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RESEARCH ARTICLE

A Target Classification Optimization Recognition and Information Extracting Method of Laser Fuze Detection System Based on Fuzzy C-Means Incremental Update and Neural Network

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ABSTRACT With the rapid development of laser fuze technology, the ability of fuze to recognize target has become increasingly important. To effectively improve the recognition rate of laser fuze against interference signal and target signal, based on the two-channel symmetric laser scanning detection system, this paper proposes a classification method based on fuzzy C-means incremental update under the condition of small sample test data. The classification model is established using the fuzzy C-means algorithm, which uses the time-domain entropy, frequency-domain entropy and frequency domain exponential entropy of the reflected laser echo signal as the feature variables; The classification model is adaptively adjusted by adopting an improved fuzzy C-means incremental update algorithm to obtain the high accuracy classification results; Combining with the target's signal features extracted by discrete binary wavelet transform, the classification results of real target signal are optimally recognized by wavelet neural network. The experimental results show that compared with the wavelet neural network recognition method, the target recognition method proposed in this paper based on fuzzy C-means incremental update and neural network can achieve higher target recognition rate under conditions of low signal-to-noise ratio and high threshold signal-to-noise ratio. Moreover, fuzzy c-means incremental update method reduces time-consuming of classification model, significantly improves the anti-interference ability, the results provide reference significance for future applications of neural network recognition method in laser fuze detection systems.

INDEX TERMS Reflected laser echo signal, fuzzy C-means incremental update, wavelet transform, neural network, target recognition.

I. INTRODUCTION

For traditional detectors in non-intelligent weapon ammunition, the common detection method for targets uses a certain threshold amplitude in the time domain, this method is susceptible to noise signal during the detection process of the system, and this phenomenon limits the application range of the ammunition. When detection targets are new type, this method is difficult to achieve the detection effect. It requires further investment of manpower and resources for redesigning the detector, resulting in a wide variety of ammunition types and bringing difficulties to the users [1], [2]. Currently, the development of intelligent ammunition technology is rapidly advancing, the damage of weapons and ammunition at the optimal time is achieved by extracting the echo signal of the detected target, in particular, and the laser fuze of flying projectile has higher and higher requirements for target detection. Vigorously developing intelligent weapons and ammunition to have the ability to recognize multiple type's targets, while among the research about achieving multiple uses of one missile, improving the hit rate and damage effect of ammunition, it is necessary to focus on

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the research of target signal recognition methods. Traditional target echo signal recognition technology is based on Fourier analysis; it can only obtain the target signal's entire spectrum, making it difficult to obtain the signal's time-frequency local properties. To extract the target's characteristic signal, which is often contained in the detail spectrum, the analysis method with the ability to analyze local signal features is adopted. The wavelet transform is a type of time-frequency analysis with the characteristic of multi-resolution analysis, and it can reveal the essence of echo signals in laser fuze more deeply, which improves the damage effect of laser fuze. Zhang et al. [3] proposed an automatic recognition and processing method of fragment signals based on wavelet analysis and correlation algorithm in the laser curtain, this method can solve the problem of large noise signal and inability to automatically recognize in the laser curtain fragment velocity measurement system. The algorithm can effectively filter out high-frequency and low-frequency noise signal in fragment signals. Xing et al. [4] proposed extraction method based on wavelet transform for weak target signal detection under low signal-to-noise ratio, for a signal with this characteristic, this signals of different frequencies are decomposed into wavelet coefficients and scale smoothing terms of different layers, and the layer with the largest signal-to-noise ratio and the most significant echo on the detail layer is extracted for reconstruction and clutter suppression. This method can effectively suppress strong noise and detect targets. Ma et al. [5] studied a new radar target echo signal extraction algorithm under low signal-to-noise ratio conditions, which can effectively remove noise and extract radar target echo signals, and it has greatly improved performance compared to pulse compression algorithms and other algorithms. Lu et al. [6] proposed a laser curtain fragment signal processing algorithm based on the Variational Mode Decomposition, which solves the problem of difficult automatic recognition and low signal-to-noise ratio of fragment signals in static explosion fields, the algorithm has a certain reference value for filtering and recognition of fragments. Using deep learning for feature extraction and pattern recognition not only avoids the coupling effect of traditional recognition methods due to step by step feature extraction and pattern recognition, but also further improves the recognition performance of the system. Huang et al. [7] proposed an underwater target recognition algorithm for classifying and recognizing non-stationary underwater acoustic signals; this method is improved by the convolutional neural network and fuze the improved convolutional neural network with wavelet decomposition, which can effectively applied to underwater acoustic target recognition. Shi et al. [8] proposed underwater target recognition method based on a wavelet transform and probabilistic neural network, which takes into account the complexity of the underwater environment. The energy feature values of the wavelet transform can effectively distinguish different target radiation noises; probabilistic neural network has no network training process and is suitable for signal classification. Wang et al. [9] proposed a neural network-based landmine target recognition method based on the detection principle and method of time-domain multi-time wide bipolar pulse electromagnetic induction. Using the neural network model, the method distinguishes and recognizes targets from interferences and has good recognition ability for low-metal-content personnel mines and typical interference targets. Ma et al. [10] proposed a target recognition and classification method based on wavelet transform and neural network according to the characteristics of ship-axis frequency electric field signals. Using the wavelet transform to calculate the power spectrum of the axis frequency electric field signal and extract features, the method recognizes ship targets and the ocean environment based on the average cumulative power spectrum of the axis frequency electric field. According to the power spectrum analysis of the axis frequency electric field signal, different types of ship targets can be recognized, and a BP neural network is used to classify different types of ship targets and the ocean environment. Gui et al. [11] studied the radio detection target technology using wavelet transform and BP neural network theory, and verified that the recognition algorithm has a high target recognition rate with measured data. In order to further improve the recognition probability of terminal-sensitive warheads against ground armored targets in complex battlefield environments, Wu et al. [12] proposed a composite detection and recognition method of infrared images and distance images based on a lightweight convolutional neural network, this network can effectively recognize armored targets in complex background environments while having a small computational complexity. Using a carrier free ultra wideband fuze for terrain recognition provides a prerequisite for the adaptive determination of the optimal burst height of the fuze. Li et al. [13] used a small sample terrain target recognition method based on 1DC-CGAN and wavelet energy features for the fuze. In the detection process of the fuze under external environment, the echo signal received by the fuze receiver contains noise and ground clutter, especially in the working process of the projectile proximity fuze, the impact of ground clutter is particularly prominent. At the same time, the acquisition of a large number of terrain echo signals require a large amount of manpower and material resources, there's not a lot of echo data, the lack of sample data will lead to over fitting phenomenon in target recognition using neural networks, reducing the accuracy of target recognition. Therefore, it is crucial to quickly and accurately recognize targets during the detection process of laser fuze detection system [14], [15], [16].

