Comparison of analysis methods for separating and recognizing multicomponent radar signals

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ABSTRACT

This paper proposes a model for separating and recognizing a mixture of radar signals using combined multiresolution methods and convolution neural networks. The model involves three main steps: separating the signal into individual components using the Multiresolution analysis (MRA) methods: Empirical mode decomposition (EMD), Variational mode decomposition (VMD), and Maximal overlap discrete wavelet packet transform (MODWPT); transforming these components into the time-frequency domain using Wigner-Ville distribution (WVD) and storing them as images; and then feeding these images into the SqueezeNet for recognition. These multiresolution methods are then compared based on three criteria: The number of successful separations, the SNR ratio of the input signal, and the correlation between the separated signal components and the original signal components. Additionally, we evaluate the performance of the SqueezeNet with real-time signals.

Keywords: Radar signals; Multiresolution analysis; Maximal overlap discrete wavelet packet transform details; Empirical mode decomposition; Variational mode decomposition.

1. INTRODUCTION

In modern electronic warfare, radio reconnaissance plays a vital role in detecting and recognizing enemy radar signals, especially when handling overlapping signals in complex noise environments. Deep learning methods such as Convolutional Neural Networks (CNNs), Recurrent Neural Networks [1], Long Short-Term Memory networks [2], and Autoencoders have proven effective in feature extraction and signal classification but are mainly applied to single signals. In contrast, multiresolution analysis methods are more effective for nonlinear, non-stationary signals, enabling the separation of individual signal components.

This paper proposes a model that combines multiresolution analysis with CNNs to separate and recognize radar signal mixtures, enhancing accuracy and operational capability in complex tactical conditions, thereby improving the efficiency of radio reconnaissance systems.

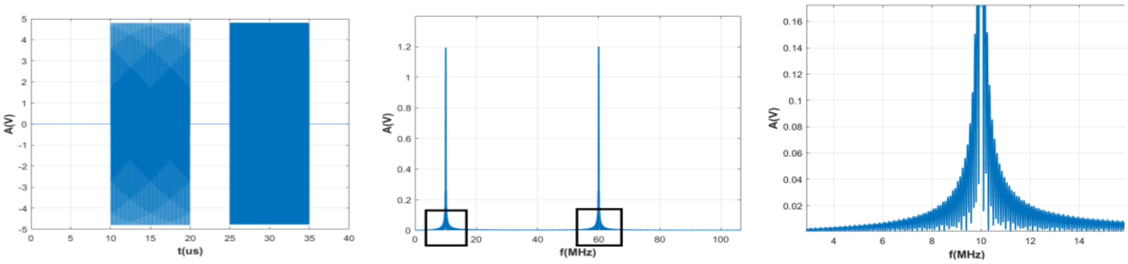
2. PROPOSED MODEL

Figure 1. *The block diagram of the proposed model.*

The block diagram of the proposed model is shown in figure 1. The block diagram of the proposed model includes three parts: Signal preprocessing; feature extraction; recognizing.

2.1. Signal preprocessing

The author proposes using one of the three MRA methods in this signal preprocessing step. The three MRA methods include EMD [3], VMD [4], and MODWPT [5]. To illustrate these three methods, the received signal consisting of a mixture of a 10 MHz Pulse signal and a 60 MHz Pulse is used. The received signal and the decomposition results are both presented in the frequency domain.



a) b) c)

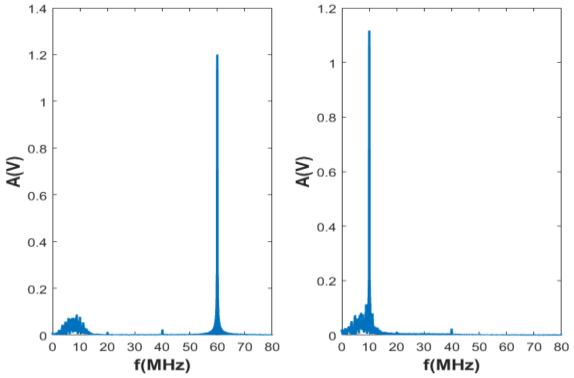
Figure 2. *Input signal: a) In the time domain; b) In the frequency domain; c) Zoomed-in view of the highlighted section in image b.*

