

Retraction

Retracted: Electronic Information Signal Recognition Based on a Stochastic Neural Network Algorithm

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This article has been retracted by Hindawi following an investigation undertaken by the publisher [1]. This investigation has uncovered evidence of one or more of the following indicators of systematic manipulation of the publication process:

- (1) Discrepancies in scope
- (2) Discrepancies in the description of the research reported
- (3) Discrepancies between the availability of data and the research described
- (4) Inappropriate citations
- (5) Incoherent, meaningless and/or irrelevant content included in the article
- (6) Peer-review manipulation

The presence of these indicators undermines our confidence in the integrity of the article's content and we cannot, therefore, vouch for its reliability. Please note that this notice is intended solely to alert readers that the content of this article is unreliable. We have not investigated whether authors were aware of or involved in the systematic manipulation of the publication process.

Wiley and Hindawi regrets that the usual quality checks did not identify these issues before publication and have since put additional measures in place to safeguard research integrity.

We wish to credit our own Research Integrity and Research Publishing teams and anonymous and named external researchers and research integrity experts for contributing to this investigation.

The corresponding author, as the representative of all authors, has been given the opportunity to register their agreement or disagreement to this retraction. We have kept a record of any response received.

References

- [1] J. Wang, "Electronic Information Signal Recognition Based on a Stochastic Neural Network Algorithm," *Journal of Control Science and Engineering*, vol. 2022, Article ID 6473392, 8 pages, 2022.

Research Article

Electronic Information Signal Recognition Based on a Stochastic Neural Network Algorithm

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In order to improve the recognition accuracy of SCN for optical fiber data, a method of optical fiber intrusion signal recognition based on SCN (TSVD-SCN) based on truncated singular value decomposition (TSVD) is proposed in this paper. TSVD-SCN performs SVD decomposition on the hidden layer output of the network and sets a threshold to remove the smaller singular values, so as to reduce the number of conditions of the hidden layer output matrix and improve the network recognition rate. This paper uses the method of duty cycle, average amplitude difference function, and FFT to calculate the energy duty cycle for feature extraction and uses TSVD-SCN algorithm to classify and recognize different intrusion vibration feature vectors. The experimental results show that the root mean square errors of TSVD-SCN and SCN networks are significantly less than RVFL. After the hidden layer node $L = 20$, the training error decline speed of RVFL tends to be gentle. When $LRVFL = L_{\max}$, the learning effect is the best, and $RMSERVFL = 0.3$. With the continuous increase of L , the training error of SCN network and TSVD-SCN network will be reduced to very small, and the training error of TSVD-SCN network is also less than SCN. *Conclusion.* The accuracy of the algorithm model proposed in this paper is higher than that of the SCN model. It can accurately identify the types of optical fiber intrusion signals, which is of great significance to improve the classification accuracy of the SCN network in practical applications.

1. Introduction

An early warning of optical equipment is to identify external vibrations from ground burial lines. It has the advantages of strong protection against electromagnetic interference, wide range of control, good electrical insulation, and high sensitivity [1]. However, when monitoring the vibration signal, a false alarm can affect the control results. For example, fiber-optic cables placed close to highways and railways can give the wrong signal to a passing vehicle and not see the real problem. In addition, the cost of false alarms is high due to the installation of fiber-optic early warning in the remote area [2]. Therefore, it is very important to determine the signal vibration of a fiber optic cable. Optical fiber warning technology has gradually become a hotspot for research in this field in recent years. Compared with the usual procedures such as hands-on monitoring, video monitoring, and the installation of security nets, fiber optic early warning has the advantages of low cost, long-term monitoring, high

sensitivity, and does not affect the environment such as weather and light. An electronic optical alarm system detects vibration signals near the pipeline by distributing electrical equipment in real time, then detects them on the operating board, sends signals for analysis, and finally shows the results of the computer. The electronic optical alarm system can provide real-time monitoring and warning in the event of a strike around the pipeline. When the intrusion occurs, the optical fiber early warning system can effectively report the specific location and type of intrusion, effectively reduce the cost of human and material resources in long-distance pipeline transportation, provide targeted early warning measures for the occurrence of emergencies [3], and protect the life and property safety and environmental safety of personnel near the monitoring and early warning area (as shown in Figure 1).