This paper proposes a target recognition method based on fuzzy C-means incremental update and neural network to improve the accuracy and effectiveness of laser fuze detection system in target recognition. The main contributions of this work are as follows:

(1) Based on the extraction of three-dimensional feature quantities such as time-domain entropy, frequency-domain entropy, and frequency-domain exponential entropy from

reflected laser echo signals, an improved fuzzy C-means incremental update algorithm is used to establish an adaptive and adjustable classification model.

(2) According to the updated classification model, the preliminary classification results of target signals and interference signals are obtained.

(3) Target features of reflected laser echo signals are extracted using discrete binary wavelet transform, target features are input parameters for wavelet neural networks, and the real target classification results are optimally recognized using wavelet neural networks.

The remainder of this paper is organized as follows. Section II states the principle of laser fuze detection system. Section III states the classification model based on fuzzy C-means incremental update of target signal and interference signal. Section IV states target signal features extracting method using discrete binary wavelet transform. Optimization recognition method based on wavelet neural network is described in section V. Section VI gives the calculation and analysis. Finally, Section VII concludes the paper.

II. PRINCIPLE OF LASER FUZE DETECTION SYSTEM

Figure 1 is the schematic diagram of the laser fuze detection system, and this system uses two-channel symmetric laser scanning detection method. The core of the laser fuze detection system is mainly composed of two pulsed laser emission modules, two photoelectric receiving modules, signal recognition and processing module, amplification circuit, and pulse modulation circuit. Among, the pulsed laser emission field is synchronized with the photoelectric detection receiving field. Two pulsed laser emission modules and two photoelectric detection modules is designed by symmetrical structure principle, the optical detection mechanism of the two channels is the same in the scanning detection of the projectile's body, and the control function of the fuze is to obtain the appropriate echo energy of target under the detection process of the two channels laser scanning, which provides the basis for the proximity control of the fuze.

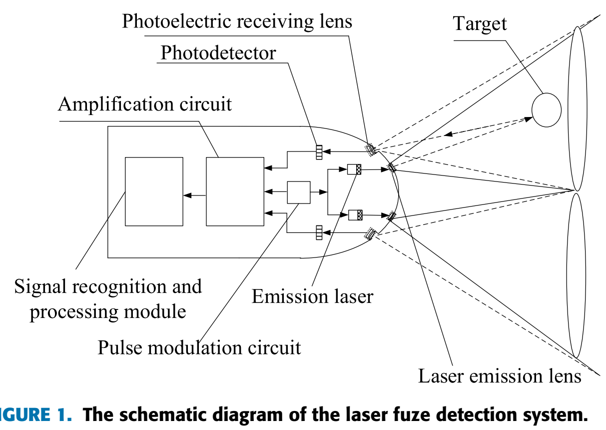

FIGURE 1. **The schematic diagram of the laser fuze detection system.**

As shown in Figure 1, each laser emission module mainly includes a pulse modulation circuit, an emission laser, and a laser emission lens. Under the pulse modulation circuit, a high-power pulse laser continuously are generated, and form narrow laser beam, namely, the narrow laser beam formed by the laser emission lens cooperates with the rotation of the projectile itself to form a laser scanning area. Each photoelectric receiving module is mainly composed of photoelectric receiving lens, photodetector and amplification circuit. The detection area formed by the photoelectric detection module matches with the scanning area of the corresponding laser beam. When the laser scanning beam illuminates the ground target, the surface of the ground target will diffusely reflect, and then, form a reflected laser echo signal. The photoelectric detection module captures the reflected laser echo signal and processes it. According to the set initiation criterion, when the reflected laser echo energy received by the photoelectric receiving module is greater than the set threshold condition, the photoelectric receiving module generates an initiation control command, and achieves the purpose of precise guidance of terminal-sensitive projectile.

III. THE CLASSIFICATION MODEL BASED ON FUZZY C-MEANS INCREMENTAL UPDATE OF TARGET SIGNAL AND INTERFERENCE SIGNAL

Based on the principle of laser fuze detection system, for the two photoelectric detection paths, their signal recognition and processing methods are the same, in this paper, we use any optical path detection principle to illustrate the signal recognition method of the target.