2.1.1. Empirical mode decomposition

The EMD is a method for decomposing a signal into components called Intrinsic mode functions (IMFs). The EMD process involves a sifting process to extract the IMFs. Each IMF must satisfy two conditions: (1) the number of extrema and the number of zero-crossings must be equal or differ at most by one, and (2) the mean value of the envelopes defined by the local maxima and minima must be zero. The sifting process is repeated until the original signal $x(t)$ is decomposed into IMFs $c_i(t)$ and a residual component $r(t)$:

$$x(t)=\sum_{i=1}^{n} c_i(t)+r(t) \tag{1}$$

The results of EMD with the received signal are shown in Fig. 3. Although the 10 MHz and 60 MHz signals have been separated, frequencies below 20 MHz with low amplitudes have also appeared, indicating that the EMD method was not entirely effective in signal separation.



a) b)

Figure 3. *Results of EMD: a) IMF 1; b) IMF 2.*

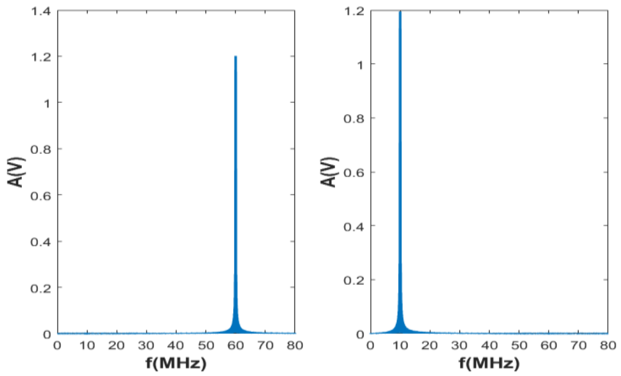
2.1.2. Variational mode decomposition

The VMD is a more advanced technique developed based on the principles of EMD. VMD decomposes a signal into modes by simultaneously optimizing both the bandwidth and center frequency of the signal components. VMD addresses the following optimization problem:

$$\min_{\{u_k\},\{\omega_k\}}\left\{\sum_k\left\|\partial_t\left[\left(\delta(t)+\frac{j}{\pi t}\right)*u_k(t)\right]e^{-j\omega_k t}\right\|_2^2\right\} \tag{2}$$

Where $u_k(t)$ are the modes to be decomposed; ω_k are the center frequencies of the modes; $*$ denotes convolution; ∂_k is the partial derivative with respect to time; $\delta(t)$ is the Dirac delta function.

The results of VMD with the received signal are shown in Fig. 4. VMD successfully separated the 10 MHz and 60 MHz signals.



a) b)

***Figure 4.** Results of VMD: a) IMF 1; b) IMF 2.*

2.1.3. Maximal overlap discrete wavelet packet transform

The MODWPT is an advanced wavelet transform technique that analyzes signals in the time-frequency domain. Unlike the traditional Discrete wavelet transform (DWT), MODWPT does not decimate the signal, which preserves the temporal alignment and is shift-invariant. This property is particularly beneficial for analyzing non-stationary signals like radar signals.

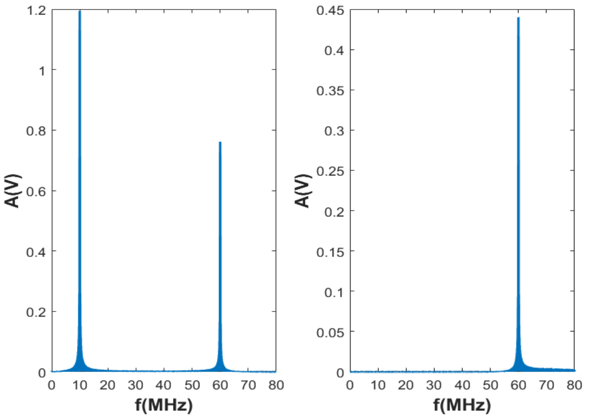
The MODWPT decomposes a signal into a set of wavelet packets by iteratively applying high-pass and low-pass filtering operations without downsampling. This process results in a highly redundant representation that captures more detailed frequency information at various scales.