Ran and others proposed the use of a parameter analysis method for time-domain feature extraction of optical fiber signals. This method has the advantages of simplicity,

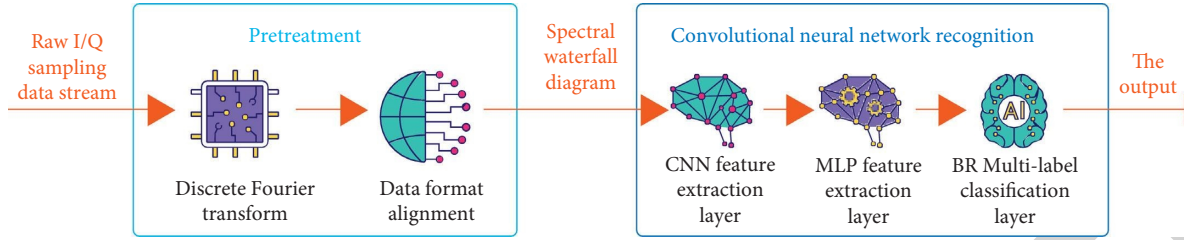


FIGURE 1: Electronic information signal recognition technology based on the stochastic neural network algorithm.

practicality, and low computational complexity. It is widely used in practice, but it often has the problem of low accuracy [4]. Yuan, and others divided the time-domain features of signals into short-time features of extracting signal envelope and long-time features of extracting signal features within a period of time, so as to analyze signals from multiple time scales and improve classification accuracy. Due to the inherent periodicity of mechanical signals, correlation analysis is also an important feature extraction method [5]. The traditional methods mostly use autocorrelation operation, which leads to high computational complexity due to the large application of multiplication operation. The pitch period is widely used in language recognition. Lee, and others introduced the pitch period into optical fiber data feature extraction and proved through mathematical methods that the pitch period has the effect similar to autocorrelation, but the computational complexity is significantly reduced. The above procedure removes the material by some length of the signal fiber, regardless of the time and frequency characteristics of the signal, which makes it very easy to lose the height of the light red. Therefore, this paper presents a way of distinguishing the fiber signal according to the time-frequency analysis, which is the most important [6]. Zhong and others first applied the random learning algorithm model RVFL network to optical fiber signal recognition, which not only ensures that the classifier has strong learning ability but also has short-time consumption. The RVFL network is a representative kind of the stochastic algorithm. Under the premise of appropriate random parameter setting, the RVFL network can approximate any continuous function, but the unconstrained assignment method of the RVFL network cannot guarantee its general approximation property [7]. Ait Allal and others have devised a way to test fiber-optic brake signals based on the stable alarm (CFAR) algorithm, which improves the performance of fiber optical stop signals of transitions to different sounds [8].

To address the above issues, this paper aims to define a fiber optic signal input based on TSVD-SCN (single-rate stochastic configuration network). The feature extraction of fiber vibration signal is carried out by using duty cycle, signal average amplitude difference function over mean rate, and short-time Fourier transform operation method to extract signal energy proportion. The TSVD-SCN-based algorithm is used to classify and identify different types of attacks. We collected data observations outside the site, tested different types of signal, and used data collection to implement algorithms, which further improved the speed of fiber optic intrusion lighting.

2. Research Methods

2.1. Introduction to Optical Fiber Early Warning System.

Optical fiber warning systems and ground systems often use ground beams to detect and identify external interference problems, including debris that sends signals against vibration and use vibration data to operate the ground optics line. These vibrations convert the optical signal transmitted to the optical glass and eventually transmit the vibration data to the optical signal. In this experiment, single-mode optical wire buried about 15~30 cm in the ground was used. The phase of the signal generation [9] is as follows: first, the laser is transmitted by a laser and an optical pulse is generated by an acoustic modulator. When the generated optical pulse is inserted into the connector, it transmits to the optical fiber via an underground optical cable. Under the influence of light propagation, the scattered light is absorbed by the connector, injected into the photoelectric converter, and then amplified. The A/D converter then converts the optical signal into a digital signal. The system captures and records attack signals in the event of an external attack, such as a walkway or mechanical design around an optical device.

According to the requirements of the actual situation, the optical fiber vibration signals are mainly divided into two categories: construction machinery signals (such as electric pick signals and electric drill signals) and artificial signals generated by human activities (such as walking signals and pick planing signals). Due to the complexity of the actual working environment, as well as the changes of buried media and even external factors such as temperature and humidity, the collected signals will be affected. Therefore, this paper selects the data of soft sandy soil and asphalt road collected in winter and summer to build the network model, so as to ensure the diversity of samples and avoid the occurrence of over fitting.