In the detection process of target using laser fuze detection system, the real-time performance of the fuze is required to be high. In order to meet the requirement of shorter time consumption, this paper adopts the fuzzy C-means algorithm, which has lower complexity. According to the concept of entropy in information theory, feature extraction is performed on the reflected laser echo signal using the difference in entropy. Assuming the time-domain amplitude distribution of the reflected laser echo signal is $X = \{x_1, x_2, \cdots, x_{i'}, \cdots, x_l\}$, $i' = 1, 2, \cdots l$, $x_{i'}$ is the amplitude of the reflected laser echo signal at the moment i', the occurrence probability of a certain amplitude in the time-domain amplitudes of the signal at a certain time is $p^x_{i'}$, and the calculation expression is shown in (1). Its frequency-domain amplitude distribution is $H' = \{h_1, h_2, \cdots, h_{i'}, \cdots, h_l\}$, $h_{i'}$ represents the amplitude of the i'-th frequency component, the occurrence probability of a certain amplitude in the frequency-domain amplitudes of the signal at a certain frequency is $p^h_{i'}$, and can be calculated by formulas (1) and (2).

$$p^x_{i'} = \frac{x^2_{i'}}{\sum\limits_{i'=1}^{l} x^2_{i'}} \tag{1}$$

$$p^h_{i'} = \frac{h^2_{i'}}{\sum\limits_{i'=1}^{l} h^2_{i'}} \tag{2}$$

According to the definition of entropy of random variable, the time-domain information entropy and frequency-domain information entropy of reflected laser echo signal can be obtained by formulas (3) and (4).

$$T_1(x) = -\sum_{i'=1}^{l} p_{i'}^{x} \log_2^{p_{i'}^{x}} \tag{3}$$

$$T_2(h) = -\sum_{i'=1}^{l} p_{i'}^{h} \log_2^{p_{i'}^{h}} \tag{4}$$

Exponential entropy is used to compensate for the non-convergence of Shannon entropy in the calculation process [17], [18]. If $p_{i'} = p_{i'}^{x}, p_{i'} = p_{i'}^{h}$, when the time-domain information entropy and frequency-domain information entropy approach zero, the entropy increment tends to infinity. Based on the definition of exponential entropy, the frequency-domain exponential entropy calculation function of reflected laser echo signal is obtained by formula(5).

$$T_3(s) = \sum_{i'=1}^{l} p_{i'} e^{(1-p_{i'})} \tag{5}$$

According to the time-domain information entropy, frequency-domain information entropy and frequency-domain exponential entropy of the reflected laser echo signal, its three-dimensional characteristic quantity T is obtained, and $T = [T_1(x), T_2(h), T_3(s)]$.

In the classification training stage, a certain number of samples are collected, the three-dimensional feature quantity of the samples are extracted. Then, using the fuzzy C-means algorithm, the clustering center is classified and determined, and a classification model is established. However, due to the complexity and variability of the background and interference signals in the real battlefield environment, the signal-to-noise ratio of signal detected by the system can change at any time. When the power of interference signal increases, the signal-to-noise ratio of the system decreases, and the time-domain and frequency-domain distribution of reflected laser echo signal becomes complex, resulting in the corresponding time-domain information entropy, frequency-domain information entropy and frequency-domain exponential entropy increasing, which reduces the classification effect of the classification model trained in advance under a certain signal-to-noise ratio condition. The update model of fuzzy C-means clustering can be divided into global data model and local data model [19]. As the global model needs to recluse all data, the time of this model is seriously increased due to the increase in data volume, and it cannot meet the real-time requirements of laser fuze detection system. Therefore, this paper adopts the fuzzy C-means incremental update improvement method based on the local data model, uses the fuzzy C-means algorithm to classify the target signal and interference signal in the detected signal of the system, in order to obtain the optimal classification, an objective function similar to the sum of error squares criterion is constructed. Meantime, the classification model is dynamically adjusted by online updating and increasing the weight factor. While maintaining minimal time consumption, it improves the accuracy of the update results, specifically:

$$\begin{cases} J_k = \sum_{i=1}^{e'} \sum_{j=1}^{d} \mu_{ij}^{k} \left\| x_j - u_i \right\|^2 \\ u_i(t+1) = \alpha \cdot u_i(t) + \dfrac{\sum_{r=1}^{M} \mu_{ir}^{k}(t+1) \cdot \beta_r x_r}{\sum_{r=1}^{M} \mu_{ir}^{k}(t+1) \cdot \beta_r} \end{cases} \tag{6}$$

where, J_k is the sum of squared weighted distances from all samples to the cluster center; $e$is the number of cluster centers; d is the number of samples; μ_{ij} is the degree of membership of x_j to u_i, $\sum_{i=1}^{e'} \mu_{ij} = 1, 0 < \mu_{ij} < 1$;$u_i$ is the cluster center of class i; k is the fuzzy index;t is the number of cluster updates;$\alpha = t/t+1$; $u_i(t)$ is the clustering center of class i after the t clustering updates; $u_i(t+1)$ is the cluster center of the class i after $t+1$ clustering updates; $\mu_{ir}(t)$ is the membership degree of x_r to $u_i(t)$; M is the number of samples used for each update; $\beta_r = \left[1/(M(t+1)), \cdots, 1/(M(t+1))\right]_{1\times M}$. In the clustering process, the objective function is minimized by assigning appropriate membership degrees to each sample.

The incremental update using the fuzzy C-means classification model is mainly divided into three steps, specifically as follows:

(1) Determine whether the system has received interference signals based on the current fuzzy C-means classification model. If the system has been received interference signals, the interference signal is used to the input signal. If there is no interference signal, continue waiting until the interference signal appears.

(2) Obtain a new clustering center based on the input signal.

(3) Use the obtained new fuzzy C-means classification model as the classification basis for the next signal to be tested.

Therefore, according to the change of signal to noise ratio, the classification model is updated and adjusted, and the recognition rate of the system is higher.