The signal $x[n]$ is decomposed using a pair of filters: a high-pass filter $g[n]$ and a low-pass filter $h[n]$. The MODWPT at level j for a node k can be written as:

$$W_j^k[n] = \sum_{m=0}^{L-1} h[m] W_{j-1}^{2k}[n-m] + \sum_{m=0}^{L-1} g[m] W_{j-1}^{2k+1}[n-m] \tag{3}$$

Where $W_j^k[n]$ represents the wavelet packet coefficients at level j and node k; $h[m]$ and $g[m]$ are the coefficients of the low-pass and high-pass filters, respectively; n is the time index; L is the length of the filters. At the initial level $j=0$, the input signal $x[n]$ is used $W_0^0[n] = x[n]$.

The results of MODWPT with the received signal are shown in Fig. 5. It can be seen that MODWPT has yet to completely separate the two signals.



a) b)

***Figure 5.** Results of MODWPT: a) Component 1; b) Component 2.*

2.2. Feature extraction

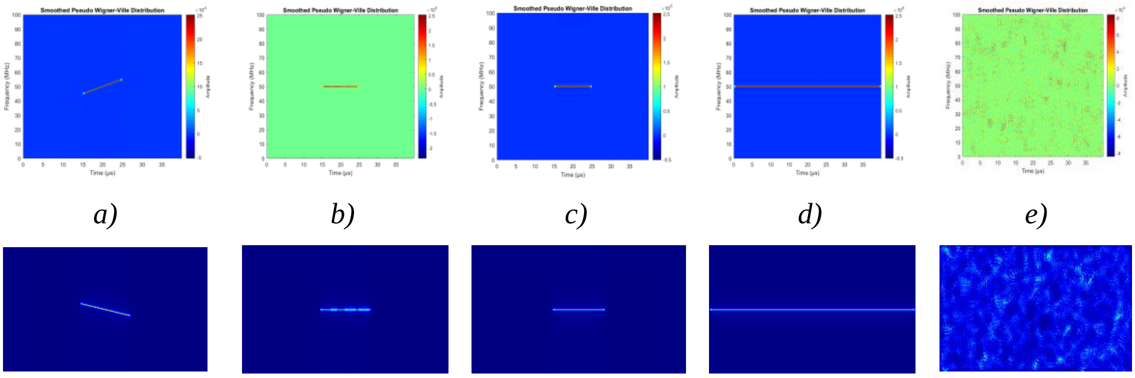
In this part, the signal will be transformed into the time-frequency domain using the WVD [6] method. The Wigner-Ville Distribution is a powerful signal analysis tool and is widely applied in various fields such as radar, audio, and biomedical signal processing. Mathematically, the WVD is described as follows:

$$W_x(t,f)=\int_{-\infty}^{+\infty} x\left(t+\frac{\tau}{2}\right)x^*\left(t-\frac{\tau}{2}\right)e^{-j2\pi f\tau}d\tau \tag{4}$$

where $x(t)$ is the input signal; $W_x(t,f)$ is the WVD of the signal $x(t)$; $x^*(t)$ is the complex conjugate of $x(t)$; τ is the time lag variable; f is the represents frequency; j is the imaginary unit.

Through the signal processing procedure, the authors selected the following parameters for the WVD to reduce noise and cross-interference, making it suitable for nonlinear signals: the Smoothed Pseudo mode, 1024 time points, 1024 frequency points, and a Kaiser 511 filter for both the time and frequency windows.

After the signal is transformed using WVD, the time-frequency distribution (TFD) data is converted into a 227x227 RGB color image. First, the TFD values are normalized to the range [0, 1], then the image is resized to 227x227. Next, the 'jet' colormap is applied to create clear distinctions between intensity levels in the image. Finally, the image is converted to RGB format, ready to serve as input for image recognition models. When converted to image form, the influence of signal parameters becomes less significant, as the CNN focuses on the shape of the object (the shape of the signal in the time-frequency domain).



a) b) c) d) e)

f) g) h) j) k)

Figure 6. *Results of WVD: a) LFM; b) Barker code; c) Pulse; d) CW; e) Noise Input of SqueezeNet: f) LFM; g) Barker code; h) Pulse; j) CW; k) Noise.*

2.3. Recognizing

Among the various types of CNNs, the author selects SqueezeNet because it is a compact and efficient CNN designed to reduce model size while maintaining performance. The SqueezeNet [7] architecture, consisting of 68 layers, was proposed to achieve AlexNet-level accuracy while using 50 times fewer parameters. The primary goal of SqueezeNet is to offer size and performance benefits, optimizing the training process and deployment on resource-constrained devices like autonomous vehicles and microcontrollers.