Identification is an important part of optical fiber early warning system, which aims to determine the intrusion type by analyzing the collected optical fiber vibration signal [10]. The determination of the intrusion type is related to the accurate and effective early warning action. Because the system application environment is complex and the intrusion types are complex and diverse, the requirements for recognition accuracy are high. However, the collected data are the original optical fiber vibration time-domain signals, and their characteristics are not obvious, which is not conducive to model learning and classification. Moreover, the data dimension is too large, resulting in too many corresponding input nodes, too complex model and more difficult to learn [11]. Therefore, it is necessary to extract the characteristics of the collected optical fiber signal.

2.2. Applications of the TSVD-SCN Network in an Optical Fiber Early Warning System

2.2.1. Introduction to the SCN Network. Similar to the RVFL network, SCN is a single hidden layer random learning model [12]. Its network structure is shown in Figure 2.

The advantage of SCN over other networks is that the network input is not modified to limit interference with the network residue, and the process of hiding nodes is created by iterations. The stop loop event is when the number of hidden layers reaches the number of hidden layers, or the error reaches the minimum error. Therefore, the SCN network has the advantages of a simple RVFL network structure (single layer encryption) and fast operation but also avoids the problem of traditional network connection easy access to the minimum zos. At the same time, the introduction of constraints and variables solves the problem of setting the super parameter at the number of nodes in the encryption process [13]. In addition, because SCN introduces the following limitations, the structure is more compact and the training effect is in the same layer of quality than the RVFL. The constraint condition of network (SCN) is shown in the formula below [14].

$$\zeta_{L,q} = \frac{(e_{L-1,q}^T(X) \cdot h_L(X))^2}{h_L^T(X) \cdot h_L(X)} - (1-r-\mu_L)e_{L-1,q}^T(X)e_{L-1,q}(X) > 0, \quad (1)$$

where L is the number of network hidden layer nodes and e_{L-1} is the network residual. h_L is the output of the L -th hidden layer node. r is a sequence greater than 0 and less than 1, which can change in the process of finding parameters. μ_L is a sequence of nonnegative real numbers, $\mu_L \leq 1-r$ and $\lim_{L \rightarrow \infty} \mu_L = 0$.

2.2.2. Introduction to the TSVD-SCN Algorithm. After using the intercepted optical fiber signal characteristics as the input of SCN network for training, it is found that the SCN network has the problem of classification error for some data [15]. Through the analysis of these misclassified data, it is found that some input data are approximately related, resulting in a high number of output conditions of the hidden layer of the SCN network, which leads to the decline of the recognition rate of the SCN network.

Since the hidden layer to an output layer of the SCN network is a linear regression method, it can be seen from the least square method:

$$X_{ls} = (A^T A)^{-1} A^T y, \quad (2)$$

where X_{ls} is the required solution, that is, β in the SCN network, A is the $n \times t$ -dimensional coefficient matrix, that is, the hidden layer output matrix of the SCN network, H , and y is the label of data [16].

We perform singular value decomposition on the coefficient matrix A to obtain the following formula:

$$A = U \Sigma V^T = \sum_{i=1}^t \sigma_i u_i v_i^T, \quad (3)$$

where U and V are orthogonal matrices of $n \times t$ and $t \times t$, respectively, and u_i and v_i are columns i of U and V , respectively. $\Sigma = \text{diag}([\sigma_1, \sigma_2 \dots \sigma_t])$, $\sigma(i = 1, 2 \dots t)$ is the singular value of A , which is brought into (2) to obtain the following formula:

$$X_{ls} = V (\Sigma^T \Sigma)^{-1} \Sigma^T U^T y = \sum_{i=1}^t \frac{u_i^T y}{\sigma_i v_i}. \quad (4)$$

The corresponding mean square error is the following formula:

$$\text{MSE}(X_{ls}) = \sigma_0^2 (A^T A)^{-1} = \sigma_0^2 \sum_{i=1}^t \frac{1}{\sigma_i^2}. \quad (5)$$