IV. TARGET SIGNAL FEATURES EXTRACTING METHOD USING DISCRETE BINARY WAVELET TRANSFORM

According to the classification model based on fuzzy C-means incremental update of target signal and interference signal, the system cannot achieve 100% correct recognition rate. In order to further optimize recognition results and improve the real target recognition rate, it is necessary to extract the feature information of the target signal, which provides a prerequisite for the next step to use neural network for target signal recognition. Therefore, the research on the feature extraction method of the target signal by discrete binary wavelet transform is carried out. For the reflected laser echo signal, it contains the target features, which reflect the local fine structure of the target. According to the threshold set by the system, feature extraction is performed before reaching the threshold value. The target features can be characterized by the spatial distribution of the scattering centers on the targets and their relative scattering area. The scattering centers are reflected in the reflected laser echo signal [20], [21], [22]. Therefore, the reflected laser echo signal can be regarded as a distributed target consisting of a finite number of equivalent scatters with local features, and the wavelet transform is used to analyze the reflected laser echo signal with this local information.

Assuming $g\left(\bar{t}\right)$ is a square integrable function, and $g\left(\bar{t}\right) \in H^2(r')$, the continuous wavelet transform of $g\left(\bar{t}\right)$ is obtained by formula(7).

$$\begin{aligned} WT_g(m', n') &=< g, \varphi_{m',n'} > \\ &= \frac{1}{\sqrt{m'}} \int_{-\infty}^{\infty} g(\bar{t})\varphi * \left(\frac{\bar{t}-n'}{m'}\right) d\bar{t} \end{aligned} \tag{7}$$

If $\varphi(\bar{t})$ is the mother wavelet, it generates the wavelet function $\varphi_{m',n'}(\bar{t})$ through translation and dilation, and $\varphi_{m',n'}(\bar{t}) = \frac{1}{\sqrt{m'}}\varphi\left(\frac{\bar{t}-n'}{m'}\right)$, $m' > 0$, where m' is the dilation factor and n' is the translation factor [23], [24]. If $m' = 2^q$, $n' = 2^q k'$, the discrete binary wavelet of $\varphi(\bar{t})$ can gain by formula(8).

$$\varphi_{q,k'}(\bar{t}) = 2^{q/2}\varphi(2^q\bar{t} - k')q, k' \in Z \tag{8}$$

Therefore, the discrete binary wavelet transform of $g\left(\bar{t}\right)$ in the formula (7) is given by formula(9).

$$\begin{aligned} & WT_g(m', n')|_{m'=2^q,n'=2^q k'} \\ &=< g, \varphi_{q,k'} >= \int_{r'} 2^{-q/2} g\left(\bar{t}\right) \cdot \varphi * (2^{-q}\bar{t} - k')d\bar{t} \end{aligned} \tag{9}$$

The basic idea of tower type multi resolution decomposition and synthesis algorithms for signals is: if the discrete approximation of $g\left(\bar{t}\right)$ at resolution 2^{-q} is $E'_q g(\bar{t})$, then the discrete approximation of $g\left(\bar{t}\right)$ at resolution $2^{-(q+1)}$ is $E'_{q+1}g(\bar{t})$, which is obtained by filtering $E'_{q1}g(\bar{t})$ with a discrete low-pass filter. $\vartheta(\bar{t})$ and $\varphi(\bar{t})$ are defined as scaling functions and wavelet functions of function $g\left(\bar{t}\right)$ under resolution 2^{-q} approximation, respectively, its discrete part $E'_q g(\bar{t})$ and detail part $B'_q g(\bar{t})$ are represented by (10) and (11).

$$\mathrm{E}'_q g(\bar{t}) = \sum_{k'=-\infty}^{\infty} E_{q,k'}\vartheta_{q,k'}(\bar{t}), \mathrm{B}'_q g(\bar{t}) = \sum_{k'=-\infty}^{\infty} C_{q,k'}\vartheta_{q,k'}(\bar{t}) \tag{10}$$

$$\begin{aligned} \mathrm{E}'_q g(\bar{t}) &= \mathrm{E}'_{q+1}g(\bar{t}) + \mathrm{B}'_{q+1}g(\bar{t}) \\ &= \sum_{l'=-\infty}^{\infty} E_{q+1,l'}\vartheta_{q+1,l'}(\bar{t}) + \sum_{l'=-\infty}^{\infty} C_{q+1,l'}\vartheta_{q+1,l'}(\bar{t}) \end{aligned} \tag{11}$$

where, $E_{q,k'}$ and $C_{q,k'}$ represent the coarse image coefficient and detail coefficient at resolution 2^{-q}, respectively. As the signals detected by laser fuze detection system in practical applications are band-limited signal, the coarse image and detail coefficients can be obtained through the recursive formulas.

$$\begin{cases} E_{q,k'} = \sum_{j'} G^*(j' - 2k')E_{q-1,j'} \\ C_{q,k'} = \sum_{j'} \bar{H}^*(j' - 2k')E_{q-1,j'} \end{cases} \tag{12}$$

where, $k' = 1, \cdots, N'/2^q$; $q = 1, \cdots, Q$; $G(j')$ is the low-pass filter coefficients, it applies on the signal to obtain a low-frequency smoothing profile; $\bar{H}(j')$ is the high-pass filter coefficients, it applies on the signal to obtain high-frequency details; N' is the samples number of the signal, and Q is the maximum decomposition level. The reconstructed result after decomposition can gain by formula(13).

$$E_{q,k'} = \sum_{j'} G(k' - 2j')E_{q+1,j'} + \sum_{j'} \bar{H}(k' - 2j')E_{q+1,j'} \tag{13}$$

where, $k' = 1, \cdots, N'/2^q$; $q = Q-1, \cdots, 0$.

