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Radar Signal Recognition Using the Continuous Wavelet Transform and Artificial Neural Network

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Abstract: Radar signal recognition algorithms have proven to be highly valuable in various fields such as intelligent radio, surveillance systems, and electronic warfare. The ability to quickly and accurately identify different signals and their emitters is crucial in the rapidly changing electromagnetic environment. The use of CWT is an effective method for extracting signal and modulation features for classification purposes. The paper focuses on the ability of various types of radar signals to be recognized, such as linear frequency modulated signals (LFM) and stepped frequency modulated signals (SFM), phase-coded waveforms (PCW) signals with Barker code, and rectangular pulses (Rec). The algorithm proposes using higher-order statistics (HOS) of CWT coefficients as signal features. PCA is used to reduce the dimensionality of the feature space. PCA identifies and reduces the dimensions of the most important features while retaining as much relevant information as possible. Finally, as the classifier, a feed-forward neural network is used to classify the signals based on the extracted features. The paper explores the effectiveness of using CWT and its coefficients for signal recognition. The HOS-based approach with PCA and a feed-forward neural network offers a more traditional feature extraction and classification pipeline. Overall, algorithms provide viable methods for signal recognition, and their suitability may depend on factors such as the nature of the signals, available training data, and computational requirements.

Keywords: radar signal recognition; continuous wavelet transform (CWT); feature extraction; artificial neural network (ANN).

I. INTRODUCTION

Radar signal recognition is a critical task in many applications, including military surveillance, target tracking, and air traffic control. Accurately identifying and classifying radar signals based on their modulation characteristics is essential for effective signal processing and decision-making. The CWT is a powerful tool for time-frequency analysis, allowing for simultaneous analysis of the time and frequency content of signals. It delivers superior frequency localization at long scales and increased time resolution at short scales when compared to standard transforms such as the Short-Time Fourier Transform [1]. The CWT can effectively extract important modulation features such as amplitude, frequency, and phase shifts from radar signals. Artificial Neural Networks, specifically feed-forward networks, have demonstrated their ability to learn complex patterns and classify signals based on learned representations. By training an ANN with appropriate features extracted from radar signals, it can learn to accurately recognize and classify different modulation types. The main objective is to develop an automated and accurate approach for classifying radar signals based on their modulation types and other key characteristics. Concentrate on analyzing specific types of radar signals, such as linear frequency modulated (LFM) and stepped frequency modulated (SFM), phase-coded waveforms with Barker code, and rectangular pulses. The proposed methodology consists of two main steps. First, the CWT is applied to the radar signals, extracting relevant features related to the modulation characteristics. The CWT coefficients are used as input to the subsequent classification step. Second, an Artificial Neural Network, specifically a feed-forward network, is trained using the extracted CWT coefficients. The trained network is then capable of classifying new radar signals based on their modulation types.

II. FEATURE EXTRACTION OF CONTINUOUS WAVELET TRANSFORM

The Continuous Wavelet Transform (CWT) studies radar waveforms by collecting transient characteristics such as amplitude and frequency variations, as well as phase shifts, that are common in modulated signals. The CWT provides a time-frequency representation that allows for the analysis of these signal characteristics. The CWT of a radar waveform, denoted as CWT (τ, a), is defined using the integral representation as [2]:

$$CWT\ (\tau, a) = (1/\sqrt{|a|}) * \int [x(t)\ \psi^*\ ((t-\tau)/a)]\ dt$$

where x(t) denotes the radar waveform, ψ(t) is the mother wavelet, τ represents the time translation parameter, and a represents the scaling constant. The term ψ* ((t-τ)/a) refers to the baby wavelet, which is a translated and scaled version of the mother wavelet.

The integral in the previous Equation can be substituted by a summation in the case of digital CWT implementation. Assume z = nT = n and t = kT = k. (where T is the sampling interval), and considering that the scale is an even integer, the CWT can be expressed as [3]:

$$CWT\ (n, a) = (1/\sqrt{a}) * \sum x(k)\ \psi^*\ ((k - n)/a)$$

where x(k) represents the radar waveform samples, and the summation is performed over the appropriate range.

By utilizing the CWT, the signal features obtained represent the signal's modulation and frequency characteristics, which are crucial for distinguishing between different types of radar signals. Figure (1) represent the flow diagram of the work.

