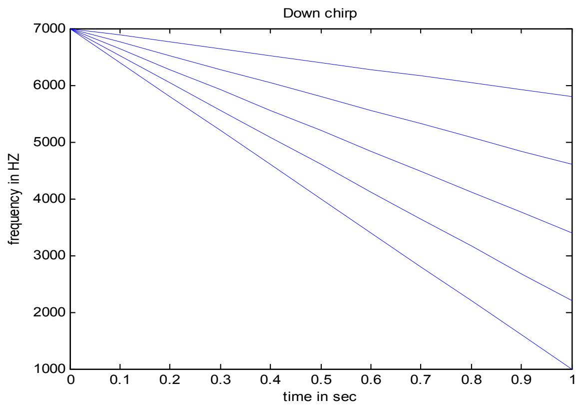

Figure 2 Time-frequency domain for down chirp

Where:

$$\alpha_k = \frac{B}{M} \times k \qquad k = 1,2,\ldots,5 \tag{5}$$

$$f_k = f_c + \alpha_k t \quad \text{for up chirp} \tag{6}$$

$$f_k = f_c + B - \alpha_k t \quad \text{for down chirp} \tag{7}$$

III. FEATURE EXTRACTION

A. Discrete Wavelet Transform

Wavelet analysis is a tool for the decomposition of signals into different frequency components. The signal can be represented as a superposition of a set of wavelets. There are a single prototypes wavelet or mother wavelet Ψ (t). Baby wavelets $\Psi_{a,b}$ are obtained by scaling (by a factor of a) and translations (by an amount of b) .

$$\Psi_{a,b}(t) = \frac{1}{\sqrt{|a|}}\Psi\left(\frac{t-b}{a}\right) \tag{8}$$

The parameter a is the scale, and b is the translation, by setting:

$$a = a_0^j$$

$$b = kb_0a_0^j$$

Where j and k are integers.

DWT , basis function is as follows [18]

$$\Psi_{j,k}(t) = a_0^{-j/2}\Psi\left[a_0^{-j}(t - kb_0a_0^j)\right] \tag{9}$$

If DWT is regarded as a filter bank, DWT of a signal can be considered as passing the signal through this bank. The approximation coefficients are high-scale and low frequency components. The detail coefficients are low-scale and high frequency components. In this paper detail coefficients Haar DWT are proposed to extract the feature before high order moments are applied.

B. High Order Moments

The moment is the concept of expected value, the general expressions for the moment order i of random variable X is:

$$\mu_i = E[(X - E[X])^i] \tag{10}$$

$$\mu = E[X] \tag{11}$$

$$\mu_i = \frac{1}{N}\sum_{j=0}^{N-1}(X_j - \mu)^i \tag{12}$$

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

IV. OVERVIEW OF ANFIS

ANFIS is a hybrid neuro-fuzzy system equivalent in function to a fuzzy inference system but its parameters are trained by neural network learning algorithms. ANFIS network consists of five layers. The output of the first layer is the membership function, the second layer computes the firing strength of the rules, the third layer normalizes the values of firing strength, the fourth layer computes the product of the normalized firing strength and the individual rule output, and the fifth layer computes the overall system outputs. The first layer and the fourth layer have the premise and consequent parameters respectively, different learning algorithms are applicable for learning or tuning of these parameters. In this paper hybrid learning algorithm which is least-squares and gradient descend are proposed for the ANFIS training. For more details, the interested reader can consult references No. [5] and No. [8].

V. IMPLEMENTATION AND RESULTS

The proposed CSS signals are identified by applying fourth, sixth, and eighth order moments to details coefficients of DWT as a features extraction and ANFIS as a classifier, to identify the five signals, namely S1, S2, S3, S4, and S5. Each signal has two different time-frequency domain characteristics during the up chirp and down chirp, thus 10 signals needs to be identified at 0dB, 5dB, and 10dB SNR in AWGN channel. Parallel distributed processing of 5 units ANFIS proposed for classification, each ANFIS unit is assigned for particular CSS signal. The identification procedure is started with loading the vectors of the proposed features extraction as a training data, generating fuzzy inference system (FIS) with initial input number of membership function (MF)=3, input membership function type is Generalized Bell MF, and output membership function is linear, training FIS with hybrid learning algorithm (Least square and gradient descent) to tune FIS premise and consequent parameters. Figure 3 shows the structure of ANFIS unit of signal S1 after training, using MATLAB, while all the five units have the same structure but differs in the training data and function of identification.