When the error of the least square method is close to 0, it can be found that there is a large singular value of the least square method. At this time, although the result is still unbiased, it is no longer the optimal solution. We can modify the singular value of matrix A to remove the smaller singular value, so as to reduce the mean square error and improve the accuracy and reliability of the solution. Therefore, the truncated singular value method is introduced. Assuming that the minimum $(t-k)$ singular values are removed, the solution of truncated singular values can be obtained as follows:

$$X_{TSVD} = \sum_{i=1}^k \frac{u_i^T y}{\sigma_i v_i}. \quad (6)$$

For the selection of truncation parameter k , a reconstruction threshold d can be set based on the reconstruction angle, for example, $d = 90\%$, and then the minimum value that makes the following formula true by selection is as follows:

$$\frac{\sum_{i=1}^k \sigma_i}{\sum_{i=1}^t \sigma_i} \geq d, \quad (7)$$

where t is the total number of singular values of the matrix and k is the number of singular values retained after truncation.

In the model learning process of TSVD-SCN, the network first adds a node [17] in each iteration, then SVD decomposes the hidden layer output matrix to obtain $\Sigma = \text{diag}([\sigma_1, \sigma_2 \dots \sigma_t])$, detects the singular value $\sigma(i = 1, 2 \dots t)$ and removes the singular value less than the threshold. Then, we reconstruct the hidden layer output matrix and continue the iteration. Due to the truncation of the hidden layer and the singular value of the hidden layer, the output of the hidden layer is dynamically corrected to avoid the influence of the truncation of the hidden layer. The algorithm flow is shown in Figure 3.

The biggest difference between TSVD-SCN and SCN is that whenever TSVD-SCN calculates the hidden layer output matrix, SVD decomposes the hidden layer output matrix, designs the threshold based on the reconstruction angle, removes the singular value less than the threshold, and then reconstructs the hidden layer output matrix. Through

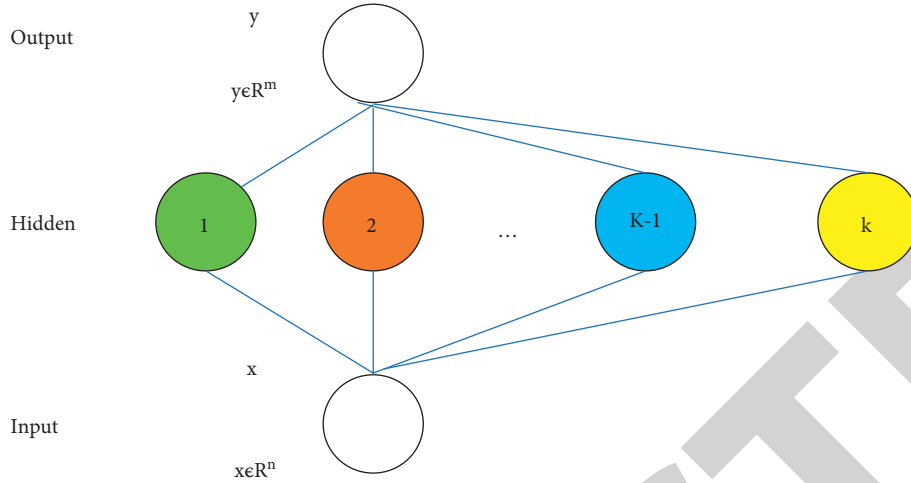


FIGURE 2: Network framework of TSVD-SCN.

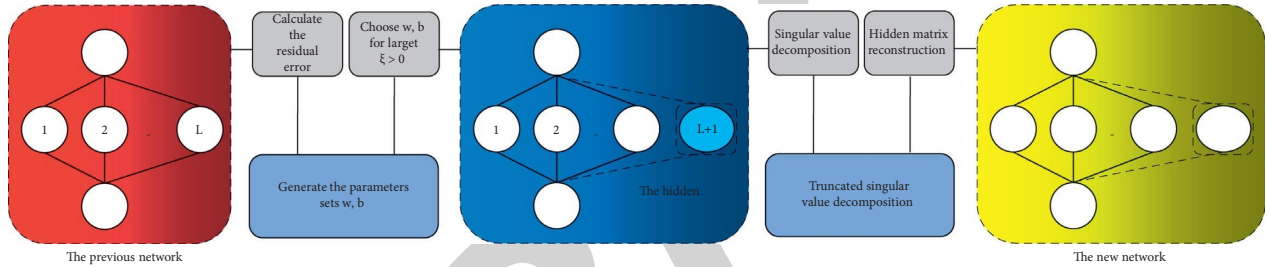


FIGURE 3: Algorithm flowchart.