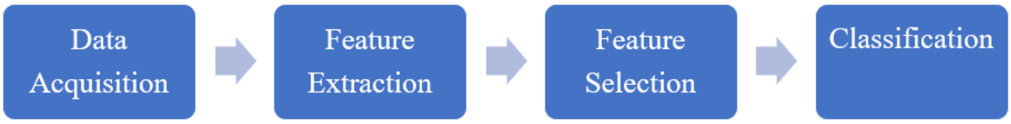

Fig1: Proposed setup for analyzing architecture

III. PROPOSED CLASSIFICATION METHODOLOGY

The first recognition algorithm described in the paper extracts features for the classification process using the CWT and its HOS. Higher-Order Statistics (HOS) are calculated from the CWT coefficients to reduce the dimensionality of the feature space and improve the discriminative power of the input features. Statistical measures such as standard deviation, skewness, kurtosis, and higher moments are computed as HOS features [4]. Next, Principal Component Analysis (PCA) is applied to the feature dataset obtained from the CWT and HOS calculations. PCA helps to reduce the dimensionality of the feature space while retaining the most important information.

In this algorithm, the feed-forward neural network (FFNN) is presented as the classifier in this approach [5]. The default network layout includes fully connected layers with two hidden layers. Figures (2) and (3) show the simulation training and testing results. The analyzed signals in this algorithm include Linear Frequency Modulated (LFM), Stepped Frequency Modulated (SFM), rectangular pulses (REC), and phase-coded waveforms with Barker codes. The confusion matrix is shown in Figure (4) & Figure (5).

IV. RESULT ANALYSIS

In the paper, 200 data were used for both training and testing. Where 140 data are for training (70%) and 60 data are for testing (30%) was used. An accuracy rate above 93% indicates that the classification model performed well during training, achieving a high level of accuracy in distinguishing different signal types. A test accuracy above 98% is considered very high in signal classification tasks. It suggests that the proposed approach using the Continuous Wavelet Transform (CWT) and Artificial Neural Networks (ANNs) was effective in extracting relevant features from the radar signals and achieving accurate classification results.