The energy of each level coefficient of the wavelet decomposition can form the target feature vector. Because the energy of the detail signal at each level represents the variation degree of signal at the corresponding scale, while the approximation signal contains the overall information of the waveform of the signal and its energy reflects the overall information of the reflected laser echo signal.

V. OPTIMIZATION TARGET RECOGNITION METHOD BASED ON WAVELET NEURAL NETWORK

The discrete binary wavelet transform is used to extract target features from reflected laser echo signals; the updated classification model is used to classify the target signal and interference signal. Based on the classification results, a wavelet neural network is combined to optimize the recognition of the target signal. The wavelet neural network is a new type of neural network model built on the foundation of wavelet theory. The wavelet neural network combines the advantages of wavelets and neural networks. On the one hand, it fully utilizes the time-frequency localization properties of wavelet transforms. On the other hand, it exploits the self-learning function of neural networks, thereby possessing strong approximation and fault-tolerant capabilities [25], [26]. Using wavelet basis functions as the activation function of the wavelet neural network, the wavelet neural network structure is shown in Figure 2. The structure mainly consists of input layer, hidden layer, and output layer, n_1, n_2 and n_3 are the node numbers, respectively.

The weights of the hidden layer are taken as the wavelet basis function, the Morlet mother wavelet is used in this layer, this wavelet is a Gaussian wavelet modulated by a cosine function and has high resolution in both time and frequency domains, it can be expressed by formula(14).

$$\varphi''(\bar{t}) = e^{-\bar{t}/2}\cos 2\bar{t} \tag{14}$$

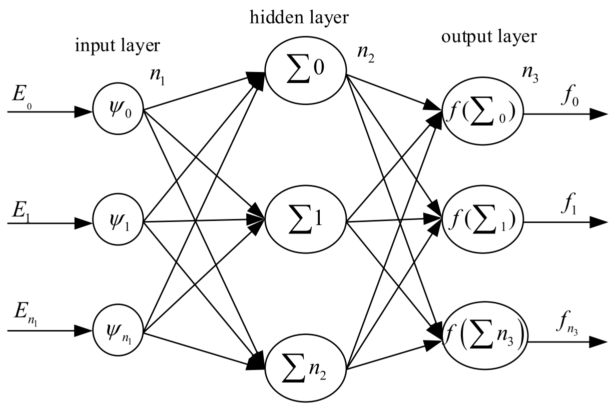

FIGURE 2. Structure diagram of wavelet neural network.

The activation function of the output layer is the Sigmoid function, which is defined by formula(15).

$$f(x) = \frac{1}{1+e^{-x}} \tag{15}$$

The output of the k'-th node in the output layer can gain by formula (16).

$$f(x_{k'}) = f[\sum_{i''=1}^{n3} \bar{W}_{k'i''} \sum_{j''=1}^{n_1} P_{n''}(j'')\varphi''(\frac{\bar{t}-n'_{i''}}{m'_{i''}})] \tag{16}$$

where $P_{n''}(j'')$ is the network input, the actual corresponding values are $E_0, E_1, \cdots, E_{n1}$.

Assuming that there are N sets of samples participating in the training, $\bar{P}_{n''}$ is the ideal output of input signal $P_{n''}$, and the correlation relationship between networks parameters $\bar{W}_{i''}, m'_{i''}, n'_{i''}$ can be expressed by formula (17).

$$Y = \frac{1}{2}\sum_{n''=1}^{n_3} (\bar{P}_{n''} - f(x_{k'}))^2 \tag{17}$$

Assuming that $\bar{t}^* = (\bar{t} - n'_{i''})/m'_{i''}, f'(x) = \frac{\partial f(x)}{\partial x} = f(x)[1-f(x)]$, the gradients $\partial Y/\partial W_{k'i''}$, $\partial Y/\partial b_{i''}$, $\partial Y/\partial a_{i''}$ of Y are calculated according to the chain rule, as shown in formulas (18)–(20), at the bottom of the page.

The conjugate gradient method is used to minimize Y, and pay attention to the selection of initial parameters such as initial weights to ensure the convergence of the wavelet neural network. The network learning is terminated by iterative refinement until Y is less than the specified allowable error. For target recognition problems, the training of the wavelet neural network is to constantly adjust the scale parameters that better match the target signal.

VI. CALCULATION AND ANALYSIS

In order to test the classification effect of fuzzy C-means incremental update classification model under different signal-to-noise ratio conditions, the signal-to-noise ratio of 10dB for reflected laser echo signals as samples were trained to obtain the fuzzy C-means initial classification model. Seven sets of data were measured at a signal-to-noise ratio of 4dB to 10dB; each set data has 200. To explain the requirement of the number of test samples on the number of updates, and verify the classification effect of the algorithm in this paper, tests are carried out under two conditions: (1) Select 10 samples from the 50 noise frequency modulation data and 50 noise amplitude modulation data tested in each group as input samples for fuzzy C-means incremental update classification model, and 10 updates is carried out. The remaining 90 noise data and 100 target data in each group were used as test data to obtain the classification accuracy of updated model and no updated model. Meantime, in order to verify the impact of update times on classification performance, data at a signal-to-noise ratio of 4dB was used as test samples, 190 training sets for classification under signal-to-noise ratio of 10dB were tested, the classification model without updating times, the fuzzy C-means classification model with updating 5 times and the fuzzy C-means classification model with updating 10 times were respectively applied in the test, the average accuracy from 100 experiments was obtained in Figure 3, and the classification effect was obtained as shown in Figures 4-6. (2) Select 50 samples from the 250 noise frequency modulation data and 250 noise amplitude modulation data tested in each group as input samples for incremental updates of the classification model, and 20 updates is carried out. The remaining 450 noise data and 500 target data in each group were used as test data to obtain the classification accuracy of updated model and no updated model. Data at a signal-to-noise ratio of 4dB was still as test samples, 950 training sets for classification under signal-to-noise ratio of 10dB were tested, the classification

