ISTANBUL UNIVERSITY –
JOURNAL OF ELECTRICAL & ELECTRONICS ENGINEERING

YEAR : 2006 (97 - 105)
VOLUME : 6
NUMBER : 1

# THE PERFORMANCE ANALYSIS OF STFT-ANFIS CLASSIFICATION METHOD ON PULSED RADAR TARGET CATEGORIZATION

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## *ABSTRACT*

*In this paper, a pattern recognition system is developed for automatic classification of the radar target signals. Feature extraction is an important subset of the pattern recognition system. For feature extraction is used Short Term Fourier Transform (STFT) time-frequency distribution of the pulse radar target signals. Adaptive Network Based Fuzzy Inference System (ANFIS) classifier is used at classifier part of the pattern recognition system. Radar signals are obtained from pulse radar system for various targets. The classifier performance is evaluated according to the proposal method.*

**Keywords:** *Feature extraction, ANFIS, radar target classification, STFT.*

## 1. INTRODUCTION

Radar is a microwave system for detecting objects and determining their distance, or range. The word radar is an acronym of the words radio detection and ranging. An elementary radar consists of a transmitter, a receiver, transmit and receive antennas, and an indicator. A radio signal is generated by the transmitter and radiated by the transmitting antenna. Part of the transmitted signal strikes a reflecting object, or target, and is scattered in all directions.

Some of the signal from the target is reflected back to the radar. This signal, called the echo, is captured by the receiving antenna. The receiver then detects the echo signal which is demodulated to produce a video signal. The video signal is sent to the indicator which indicates the presence of a target. The indicator may also indicate target distance, direction, velocity etc.

In practice, the transmitter and receiver usually share the same antenna, as shown in Figure 1. the antenna usually directs the signal into a narrow beam which is systematically swept through the region where targets are expected.

### 1.1. Pulsed Radar Systems

Radars are most often classified by the types of waveforms they use, or by their operating frequency. Considering the waveforms first, radars can be Continuous Wave (CW) or Pulsed

*Received Date : 20.07.2004*
*Accepted Date: 10.11.2005*

Radars (PR). CW radars are those that continuously emit electromagnetic energy, and use separate transmit and receive antennas. Unmodulated CW radars can accurately measure target radial velocity (Doppler shift) and angular position. Target range information cannot be extracted without utilizing some form of modulation. The primary use of unmodulated CW radars is in target velocity search and track, and in missile guidance. Pulsed radars use a train of pulsed waveforms (mainly with modulation). In this category, radar systems can be classified on the basis of the Pulse Repetition Frequency (PRF), as low PRF, medium PRF, and high PRF radars. Low PRF radars are primarily used for ranging where target velocity (Doppler shift) is not of interest. High PRF radars are mainly used to measure target velocity. Continuous wave as well as pulsed radars can measure both target range and radial velocity by utilizing different modulation schemes.

The pulsed radar is most used in radar types [1], [2]. In a pulsed radar system, short bursts of radio frequency (RF) energy are generated for transmission. This is usually accomplished by first generating a train of narrow, rectangular-shape pulses and using these to amplitude-modulate a sinewave RF carrier. The pulsed RF signal is transmitted by antenna. If the signal strikes a target, a portion of the signal will be reflected back to the radar as an echo. The antenna captures the echo pulses which are sent to the receiver. The received pulses are then demodulated and converted to a video signal for display.