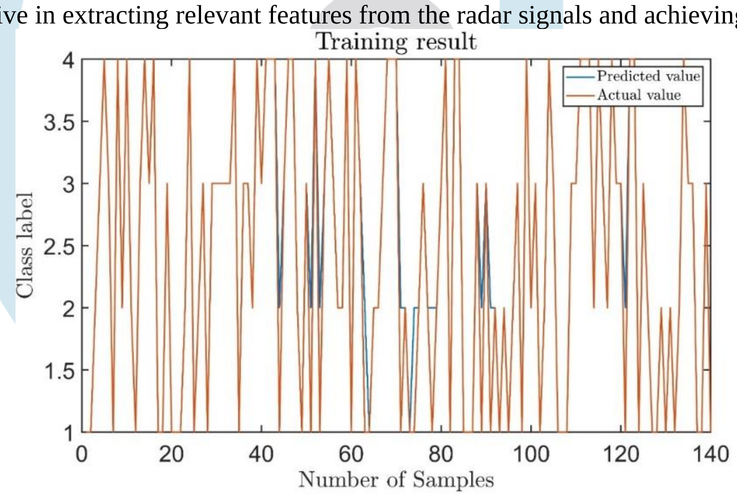

Fig:2 Training Result

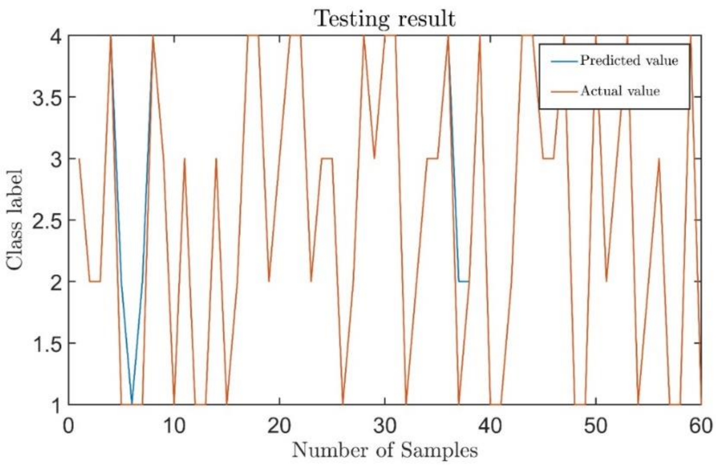

Fig:3 Testing Result

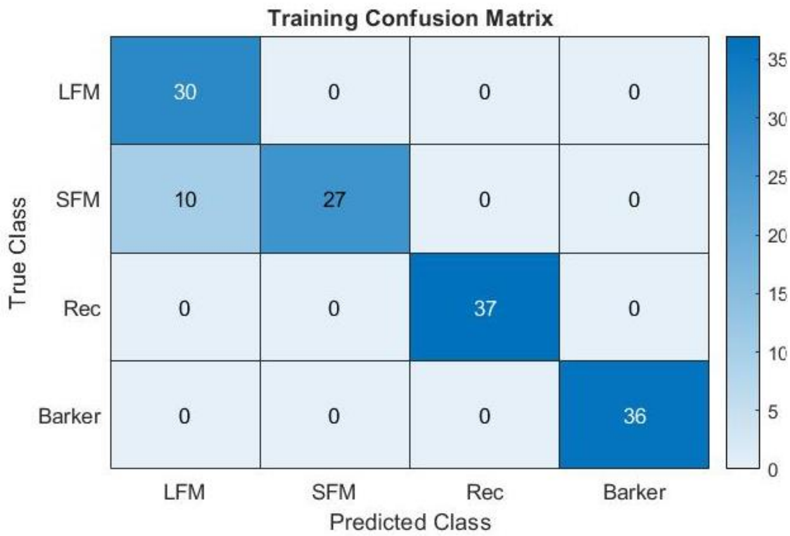

Fig.4 Training confusion matrix

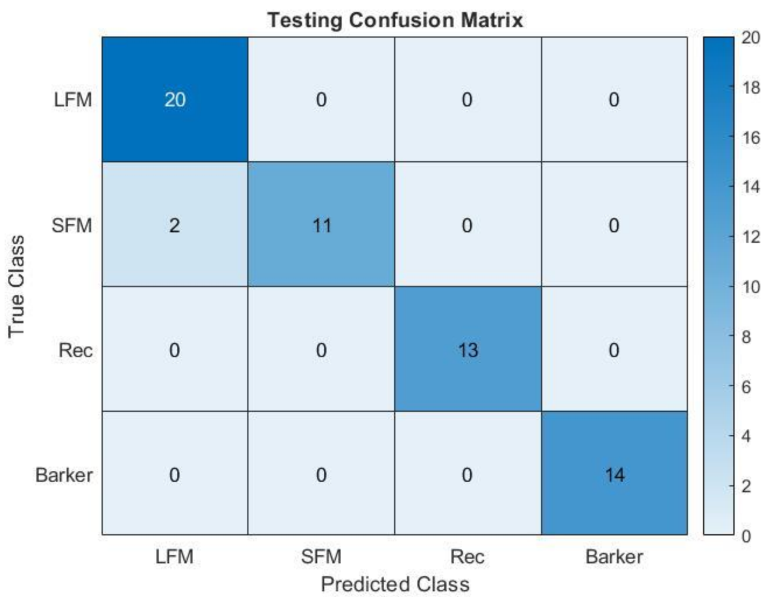

Fig.5 Testing confusion matrix

V. CONCLUSION

In this paper, the effectiveness of two recognition algorithms for radar signal identification using the CWT and ANN. One of the primary requirements for these algorithms was robustness to high levels of noise. The obtained results demonstrated the efficacy of the CWT and ANN-based approaches across a wide range of SNR. The algorithms achieved a high percentage of correctly classified signal types, with accuracy rates above 95%. The first algorithm incorporated Principal Component Analysis (PCA) for feature number reduction. By using PCA, the dimensionality of the feature space was reduced, allowing for more efficient processing and classification.

Future research will look into a broader range of signals, such as pulse width, intra-pulse modulation, pulse envelope, phase coding, pulse repetition time types, and so on. In the future, more wavelet type and related parameter evaluations will be performed. There are also plans to conduct research with radar signals.

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