$$\partial Y/\partial W_{k'i''} = -\sum_{n^*=1}^{n_3}\sum_{j''=1\, n'}^{n_1}\left(\bar{P}_{n'} - f(x_{k'})\right) f'(x) P_{n^*}(j'') \cos 2\bar{t}^* \cdot e^{-(\bar{t}^*)^2/2} \tag{18}$$

$$\partial Y/\partial b_{i^n} = -\sum_{n^n=1}^{n_3}\sum_{j^n=1\, n'}^{n_1}\left(\bar{P}_{n^n} - f(x_{k'})\right)\left[f'(x)P_{n^n}(j'')\,\bar{W}_{i^n}\left(2\sin 2\bar{t}^* \cdot e^{-(\bar{T}^*)^2/2}\cdot\frac{1}{a_i} + \cos 2\bar{t}^* \cdot \frac{\bar{t}^*}{a_i}\cdot e^{-(\bar{t}^*)^2/2}\right)\right] \tag{19}$$

$$\partial Y/\partial a_{i^*} = -\sum_{n^n=1}^{n_3}\sum_{j''=1\, n'}^{n_1}\left(\bar{P}_{n^n} - f(x_{k'})\right)\left[f'(x)P_{n^n}(j'')\,W_{i^*}\left(-2\sin 2\bar{t}^* \cdot e^{-(\bar{t}^*)^2/2}\cdot\frac{1}{a_i^2} + \cos \bar{t}^* \cdot \frac{\bar{t}^*}{a_i^2}\cdot e^{-(\bar{t}^*)^2/2}\right)\right](\bar{t} - b_i) \tag{20}$$

model without updating times, the fuzzy C-means classification model with updating 10 times and the fuzzy C-means classification model with updating 20 times were respectively applied in the test, and the classification effect was obtained as shown in Figures 7-9.

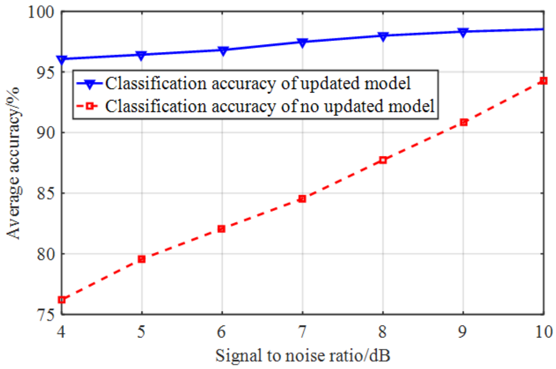

FIGURE 3. **Classification accuracy under different signal-to-noise ratios.**

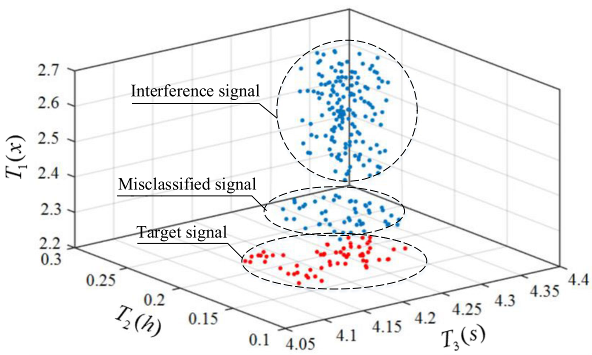

FIGURE 4. **Classification effect of the model without updating times.**

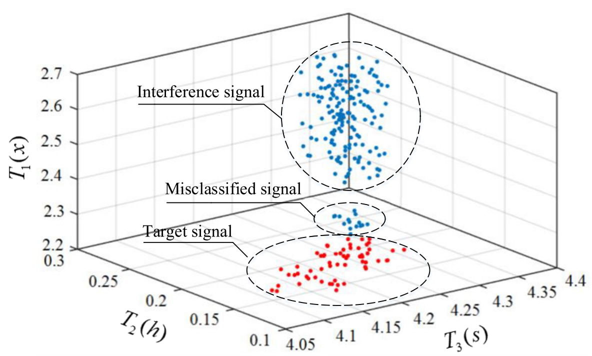

FIGURE 5. **Classification effect of the model with updating 5 times.**

The comparison results in Figures 4-6 show that the classification model trained at the signal-to-noise ratio of 10dB was no longer able to effectively classify the sample data at the signal-to-noise ratio of 4dB, as shown by the large number of misclassified signals in Figure 4. Therefore, it is