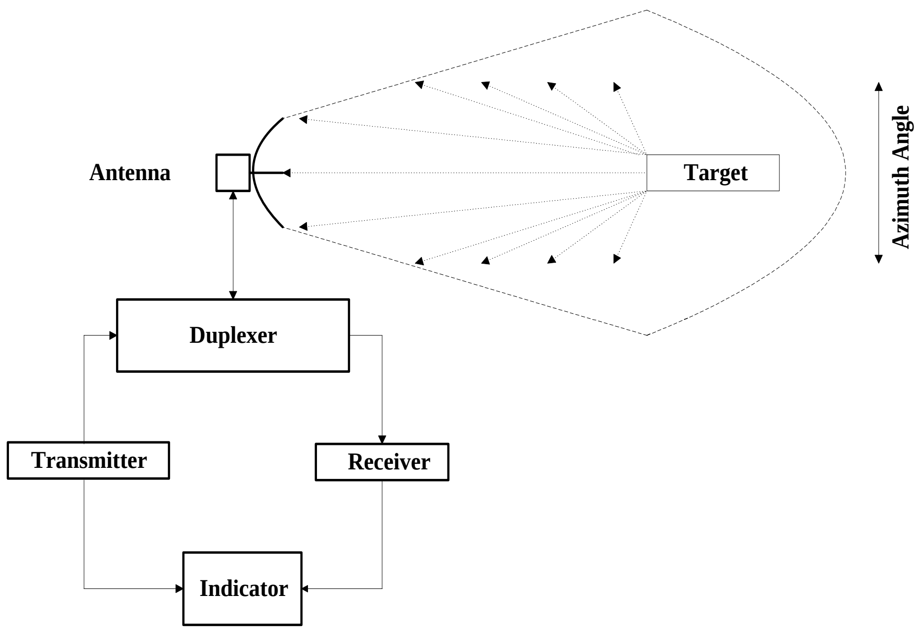


***Figure 1. Simplified radar system.***

## 1.2. Short Term Fourier Transform (STFT) Time-Frequency Distribution

Figure 2 shows a block diagram of the target identification used in this work. For accuracy of the early-time response, we use the inverse Fourier transform. Feature Extraction from STFT: The STFT is the basic method for analyzing no stationary signals. In STFT, the signal is divided into small segments, where these segments of the signal can be assumed to be stationary [3]. For this purpose, a window function is chosen. The STFT is defined in the time domain as follows:

$$\mathrm{STFT}(\tau,\Omega)=\int_{-\infty}^{\infty}\left[f(t)\,w^{*}(t-\tau)\right]\exp(-j\,\Omega\,t)\,dt \quad (1)$$

where $f(t)$ is a time-domain signal and $w(t)$ is a window function. From the given frequency-domain backscattering data, we can obtain the transient response $f(t)$ using IFFT. Then, an $M \times N$ STFT matrix of M frequency points and N time points is computed using Equation 1 [4]. But, an $M \times N$ matrix is too large to act as the neural network input. Consequently, some form of data reduction is required. First, the STFT matrix is divided into J time bands and K frequency bands. Generally, J and K are determined considering the time and frequency resolutions. Then, the STFT is integrated within each of these time and frequency bands. The component of the feature matrix in the $k_{th}$ frequency band and $j_{th}$ time band is denoted as $F_{k,j}$, and is defined as

$$F_{k,j} = \int_{(j-1)\Delta_\tau}^{j\Delta_\tau} \int_{(k-1)\Delta_\Omega}^{k\Delta_\Omega} STFT(\tau,\Omega)\, d\Omega\, d\tau. \quad \text{for} \quad k = 1,.....,K \text{ and } j = 1,.....,J \qquad (2)$$

where

$$\Delta_\tau = T_{final} / J \text{ and } \Delta_\Omega = BW / K \qquad (3)$$

are the width of each time and frequency band, with $T_{final}$ and BW being the final time and bandwidth, respectively. Using the above process, an $M \times N$ STFT matrix can be represented by a $K \times J$ (where $K, J << M, N$) feature matrix. The final feature vector of $K \cdot J$ dimension is represented by

$$X = \left[ F_{1,1}, F_{1,2}, ...., F_{1,J}, F_{2,1}, F_{2,2}, ...., F_{K,J-1}, F_{K,J} \right]^T. \qquad (4)$$

We can use these feature vectors as the neural network input. However, a further data transform is needed because a $K \cdot J$-dimensional input space is still large, and each of these vectors has many redundancies, especially in the high-frequency region of the late-time period.

### 1.3. Pattern Recognition

Pattern recognition is the research area that studies the operation and design of systems that recognize patterns in data. It encloses subdisciplines like discriminant analysis, feature extraction, error estimation, cluster analysis (together sometimes called statistical pattern recognition), grammatical inference and parsing (sometimes called syntactical pattern recognition). These important application areas are radar target recognition, image analysis, character recognition, speech analysis, man and machine diagnostics, person identification and industrial inspection [5].