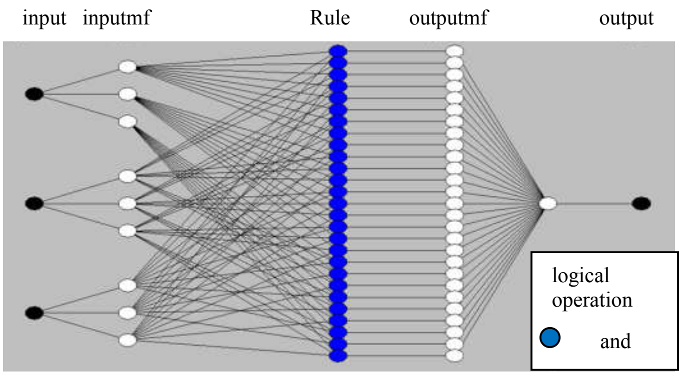

Figure 3 Structure of ANFIS

The hybrid learning algorithm minimizes the error to $2.6822*10^{-6}$ after 20 epochs, the error minimization graph is shown in Fig. 4.

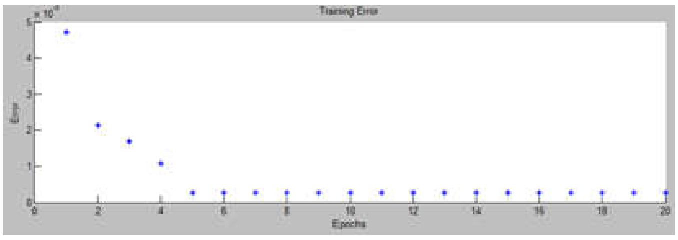

Figure 4 error minimization graph

The surface graphs for CSS signal (S1) identification at 0dB up chirp as an example are shown in Figures 5, 6, and 7. From the surface graph, the influence of the input to the output (correct identification) can be clearly shown. The output in the training vectors is represented with number (1). For any ANFIS unit, the system encounters different of CSS signals, when the output is 1 means it copes with CSS signal type which is assigned for it. The identification technique is tested using CSS simulated signals at, 0dB, 5dB, and 10dB. The system exhibits 93.3% correct recognition ratio at 0dB, 100% correct recognition ratio at 5dB, and 10dB.

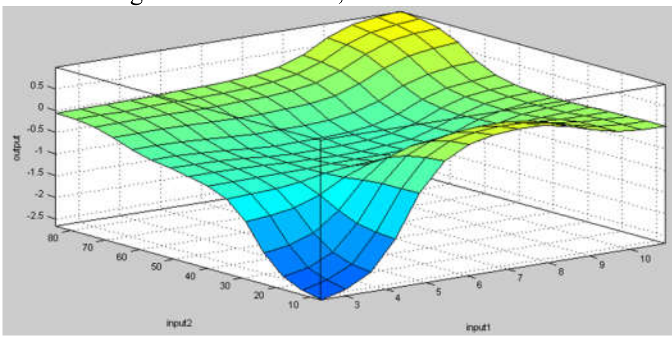

Figure 5 Surface graph of input1, input2 and output

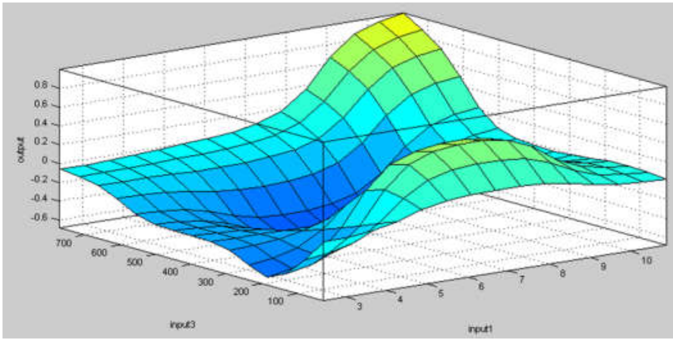

Figure 6 Surface graph of input1, input3 and output

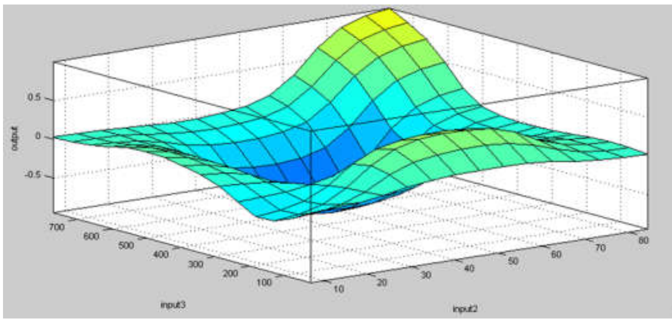

Figure 7 Surface graph of input2, input3 and output

Input 1, input 2, and input 3, represent the fourth, sixth, and eighth order moments for detail coefficients of DWT to the signal S1 at 0dB.