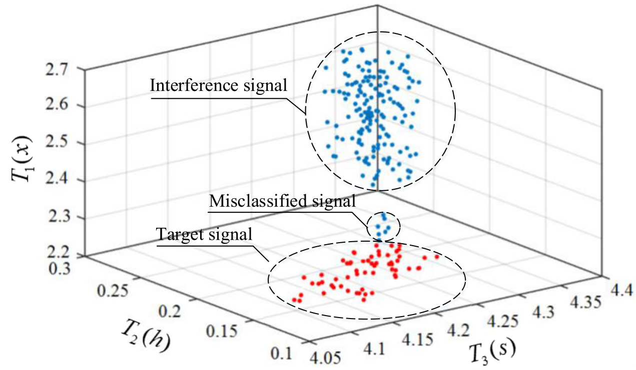

FIGURE 6. **Classification effect of the model with updating 10 times.**

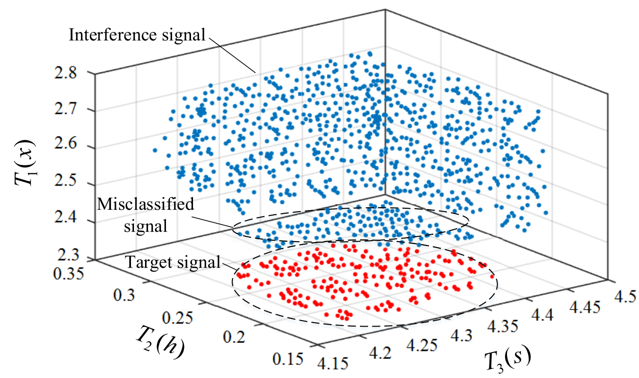

FIGURE 7. **Classification effect of the model without updating times.**

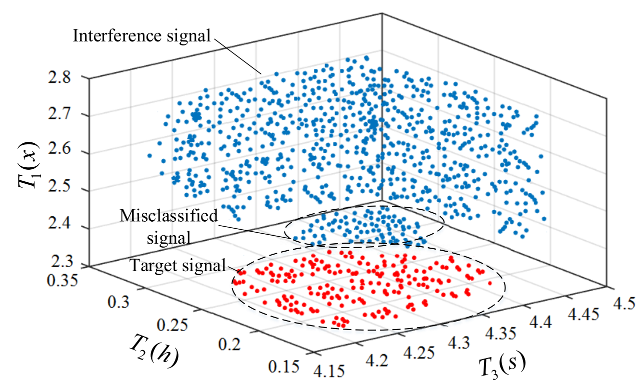

FIGURE 8. **Classification effect of the model with updating 10 times.**

necessary to update the classification model. As the number of updates increases, the classification effect gradually improves. After ten updates, the classification accuracy has reached 93%. The comparison results in Figures 7-9 show that when the number of test samples increases, the number of updates of the classification model should also increase to make the classification effect higher. When the number of updates is 20, the classification accuracy reaches 95%. The difference is small compared to the results of the smaller test sample, the test results show that the fuzzy C-means classification algorithm based on incremental updates can

TABLE 1. Characteristics of background signal and signal containing target echo signal.

	$\tilde{E}_0$	$\tilde{E}_1$	$\tilde{E}_2$	$\tilde{E}_3$	$\tilde{E}_4$
Signal containing target echo signal	271.2658	638.8561	317.6409	280.2548	457.7454
	276.4678	679.7646	269.6605	289.3468	501.3536
	526.2499	572.4143	420.5335	544.8443	514.2312
	402.7143	575.7534	383.7514	423.4613	439.7885
	439.2356	696.7543	279.3987	454.2689	548.6743
	$\tilde{E}_0$	$\tilde{E}_1$	$\tilde{E}_2$	$\tilde{E}_3$	$\tilde{E}_4$
Background signal	293.4522	452.5647	233.4674	318.0518	437.8229
	385.5614	323.4274	316.4579	406.3789	487.1247
	232.5464	563.7951	253.1589	253.1464	502.638
	247.6163	524.5053	283.169	246.0647	428.8061
	252.2357	429.4548	304.6503	268.4371	543.2685

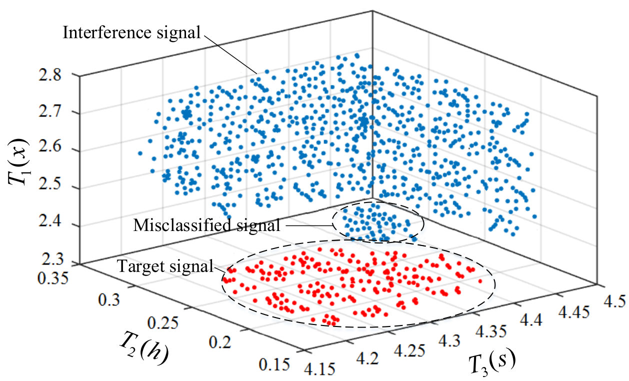

FIGURE 9. Classification effect of the model with updating 20 times.

adjust the classification model according to the changes in target signal entropy characteristics under different signal-to-noise ratio conditions, ensuring that the system achieves good classification performance of target signals and interference signals under very low signal-to-noise ratio condition.

During the testing process, Gaussian white noise was used to simulate background noise, and mixed signals of target and background noise were simulated multiple times. The signal-to-noise ratio of the system was defined as:

$$SNR = 10\log(\sum_{q''=1}^{Q''} s(q'')^2 / \sum_{q''=1}^{Q''} \eta(q'')^2) \tag{21}$$

where $s(q'')$ represents the target signal, $\eta(q'')$ represents the background noise, and Q'' represents the number of detections under the same test conditions [26].

In the experiment of target feature extraction and recognition of reflected laser echo signal for typical laser fuze detection system, the reflected laser echo signals were decomposed using wavelet transform, and the energy of corresponding frequency bands was extracted as the feature quantity according to the target signal feature extraction method. Among them, the feature quantities of five simulated background signals and five signals containing target echo signal were represented by X'', $X'' = (\tilde{E}_0, \tilde{E}_1, \tilde{E}_2, \tilde{E}_3, \tilde{E}_4)^T$ [27], as shown in Table 1. Fisher discriminant analysis is used to analyze two sets of feature values, the discriminant function is obtained by formula(22).

$$\begin{aligned} y = 0.0011\tilde{E}_0 + 0.0013\tilde{E}_1 + 0.0012\tilde{E}_2 \\ + 0.0011\tilde{E}_3 + 0.0014\tilde{E}_4 \end{aligned} \tag{22}$$