During training, due to the clear characteristics of different types of signals in the time-frequency domain, there is a risk of overfitting. To better fit the training dataset and avoid overfitting, SqueezeNet is adjusted as follows (figure 7):

The Convolutional layer - Conv10 (blue) was modified from 1000 to 5 filters. Since the default output of SqueezeNet is 1000, but our required output is 5.

A 50% Dropout layer – Drop10 (green) was added. The Dropout layer is a regularization technique that helps reduce overfitting. Dropout works by randomly 'dropping out' (setting to zero) a percentage of neurons in the hidden layer during training.

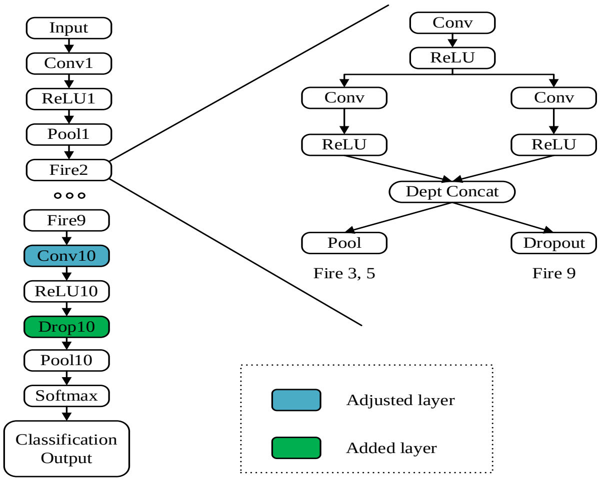


Figure 7. *The block diagram of SqueezeNet.*

3. SIMULATION AND EXPERIMENTAL RESULTS

3.1. Database

To evaluate and train the multiresolution signal processing methods and the SqueezeNet for recognition, the author created a simulated database in MATLAB and used actual data from the E8267C transmitter. Signal types include Linear frequency modulation (LFM), Barker code, Continuous wave (CW), Pulse, and Gaussian noise. The critical parameters of signals are shown in table 1.

Table 1. *Key parameters of the database.*

Key parameters	**Notation (Dimension)**	**Value**
Sampling frequency	$f_s(MHz)$	$\{200;500\}$
Carrier frequency	$f_c(MHz)$	$5 \div 80$
Pulse width	$\tau(\mu s)$	$10 \div 20$
Bandwidth of LFM	$B(MHz)$	$5 \div 20$
Number of bits Barker code	N	$\{5;7;11;13\}$
Signal to noise ratio	$SNR(dB)$	$-10 \div 10$

3.2. Training SqueezeNet

The training database for SqueezeNet consists of time-frequency domain images of LFM, Barker code, Pulse, CW, and Gaussian noise, with parameters randomly selected within the value ranges specified in table 3. Each type of signal has 1,500 samples with randomly generated parameters, totaling 7,500 samples. These are split into 80% for training, 10% for testing, and 10% for validation. The training options are shown in table 2.

Table 2. *Key options of SqueezeNet.*

Key options	**Selected options used**	**Key options**	**Selected options used**
Solver for training	Adaptive moment estimation	Validation data	10% of the training database
Number of training epochs	5	Shuffle	Every epoch
Initial learn rate	0.001	Plots	Training progress
Mini-batch size	128	Verbose	False

3.3. Evaluation of results

3.3.1. Evaluation with simulated signals

a) Comparison of MRA methods

A comparison of multiresolution methods is conducted by using input signals in iterative pairs (pulse and Barker code, LFM and CW). The separated signals were evaluated based on the signal-to-noise ratio of the input signal, the number of successful separations, the correlation coefficient of the separated components with the original input signal components, and the processing time. Each signal-to-noise ratio level will be evaluated 1000 times. Successful separation is counted when at least one of the separated components contains only one of the original input signal components and has a correlation coefficient with that signal component of no less than 0.5. Additionally, at least one other separate component must meet the same condition as the other input signal component.