TSVD processing, the condition number of the hidden layer output matrix is reduced, the influence of matrix ill condition on subsequent linear regression is solved, and the error of network is reduced. Especially in the case of noise and interference in the input data, TSVD-SCN has higher learning accuracy than SCN [18].

2.2.3. Feature Extraction of Optical Fiber Intrusion Signal.

Traditional fiber optic stop signal analysis techniques generally study the characteristics of the signal in a specific time, frequency, or time-frequency domain for the purpose of math learning and knowing a direction. It is easy to drop the high section of the signal by one length. Most importantly, the physical meaning of the stop signal has not been studied. Thus, this article attempted to isolate the signal vibration energy of fiber optic cables by various lengths. In this paper, the signal characteristics of a fiber optic cable are given by several factors, such as the operating cycle of the optical fiber vibration signal, the average speed of the AMDF, and the energy ratio of fft occurs [19], and the material can be obtained or used as the input, TSVD-SCN network.

- (1) Duty cycle. Due to the inherent characteristics of optical fiber vibration signal, the duty cycle of mechanical signal is larger than that of manual signals such as walking and pickaxe planing. Therefore, the duty cycle characteristics of signal can be extracted to

identify mechanical signal and manual signal. We set the experimental unit time as 1 s, that is, we calculate the proportion of alarm points in the total number every 1024 points, and save the calculated duty cycle data as a vector as the input feature of the network. The duty cycle distribution of optical fiber vibration signal is shown in Table 1.

- (2) MDF over average rate. The study of optical fiber vibration signals shows that the frequency of the signal is a characteristic because all the signals are related to the false signal. Algorithms for generating signal frequency frequencies generally include the autocorrelation coefficient (ACF) and the average amplitude difference function (AMDF) [20]. Comparing the two algorithms, the performance of the AMDF algorithm is higher than that of ACF, and the performance is similar. Therefore, in this paper, AMDF uses a medium speed method to generate the signal frequency and conduct it as a network input characteristic.
- (3) Calculation of energy proportion by short-time Fourier transform. Because different types of vibration signals have different spectral distributions, the energy absorbed by the signal differs at different frequencies due to the absorption rate of the waste material at different devices the strike signal is different. According to the general data analysis, the

TABLE 1: Signal duty cycle range.

Data type	Duty cycle range	Mean duty cycle
Pickaxe signal	0.0156~0.0574	0.0252
Walking signal	0.0313~0.0638	0.0429
Mechanical signal	0.2719~0.7969	0.5541

electrical power distribution voltage is usually in the range of 40~60 Hz, while the electrical power output voltage is generally less than 20 Hz., and the noise frequency is high, which is usually higher than 80 Hz. Therefore, the data collection model (an example of 1024 points) is subjected to a short-term Fourier transform (FFT), and the resulting output is truncated at a frequency of 2~61 Hz and divided into three sections. The purpose of this resistor is to eliminate interference caused by the 1 Hz DC component and background noise [21]. To calculate the force of each frequency band, all the data are mixed together, and then the ratio of the force to the total force is calculated, and the results are taken to be three characteristics of the network. The steps to solve the power ratio are shown in Figure 4.



FIGURE 4: Frequency domain feature extraction.

3. Result Analysis

3.1. Introduction of Experimental Data. This experiment used two optical mirrors in two different buried environments, sand and asphalt. A total of 2,000 sets of vibration data systems were collected, including 1,000 sets of vibration data and 1,000 sets of electric drilling data; we record 2,000 groups of guides, including 1000 pixel signal and 1000 walking directions [22]. Half of the data are collected for winter and half for summer. In this way, to ensure the diversity of information, various options for the operation of fiber optic early warning are determined as much as possible. Pre-processing the test data collection. First, the vibration detection data were cut at 1024 points (1 second) in each segment and the closed samples were filtered by a 64 Hz high-pass filter. The model is then standardized, and then the features are extracted from the standardized data. Finally, we write a special result matrix. Finally, the data are divided into training procedures, validation procedures, and experimental processes in a ratio of 6:2:2 as shown in Figure 5.

