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Waveform Recognition and Analysis of Ground Penetrating Radar in Tunnel Detection

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Abstract: With the rapid development of tunnel construction, the safety and stability of its structure have become one of the key points that people pay attention to when traveling. The current tunnel detection methods have low efficiency and insufficient accuracy, due to the lack of proficiency in the application of technical means. Ground penetrating radar technology has become an important tool in the field of tunnel detection due to its advantages such as high resolution, high efficiency, and non-contact. It belongs to non-destructive testing technology and plays a pivotal role in tunnel inspection. Therefore, in this paper, waveform identification of tunnels has been carried out using geo-radar technique. This paper applies the experimental method, data comparison, using gradient optimization, the loss values obtained from the training of U-Net and ResGradNet are demonstrated, and the experimental results show that the minimum root-mean-square error value is the maximum of 0.0006, and the minimum is close to 0.0001.

1. Introduction

As underground transportation facilities, tunnels have complex structures and are affected by underground water, geological stress and other factors for a long time, which make them prone to safety hazards such as cracks, cavities and leakage. If these hidden dangers are not found and dealt with in time, they will have a serious impact on the operational safety of tunnels. Therefore, regular inspection of tunnel structures to detect and deal with potential safety hazards in a timely manner is a necessary means to ensure the safe operation of tunnels. The basic principle of geo-radar is to utilize the propagation characteristics of high-frequency electromagnetic waves in underground media for detection. When the electromagnetic wave encounters different media, the phenomena of reflection, refraction and scattering will occur. By receiving and analyzing these reflected electromagnetic wave signals, the morphology and characteristics of underground structures are accurately depicted.

Geo-radar has a resolution of centimetres in tunnel detection and is able to accurately identify minute cracks and voids in tunnel walls. It is also non-contact, non-destructive, fast and efficient, enabling real-time inspection without affecting normal tunnel operations. With the continuous development of computer technology and artificial intelligence technology, the data processing and analyzing ability of geological radar has been significantly improved. In the construction process, complex geological conditions and high construction difficulty can easily cause construction quality problems. Geo-radar technology scans, monitors and evaluates the tunnel lining and other structures.

This paper firstly describes the problems and reasons that tunnels are prone to, suggests that they should be inspected regularly, and introduces the advantages of geo-radar in tunnel inspection. Secondly, this paper discusses the related theories of geo-radar, waveform analysis and tunnel detection. In the method part, this paper firstly explains the technology and principle of geo-radar, then analyzes the method of tunnel detection, and then mentions the waveform analysis. In the experimental results part, this paper analyzes the experimental parameters and experimental methods, and analyzes the results. In the conclusion part, this paper summarizes the whole paper and puts forward the points that can be improved.

2. Related Work

During the development of geo-radar technology, many scholars and experts have conducted in-depth research and exploration on its basic principles and applications.

In order to automatically analyze the ground-penetrating radar data to detect defects and anomalies in the tunnel lining, Jian Huang utilized an improved self-monitoring learning technique to improve the accuracy and efficiency of tunnel lining detection using ground-penetrating radar [1]. Mahmut Nedim Alpdemir and Mehmet Sezgin combined a hybrid approach of reinforcement learning with ground-penetrating radar to improve the detection of buried objects, optimizing the decision-making process for identifying and locating subsurface objects [2]. Krishnendu Raha and K.P. Ray used a prototype to develop and validate a geo-radar model focusing on ground-penetrating radar models for practical implementation and testing [3]. Generative adversarial nets improve the detection process using iteration, and Pang jo Chun, M. Suzuki, and Y. Kato proposed to apply it to identify underground pipelines to enhance the detection of buried pipelines from ground-probing images, which was beneficial for infrastructure maintenance and urban planning [4]. Xin Wang discussed the application of georadar images for nondestructive testing of coal-rock interfaces in mining environments [5]. Wei Yao presented ground collapse prediction based on ground-penetrating radar and deep learning techniques, a deep learning model designed to analyze ground-penetrating radar signals to predict the likelihood of ground collapse [6].

The dataset GROUNDED is designed to facilitate the improvement of ground-penetrating radar performance under challenging environmental conditions, and was used by Teddy Ort to assess the ability of ground-penetrating radar to localize under severe weather conditions [7]. Ejup Hoxha et al. discussed the integration of robot systems with impact echo and ground penetrating radar technologies [8]. A micro aircraft equipped with ground penetrating radar can use the radar's navigation and positioning from an aerial perspective. Rik Bähnemann et al. believe that this is a new method for detecting landmines and humanitarian demining work [9]. A mechanical learning scheme for estimating the diameter of steel bars in concrete structures using ground penetrating data, and Iraklis Giannakis et al. intended to non-destructive evaluate the details of steel bars in concrete structures [10]. The focus of ground penetrating radar in characterizing the internal structure of landmines is on developing technology, and Federico Lombardi distinguished landmines from other buried objects based on their internal characteristics [11].