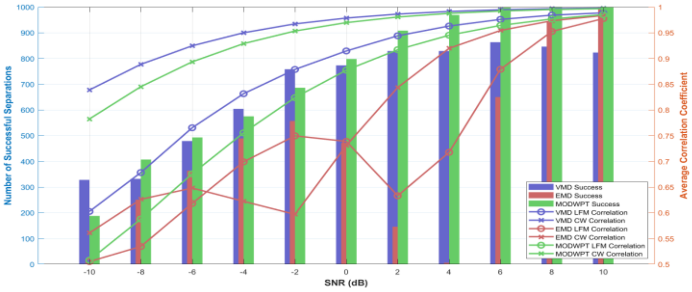


Figure 8. *Graph with LFM and CW code as input signal.*

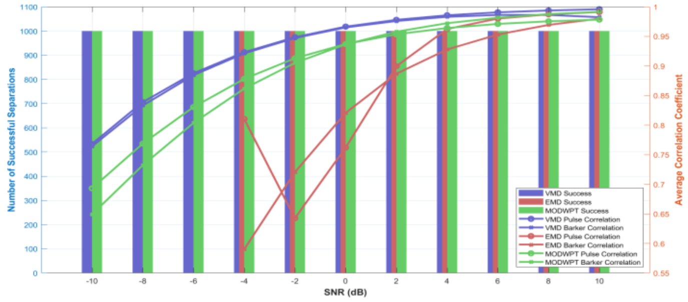
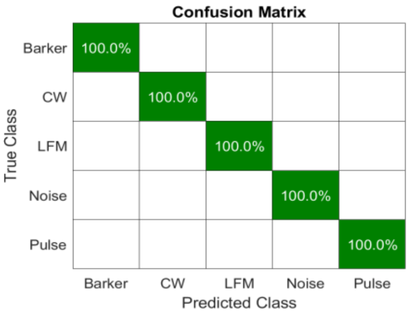


Figure 9. *Graph with Pulse and Barker code as input signal.*

From Fig. 8 and Fig. 9, we can observe that with the input dataset mentioned in section 3.1, the processing capability of EMD is significantly lower than the other two methods in low SNR regions ($SNR \le 4$). Although VMD exhibits slightly better processing quality, its processing time is considerably longer than MODWPT. The average processing times for EMD, VMD, and MODWPT are $0.014 \div 0.023s$, $1.87 \div 2.3s$ and $0.006 \div 0.007s$, respectively. A limitation of this paper is that the authors only present separation results with two signals plus noise; however, in cases with three or four signals, the model still produces similar results.



	Barker	CW	LFM	Noise	Pulse
Barker	100.0%				
CW		100.0%			
LFM			100.0%		
Noise				100.0%	
Pulse					100.0%

Figure 10. *Confusion matrix.*

b) Evaluation of SqueezeNet training results

The confusion matrix (shown in Fig. 10) indicates that the model achieved 100% classification accuracy for all classes (Barker, CW, LFM, Noise, Pulse). All the cells along the main diagonal are 100%, meaning each signal was correctly classified into its respective class without errors. With these results, the SqueezeNet model achieved perfect accuracy on the test set and demonstrated an apparent and error-free classification capability.

3.3.2. Evaluation with real-time signals

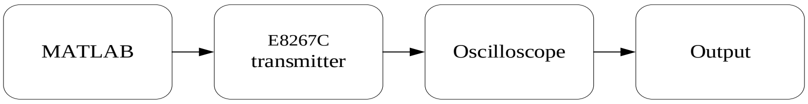


Figure 11. *The block diagram of real signal generation.*

The process of generating real-time signals is illustrated in Fig. 11 and 12. The baseband signal is generated in MATLAB and then upconverted using the E8267C generator. The output signal is displayed on an oscilloscope and then saved as a CSV file for further use. After processing signals at power levels of -10, -5, 0, 5, and 10 dBm, the model shows good recognition performance at 0 dBm and above. The results of the recognition of signals with $f_c = 5MHz$ and transmit power $0dBm$ are shown in Fig. 13.