3.2. Experimental Simulation Results

3.2.1. Network Super Parameter Selection. According to the SCN network model, the number of network iterations is determined by the super parameter of the maximum number of hidden layer nodes. Therefore, the appropriate L is the key to optimizing the overall structure and performance of the network. If the options are too small, the network will be different. Currently, the network is not ready, which does not ensure all the performance of the network, for example the loop is stopped early before seeing the agreement. However, if the choice is too large, the network will be in a very simple state. Here, as the number of iterations increases, the complexity of the structure

gradually increases, and network performance error gradually decreases, while the assembly capacity decreases and the network error decreases [23]. Test scores will increase. Figure 6 shows network training and test errors when there are too many configurations.

Therefore, we adopt the early stop method to prevent over fitting. In the training process, once the performance of the network on the test set begins to decline, we will stop training, that is, find an appropriate super parameter L_{\max} to make the test error of the network on the test set as small as possible. The selection of super parameter L requires the previously reserved verification set, that is, the training data are used to train the network, and the verification set data are used for testing. When the error of the network in the verification set begins to increase, the training is stopped, and the number of hidden layer nodes L of the output times is taken as L_{\max} of the SCN network. As can be seen from Figure 6, the best L_{\max} should be $L = 68$.

3.2.2. Network Training Error. Through the preprocessing of optical fiber vibration data, we get 2400 labeled training data, including 1200 mechanical signals and 1200 artificial signals. These data are used to train TSVD-SCN network. At the same time, the SCN network and RVFL network are used for comparative test. Network related parameters are set as $L_{\max} = 68$, $\varepsilon = 0.1$. The root mean square error of the training network is shown in Figure 7.

It can be seen from Figure 7 that in the process of optical fiber data recognition, the root mean square errors of TSVD-SCN and SCN networks are significantly less than RVFL. From the RMSE curve of RVFL, it can be seen that the decline rate of RVFL training error tends to be gentle after hidden layer node $L = 20$. When $LRVFL = L_{\max}$, the learning effect is the best, and $RMSE_{RVFL} = 0.3$. With the continuous increase of L , the training error of the SCN network and TSVD-SCN network will be reduced to very small, and the training error of the TSVD-SCN network is also less than SCN.

From the training error results, it can be seen that for the identification of optical fiber vibration data, the performance of TSVD-SCN network is not only significantly better than RVFL but also has advantages over the traditional SCN network. However, the measurement of network performance cannot only rely on the training error of the network. The following is to compare its generalization ability through the test error of the network.



FIGURE 5: Data preprocessing process.

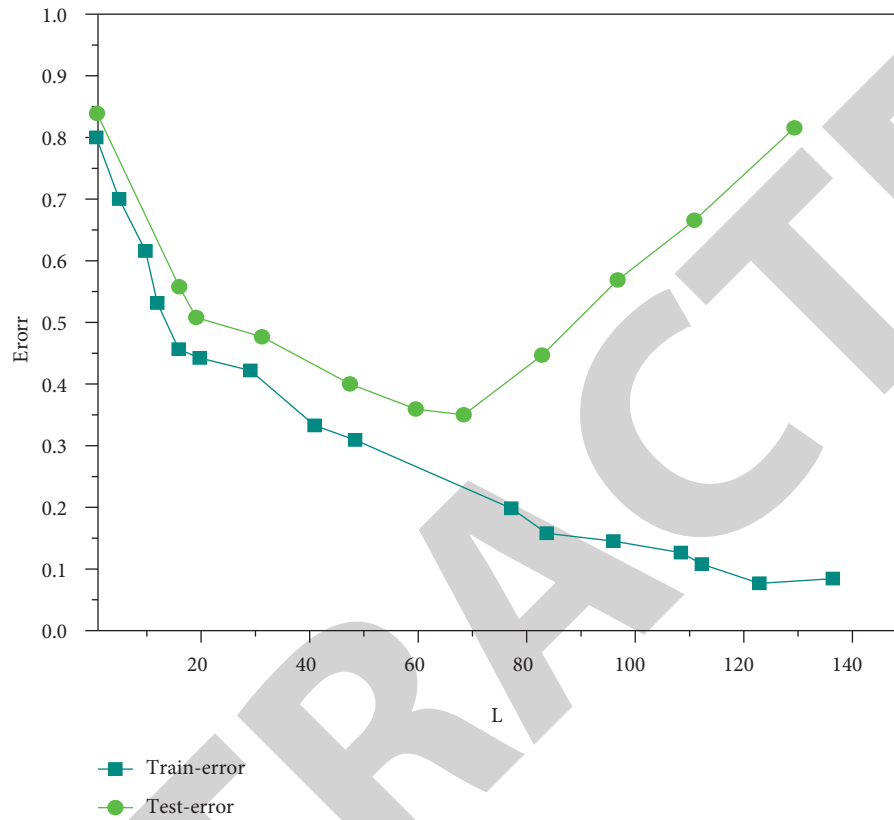


FIGURE 6: Training error and test error under over fitting.