The ability to recognize patterns is fundamental to computer vision. Here, term pattern refers to a quantitative or structural description of an object. In general, one or more descriptors form patterns. The pattern space corresponds to a measurement or an observation space. A pattern vector is referred to as an observation vector. A pattern vector often contains redundant information; hence, the pattern vector is mapped to a feature vector [6-9]. Pattern recognition systems usually consider a feature space onto which feature vectors are mapped first. The feature vector is used to decide the class to which the input sample belongs. The purpose of feature extraction is to reduce data by retaining certain "features" or "properties" that distinguish input patterns.

Features corresponding to different shapes, textures, and spectral signatures are used, as are features such as various time-frequency distributions. In this developed pattern recognition study, Short Term Fourier Transform time-frequency distributions of real radar targets Doppler signals were used for feature extraction process. Then, Adaptive Network Based Fuzzy Inference System (ANFIS) was used in this study as classifier. This used pattern recognition block diagram is shown in Figure 2 [10].

## 2. PROPOSED METHOD

An efficiency feature extraction method was developed for six target objects which are shown in Figure 3 to separate one from the others. There, pulse radar Doppler signals were used as real input space. Experimental application was realized on having educational purpose and multi function 9620/21 Model Lab-Volt radar experiment set. Pulse echo signals were received to computer media by using data accusation card has 1 Khz sample frequency.

The pulsed radar system parameters were adjusted as bellow:

Pulse width: 1 ns , RF oscillator: 9.4 Ghz, Pulse

Repeat Frequency (PRF):216 Hz

Constant Target Range: 85 cm

Used pattern recognition mechanism and calculate scheme which were given in Figure 3. We can see that the feature extraction is the most important part of pattern recognition system , and directly impresses accomplished of classifier.