VI. CONCLUSION AND FUTURE WORK

The first part of the identification technique for multi-users CSS is based on estimation of fourth, sixth, eighth order moments to the detail coefficients of DWT, these signals are embedded in white Gaussian noise, at 0dB, 5dB, and 10dB SNR. Five parallel distributed ANFIS units are successful in identifying the CSS signals, the works identify five CSS signals including up chirp and down chirp of signals. From results the recognition ratio of identification systems are improved at high SNR. Suitable time-bandwidth is requested for each certain numbers of CSS signals, narrow time-bandwidth exhibits a bad influence on the recognition ratio, minimum time-bandwidth for identification is requested as a future work, high numbers of CSS signals can be applied as future work too.

References

[1] W. Wei and Jerry M. Mendel," Maximum-likelihood classification for digital amplitude--phase modulation", IEEE transaction on communications, Vol. 48, No. 2, PP 189-193, 2000.

[2] Zhechen Zhu, and Asoke K. Nandi," Automatic modulation classification", John Wiley & sons, ltd, United Kingdom, 2015.

[3] Sattar B. Sadkhan," A proposed digital modulated signal identification based on pattern recognition", Proceedings of IEEE international multi-conference on systems, signal and devices, SSD, pp 1-6, 2010.

[4] Sattar B. Sadkhan, Ashwaq Q. Hameed, and Hadi A. Hamed," Digitally modulated signals identification based on Artificial Neural Network", ATTI Della Fondazione Giorgio Ronchi, Vol. LXX, No. 1, pp 59-75, 2015.

[5] Jyh-Shing R. Jang," ANFIS: Adaptive network-based fuzzy inference system", IEEE transaction on systems, man, and cybernetics, vol. 23, No.3, pp 665-685, 1993.

[6] T. P. Mote, Dr. S. D. lokhande," Temperature control system using ANFIS", International journal of soft computing and engineering (IJSCE), Vol.2, N0.1, pp 156-161,2012.

[7] Shrshail Hiremath, and Sarat Kumar Patra," Transmission rate prediction for cognitive radio using adaptive neural fuzzy inference system", proceedings of the ICIIS, international conference on industrial and information systems, pp 92-97, 2010.

[8] Sattar B. Sadkhan, Ashwaq Q. Hameed, Hadi A. Hamed," Digitally modulated signals recognition based on adaptive neural-fuzzy inference system (ANFIS)", International journal of advancements in computing technology (IJACT), Vol. 7, No. 5, pp57-65, 2015.

[9] M. R. Winkler," Chirp signals for communications", WESCON convention record, paper 14.2, 1962.

[10] Meng Fanyu and Gu Xuemai," A combined Chirp signal modulation technology for multiple access system", Information Technology Journal Vol. 10, No. 2, pp 416-421,2012.

[11] G. F. Gott, and J. P. Newsome," H. F. data transmission using chirp signals", proceedings of the IEE, Vol. 118, No. 9, pp 1162-1166, 1971.

[12] S. Hengsler, Dayalan P. Kasilingam, and Antonio H. Costa," A novel chirp modulation spread spectrum technique for multiple access", seventh international Symposium on Spread Spectrum Techniques and Applications, ISSSTA, Vol. 1, pp 73-77, IEEE publisher, 2002.

[13] Said E. El-Khamy," Hend A. Elsayed, and Mohamed M. Rizk," Bispectrum classification of multi-user chirp modulation signals using artificial intelligent techniques", proceedings of the 2011 international conference on artificial intelligence, ICAI, vol. 1, pp 141-147, 2011.

[14] Rene Moll." A DFT based synchronization scheme for chirped communication scheme for chirped communication", Master thesis, university of Twente, Netherlands, 2013.

[15] Robert C Dixon," Spread Spectrum systems with commercial applications", 3rd edition, John Wiley & Sons, 1994.

[16] Chales E. Cook," Linear FM Signal formats for Beacon and communication systems", IEEE Transaction on Aerospace and electronic systems, Vol. AES-10, No.4, pp 471-478, 1974.

[17] Xiaowei Wang, Minrui Fei, and Xin Li," Performance of chirp spread spectrum in wireless communication systems", In 11th IEEE Singapore international conference on communication systems, ICCS 2008, pp 466-469, 2008.

[18] Michael Medley, Gary J. Saulnier, and P. Das," Radiometric detection of direct-sequence spread spectrum signals with interference excision using the wavelet transform", Proceedings of IEEE international conference ,ICC'94, on communication, supercomm/ ICC, pp 1648-1652, vol. 3, IEEE publisher, 1994.