According to the parameters in Table 1 and the discriminant function, it is calculated that the Fisher discriminant method can process the signal-to-noise ratio of signal is about 2.46dB. In order to obtain more objective results and increase the simulation times of signals in the experiment, 500 times background signals and 500 times containing the target signals are simulated, and the characteristic quantities of these signals are given. Due to the limited space of the paper, it is not necessary to list them together, and then combine the discriminant function of formula (22). The signal to noise ratio of the system can be calculated by Fisher discriminant method to reach 2.42dB. Under the condition of different simulation times, the signal-to-noise ratio of the signal processed by the system has little change, because the experiment carried out is the signal simulated in the laboratory, the interference from the outside world is small, and there is little change in the detected signal. In the actual test of laser fuze, the external environment has great influence on its detection performance, which will not only error-trigger, but also reduce the detection ability of the system. Especially in rain, snow, fog and other weather conditions, the detection performance of the system will become worse.

Simulate 100 mixed signals of target and background noise with different signal-to-noise ratio conditions, the normalized energy for each frequency band is extracted by wavelet decomposition, it is used as an input vector to train wavelet neural networks. The number of input nodes for the wavelet neural network was 3, and the number of output layer nodes was 1. Based on experience, it is determined that the optimal number of hidden layer neurons was 5-10. When the learning rates were 0.9, 0.8, 0.7 and 0.6, respectively; the number of hidden layer neurons is 10, 9, 8, 7, 6 and 5, respectively; and the minimum mean square error was 0.001, the network was trained. The required number of training times to achieve convergence at a signal-to-noise ratio of 4.7dB was shown in Table 2.

TABLE 2. Number of training times required for the network to reach convergence.

Learning rate	Hidden layer neuron					
	10	9	8	7	6	5
0.9	1697	1387	2398	1496	1702	1805
0.8	843	645	812	970	869	986
0.7	1574	1481	1794	1245	1581	1673
0.6	1618	1586	1453	1396	1662	1794

Based on Table 2, it can be seen that the minimum training iterations required for the network to converge were achieved when the number of hidden layer neurons is 9 and the learning rate is 0.8. The results indicate that the convergence speed was the fastest, and this value was taken as the optimal network convergence parameter for a signal-to-noise ratio of 4.7dB. The network parameters under other signal-to-noise ratio conditions can also be determined using the same method.

Simulate 100 mixed signals of targets and background noise with different signal-to-noise ratios, the target recognition result obtained by using wavelet neural network was defined the recognition rate 1, detailed recognition method and process are shown in reference [28]. Based on the fuzzy C-means incremental update, target signals and interference signals were classified, and combined with wavelet neural networks, the target recognition result was defined recognition rate 2. When threshold signal-to-noise ratio condition is different, the test results were shown in Tables 3 and 4.

TABLE 3. Target signal recognition results for different signal-to-noise ratios with a threshold signal-to-noise ratio of 3.1db (two recognition methods).

Signal-to-noise ratio /dB	Recognition rate 1 /%	Recognition rate 2 /%
3.6	84	93
4.7	86	94
6.9	90	97
8.4	93	99
9.5	95	100

TABLE 4. Target signal recognition results for different signal-to-noise ratios with a threshold signal-to-noise ratio of 6.3db (two recognition methods).

Signal-to-noise ratio /dB	Recognition rate 1 /%	Recognition rate 2 /%
6.9	81	94
8.4	85	96
9.5	87	98
10.1	89	99
10.6	91	100

Table 3 presented the target signal recognition results for different signal-to-noise ratios with a threshold signal-to-noise ratio of 3.1dB; Table 4 showed the target signal recognition results for different signal-to-noise ratios with a threshold signal-to-noise ratio of 6.3dB; The method proposed in this paper and the method proposed in [28] are tested under the same test conditions, and the results are as follows: As the threshold signal-to-noise ratio set by the system increased, the recognition rate of target recognition using wavelet neural networks in [28] under the same signal-to-noise ratio conditions significantly decreased. However, the target recognition method proposed in this paper had little change in target recognition rate with the increase of threshold signal-to-noise ratio, because the recognition method proposed in this paper uses fuzzy C-means incremental update under a small number of samples, establishes a dynamic adjustment classification model for target signals and interference signals in reflected laser echo signals had improved the classification accuracy of the system. Combined with the optimization recognition of wavelet neural networks, the target recognition rate of the system had been significantly improved compared with a single recognition method.

VII. CONCLUSION

This paper proposes a target recognition method combining fuzzy C-means and neural networks in the laser fuze detection system. Based on the feature quantities of time-domain entropy, frequency-domain entropy, and frequency-domain exponential entropy extracted from the reflected laser echo signal, a fuzzy C-means incremental update is established to achieve adaptive adjustment classification model. The discrete binary wavelet transform is used to extract signal energy in different frequency bands as target features, based on the classification results, combined with wavelet neural network, the real target recognition rate is improved. Simulation analysis was conducted to improve the classification performance of the fuzzy C-means incremental update classification model under different signal-to-noise ratios. And target recognition tests were carried out neural networks under different learning rates and threshold signal-to-noise ratios to verify the proposed target recognition method. The results showed that the target recognition method based on fuzzy C-means incremental update and neural networks proposed in this paper is better than the target recognition method based on wavelet neural networks; the real target recognition rate and real-time performance have been greatly improved. The achievement can provide reference significance for future applications of neural network recognition method in laser fuze detection systems.

With the development of proximity fuze, projectile fuze explosion plays an important role in target damage [29], which is limited by the control of fuze and detection ability of fuze. Therefore, the method proposed in this paper can lay a foundation for future target damage assessment and has a broad application prospect.

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