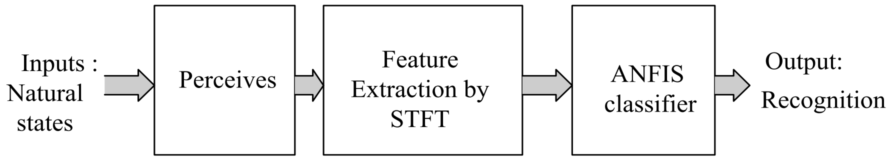


***Figure 2. Block Diagram of the Pattern Recognition System***

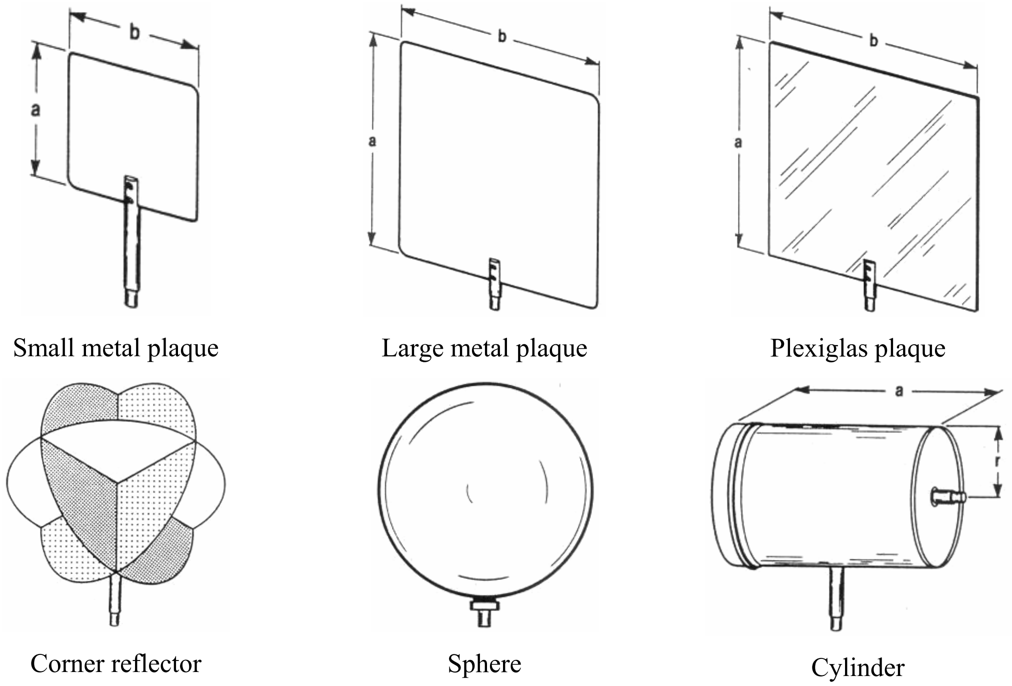


***Figure 3. Used radar targets*.**

The feature extraction is the most important part of pattern recognition and correct pattern classification key. The purposes of feature extraction from signals are to rise the accomplishment of classifier while the classification time is reduced, to reduce the data quantity will be processed to minimum level, and to prove safe of recognition system. For Extracted features isn't impressed from not be controlled parameters in system, the extracted features should be determined. Thus, the features may be generalized and safe of systems may be raised [11]. For features extraction of unstable signals commonly is interested in composition of the time-frequency region [12], [13]. Thus, definitely data which includes both transient alteration and frequency alteration can be extracted from radar Doppler signals.

In this study for feature extraction, firstly each of the different targets which were shown in Figure 3. Real Doppler signals were received from Lab-Volt Radar education set. Secondary, Short Term Fourier Transform time-frequency distribution (STFT) which was given at Equation 2 was applied to have been obtained target Doppler signals. Thirdly, Gauss white noise which was given at Equation 5 was applied to this have been obtained STFT. SNR ratios of This Gauss white noises were changed 1, 3, 5, 7, 9 respectively [14], [15]. Maximum value, minimum value, arithmetic average and geometric average of this noisy STFT time-frequency distributions which were obtained for each of target were calculated to form feature vector. Numerical values of them were regarded as for feature vector at classification stage [14], [15].

$$c = \sqrt{\frac{\sigma_s^2}{\sigma_w^2 10^{SNR/10}}} \qquad (5)$$

There, $\sigma_s^2$ is signal variance, $\sigma_w^2$ is noise variance, SNR is signal / noise ratio, c is noise scale constant

STFT time-frequency distributions of radar targets Doppler signals which were obtained Lab-Volt radar experiment set are given in Figure 4.

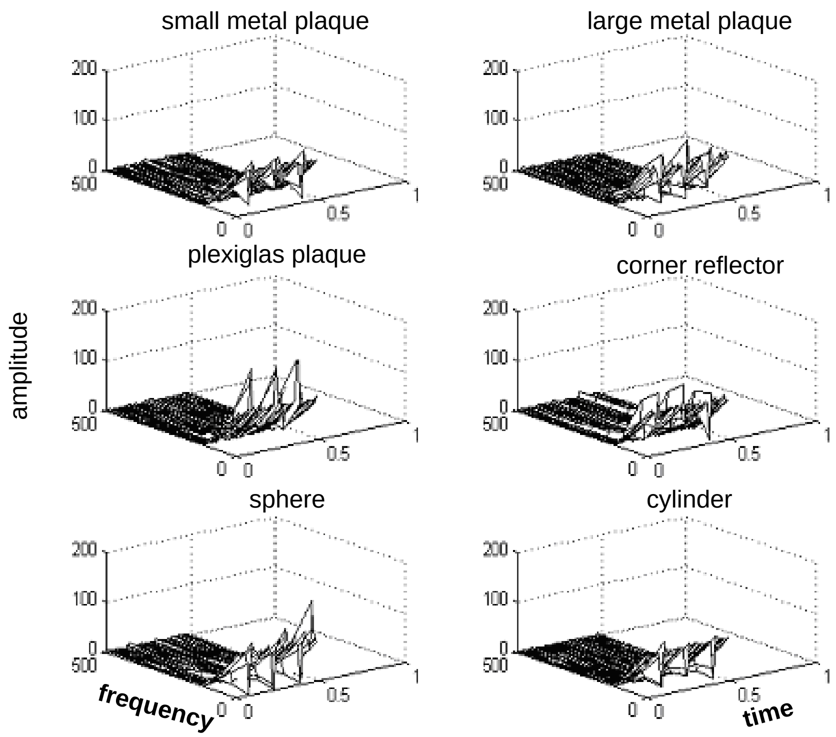


***Figure 4. To be obtained STFT time-frequency distributions of constant targets pulsed radar Doppler***

## 3. THE CLASSIFICATION STAGE

In this study, the pattern recognition input space was obtained by using feature extraction method which was given in Section 2. Then, Adaptive Network Based Fuzzy Inference System (ANFIS) classifier algorithm was used for radar targets classification.