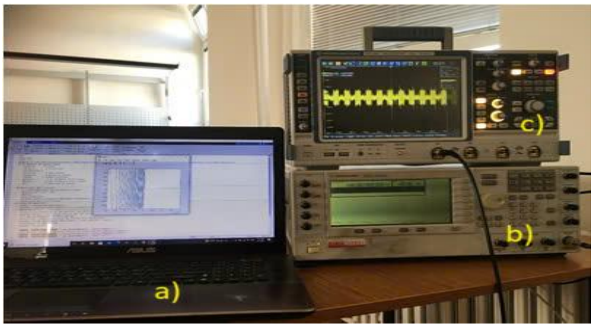
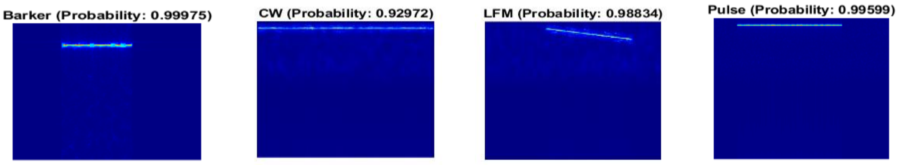


Figure 12. *Real signal generator device connection model: a) MATLAB; b) E8267C; c) Oscilloscope.*



a) b) c) d)

Figure 13. *Results of recognizing.*

Thus, testing with real-time signals shows that the adjusted SqueezeNet network achieves very high recognition accuracy for the signals tested by the author: Barker codes 99.98%, CW 92.87%, LFM 98.8%, and Pulse 99.60%.

4. CONCLUSIONS

This paper presents a model for radar signal decomposition and recognition using three multiresolution signal decomposition methods—EMD, VMD, and MODWPT—combined with the SqueezeNet network. The methods are compared based on the number of successful decompositions, input signal SNR, and the correlation coefficient of the decomposed components with the original signal. Results show that VMD and MODWPT perform better in signal decomposition, while SqueezeNet is effective in signal recognition even with varying noise levels. However, the model is currently trained only on single pulses of several signal types, without parameters for pulse repetition or antenna scanning cycles, which the authors aim to incorporate in future research. Overall, the model has significantly improved real-time radar signal decomposition and recognition, highlighting the benefits of combining multiresolution methods and CNNs in radio reconnaissance.

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TÓM TẮT

Nghiên cứu so sánh đánh giá hiệu quả của các phương pháp tách và nhận dạng hỗn hợp tín hiệu ra đa

Bài báo này đề xuất một mô hình để tách và nhận dạng hỗn hợp tín hiệu ra đa sử dụng phương pháp đa phân dải và mạng nơ-ron tích chập. Mô hình đề xuất gồm ba bước chính. Bước một được sử dụng để tách tín hiệu thành các thành phần riêng dựa trên các phương pháp phân tích đa độ phân giải (MRA): phân tích chế độ kinh nghiệm (EMD), phân tích chế độ biến phân (VMD) và phép biến đổi Wavelet kết hợp chồng lấn cực đại (MODWPT). Trong bước thứ 2, các tín hiệu sau khi tác được trích xuất đặc trưng trên cả hai miền thời gian - tần số bằng phân bố Wigner-Ville (WVD). Trong bước ba, mạng nơ ron tích chập (CNN) được sử dụng để nhận dạng các tín hiệu nói trên. Hiệu quả của các phương pháp tách được đánh giá thông qua các tiêu chí như số lần tách thành công, tỷ lệ SNR của tín hiệu đầu vào và hệ số tương quan giữa các thành phần tín hiệu trước và sau khi tách. Ngoài ra, hiệu quả của thuật toán đề xuất đã được kiểm chứng với các tín hiệu từ máy phát sóng chuẩn E8267D. Kết quả mô phỏng và thực nghiệm cho thấy, thuật toán đề xuất có tính ứng dụng thực tế cao trong bài toán tách và nhận dạng hỗn hợp tín hiệu ra đa.

Từ khóa: Tín hiệu radar; Phân tích đa độ phân giải; Phép biến đổi wavelet kết hợp chồng lấn cực đại; Phân tích chế độ kinh nghiệm; Phân tích chế độ biến phân.