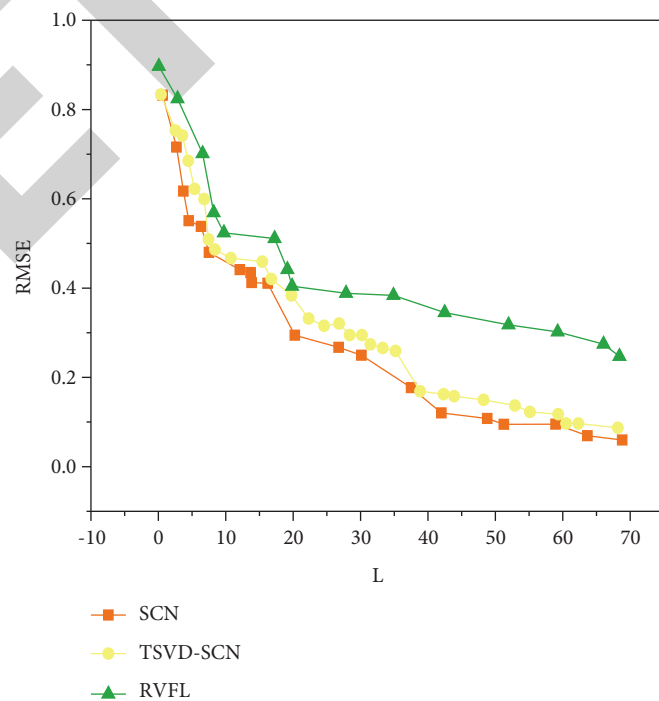


FIGURE 7: Training root mean square error.

TABLE 2: RVFL network recognition rate.

	Mechanical signal	Manual signal	Accuracy (%)
Mechanical signal	347	53	86.75
Manual signal	58	342	85.50

TABLE 3: SCN network recognition rate.

	Mechanical signal	Manual signal	Accuracy (%)
Mechanical signal	367	33	91.75
Manual signal	39	361	90.25

TABLE 4: TSVD-SCN network recognition rate.

	Mechanical signal	Manual signal	Accuracy (%)
Mechanical signal	378	22	94.50
Manual signal	25	375	93.75

3.2.3. Network Test Error. Through the previous training, we have obtained the built network and input the previously reserved test data into the network, so as to obtain the test error of TSVD-SCN, SCN, and RVFL networks, and then we measure the performance of the three networks in practical application.

The test recognition rates of TSVD-SCN, SCN, and RVFL networks are shown in Tables 2–4.

In the abovementioned table, the leftmost end is the type of test data, and the upper end represents the recognition results. From the recognition rates of the three networks, it can be seen that the recognition ability of SCN and TSVD-SCN networks for optical fiber data is significantly stronger than that of the RVFL network. It can be seen that the learning ability of the SCN network is significantly higher than that of RVFL. The recognition rate of TSVD-SCN is also higher than that of the SCN network, which shows that the TSVD-SCN network has better recognition ability for optical fiber vibration data and can better meet the high accuracy requirements of optical fiber early warning system for intrusion signal recognition.

4. Conclusion

This article describes SCN's development of the TSVD-SCN network. Compared to a traditional RVFL network, the SCN network uses a more flexible version of the encryption process, and its network access data is modified for different network constraints, which is more RVFL guarantees speed. However, due to the special nature of the fiber optic signal penetration, the SCN process bladder matrix is usually in a poor condition, which prevents further improvement in the training network. Therefore, TSVD-SCN reduces the single cost of the SCN hidden layer output matrix and eliminates the small cost to improve the communication speed. In this

paper, various types of optical fiber data storage experiments are used to design, test, and compare networks. The TSVD-SCN network has been proven to be effective in acknowledging fiber optic vibration data.

Data Availability

The data used to support the findings of this study are available from the corresponding author upon request.

Conflicts of Interest

The authors declare that they have no conflicts of interest.

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