### 3.1. Adaptive-Network-Based Fuzzy Inference System Algorithm

Both artificial neural network and fuzzy logic are used in ANFIS's architecture. ANFIS is consisted of if-then rules and couples of input-output, for ANFIS training is used learning algorithms of neural network [16], [17], [18].

For simplicity, we assume the fuzzy inference system under consideration has two inputs (x, y, t, and k) and one output (z). For a first order Sugeno fuzzy model, a typical rule set with base fuzzy if-then rules can be expressed as

If x $A_1$ y $B_1$ t $C_1$ k $D_1$ then

$$f_1 = p_1 x + q_1 y + r_1 t + s_1 k + u_1 \qquad (6)$$

Where, p, r, q, s, u are linear output parameters. The ANFIS's architecture which has four inputs and one output is showed in Figure [28]. This architecture is formed by using five layer and sixteen if-then rules:

**Layer-1:** Every node i in this layer is a square node with a node function.

$O_{1,i}=\mu_{Ai}(x)$, for i=1,2, $O_{1,i}=\mu_{Bi-2}(y)$, for i=3,4
$O_{1,i}=\mu_{Ci-4}(t)$, for i=5,6 $O_{1,i}=\mu_{Di-6}(k)$, for i=7,8 (7)

Where x, y, t, k are inputs to node i, and $A_i$, $B_i$, $C_i$, $D_i$ are linguistic label associated with this node function. In order words, $O_{1,i}$ is the membership function of $A_i$, $B_i$, $C_i$, $D_i$. Usually we choose $\mu_{Ai}(x)$, $\mu_{Bi}(y)$, $\mu_{Ci}(t)$, $\mu_{Di}(k)$ to be bell-shaped with maximum equal to 1 and minimum equal to 0, such as
inimum equal to 0, such as

$$\mu_{Ai}(x),\mu_{Bi-2}(y),\mu_{Ci-4}(t),\mu_{Di-6}(t)=\exp(-((x_i-c_i)/(a_i))^2) \quad (8)$$

Where $a_i$, $c_i$ is the parameter set. These parameters in this layer are referred to as premise parameters.

**Layer-2:** Every note in this layer is a circle node labelled $\Pi$ which multiplies the incoming signals and sends the product out. For instance,
$O_{2,i}= w_i= \mu_{Ai}(x).\mu_{Bi-2}(y).\mu_{Ci-4}(t).\mu_{Di-6}(k)$, i=1, 2, 3,….,16 (9)

Each node output represents the firing strength of a rule. (In fact, other T-norm operators that performs generalized AND can be used as the node function in this layer).

**Layer-3:** Every node in this layer is a circle node labelled N. The i[th] node calculates the ratio of the i[th] rules firing strength to the sum of all rule's firing strengths:

$$O_{3,i}=\overline{w_i}=w_i/(w_1+w_2+\ldots+w_{16}), \quad i=1,2,3,\ldots,16 \quad (10)$$

**Layer-4:** Every node i in this layer is a square node with a node function

$$O_{4,i}=\overline{w_i}.f_i=w_i.(p_i x+q_i y+r_i t+s_i k+u_i), \quad i=1,2,3,\ldots,16 \quad (11)$$

Where, wi is the output of layer 3, and $\{p_i, q_i, r_i, s_i, u_i\}$ is the parameter set. Parameters in this layer will be referred to as consequent parameters.

**Layer-5:** The single node in this layer is a circle node labelled $\Sigma$ that computes the overall output as the summation of all incoming signals:

$$O_{5,i}= \text{overall output} = \sum_i \overline{w_i} f_i = \frac{\sum_i w_i f_i}{\sum_i w_i} \quad (12)$$

In this study, to be obtained 4 x 30 feature vector which was stated in Section 2 was given inputs of ANFIS classifier as input sets. Outputs of this ANFIS classifier formed from a decision space = {small metal plaque, large metal plaque, Plexiglas plaque, corner reflector, sphere, cylinder} that represents six number different real radar targets. This real radar targets are shown in Figure 3.

This ANFIS classifier was tested by using hundred numbers noisy test data for each of six targets. Be obtained classification performance results of the ANFIS classifier are given on Table1.

***Table 1. Achievement of ANFIS Classifier (%)***

| **Target Object** | **Small Metal Plaque** | **Large Metal Plaque** | **Plexiglas Plaque** | **Corner Reflector** | **Sphere** | **Cylinder** |
|---|---|---|---|---|---|---|
| **Small Metal Plaque** | 98 | - | - | - | - | - |
| **Large Metal Plaque** | 1 | 97 | 1 | - | - | - |
| **Plexiglas Plaque** | 1 | 1 | 99 | 1 | - | - |
| **Corner Reflector** | - | 2 | - | 99 | 1 | - |
| **Sphere** | - | - | - | - | 98 | 1 |
| **Cylinder** | - | - | - | - | 1 | 99 |

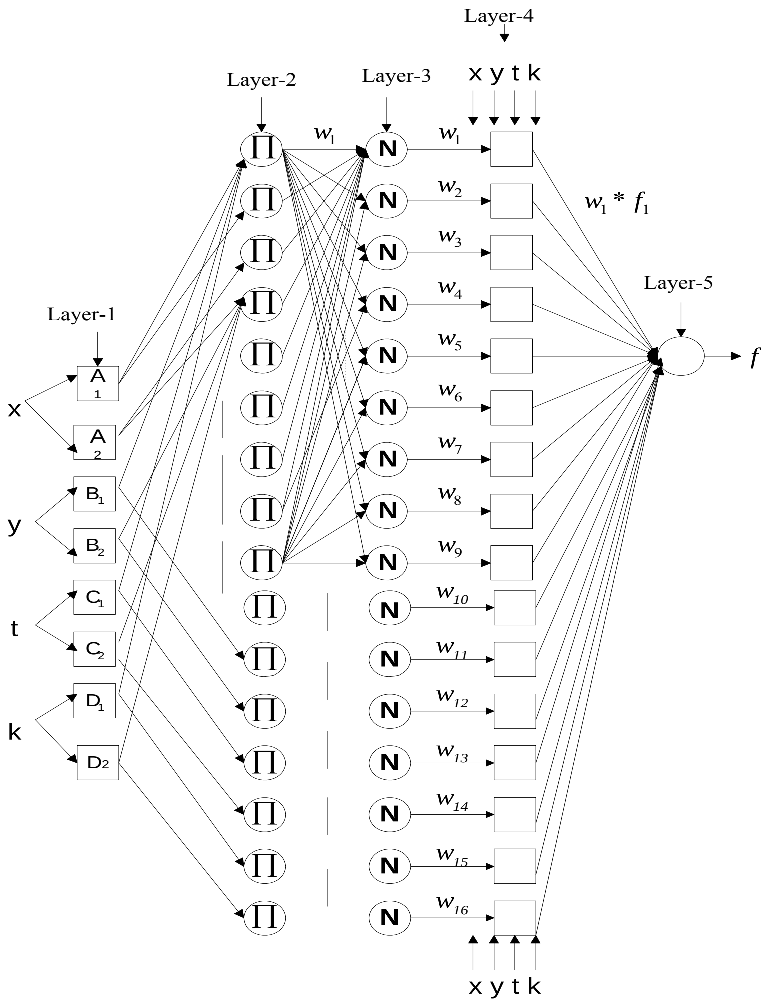


***Figure 5. Used ANFIS architecture of 4-inputs and 16-rules in this study.***

## 4. CONCLUSIONS

In this paper, proposing feature extraction method in Section 2 was applied to real pulsed radar signals. A hundred percent determination functions were composed by using ANFIS classifier. In addition to, there are clear differences among the determination functions are understand as to be seen in Table 1. These indicators show to have been extracted feature which strongly and effectively from natural inputs.

The determination functions of system at decision space are very clear. The features which were selected for feature vector very good summarize. In addition to, ANFIS is selected as classifier. Because this classifier add learning and decision extraction feature from learned to system. Thanks to proposed method in this study, to be realized basic intelligent recognition systems may be applied at wide areas.

In radar pattern recognition studies at the future, systems which are less affected by noise and environment may be realized.

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