For tunnel detection, there are also many theoretical achievements. For example, Alexander Weinrauch's variational method for surface handling and tunnel detection is a computational geometry problem related to computer graphics and topology [12]. Sim Kuan Goh used Gaussian process models to explain and predict unstable conditions in tunnels, and tracked and detected them in tunnel environments [13]. Min Xue applied intelligent fault detection to tunnel diode circuits in a fuzzy Markov jump system based on long short-term memory networks, which had high effectiveness in identifying and diagnosing complex system faults [14]. Naotake Ishikura explored tunnel detection by utilizing cached attributes to perceive features, secret data transmission, and exploration [15].

Some people have also studied waveform analysis. Among them, Yujiao Wu modeled a speaker recognition system with global information from the original audio waveform [16]. Based on the low signal-to-noise ratio of denoised cyclic autocorrelation transform, Zeliang An constructed a multimodal model for waveform recognition and used denoised cyclic autocorrelation transform to enhance the recognition of multi carrier waveforms [17]. Chunjun Zheng studied a dual channel model for speech emotion recognition, which improved the accuracy of emotion detection in speech by directly analyzing waveform data. This is valuable for the application of human-computer interaction and emotion analysis [18]. Thien Huynh used time-frequency analysis based on constant wavelets and deep convolutional networks for accurate low intercept probability radar waveform recognition [19]. Thien Huynh's research focused on waveform recognition of intelligent radar systems based on precise deep convolutional neural networks, which improved system performance by accurately identifying and classifying radar waveforms [20]. In order to improve the accuracy and efficiency of waveform recognition in radar systems, Weijian Si stated that dense convolutional neural network algorithms can accurately identify radar waveforms. He continuously optimized and improved the detection methods and algorithms of ground penetrating radar through extensive experiments and data analysis [21]. This paper uses geological radar technology to analyze the waveform of tunnels in depth, with technical and demand support.

3. Methods

3.1 Geo-Radar Technology

Geo-radar utilizes high-frequency electromagnetic wave technology to detect the distribution and nature of underground objects. The transmitter transmits pulsed electromagnetic signals with an intermediate frequency of 12.5m to 1200m and a pulse width of 0.1ns. The target to be measured is determined from the signal reflected on an oscilloscope. The simple principle of geo-radar detection is shown in Figure 1.

Surface, geological radar antenna, emitted and reflected electromagnetic waves and underground targets are important components. Firstly, the transmitting antenna discovers abnormal bodies in the tunnel geology, performs lining, receives antennas, configures controllers, graphic displays, and magnetic recording devices to detect medium structures, buried objects, etc. The geographic radar detection system mainly consists of a transmitter and a receiver. The transmitter is responsible for transmitting high-frequency electromagnetic wave pulses, and the receiver is responsible for receiving reflected, broken and transmitted electromagnetic waves and converting them into electrical signals for processing. Its detection ability is superior to ordinary electromagnetic wave detection instruments, and it can distinguish between short wave and long wave, and is suitable for shallow wave and deep wave detection.

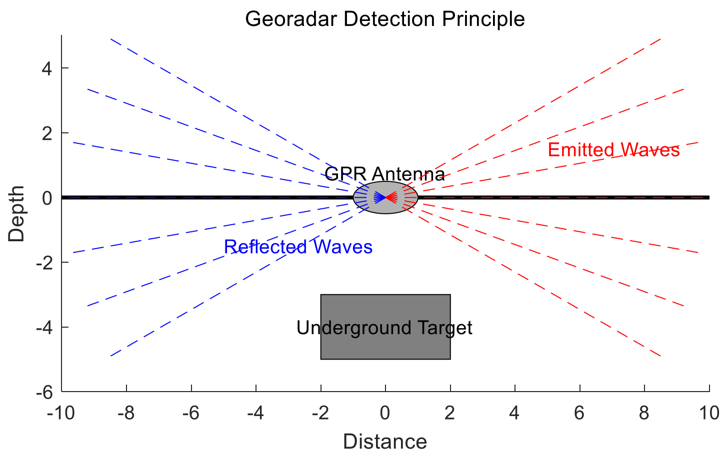

Figure 1: Simple principle of geo-radar detection.

The radar detection system consists mainly of a data acquisition computer, a main radar, a transmitting/receiving antenna, a fiber-optic survey and a tripod equipped with telemetry equipment. Manual transportation is required because of the high friction between the borehole and the antenna. In practical engineering, the depths of the two boreholes often do not coincide, because the transmitting antenna can be placed in the flatter borehole, while the receiving antenna can be placed in the deeper borehole for detection, so that the electromagnetic waves can cover as long a range as possible. During capture, the transmitter antenna is fixed in one position and the receiver antenna is scanned in another borehole for detection; the transmitter antenna is then moved to the next position and the receiver antenna is scanned again; the above steps are repeated until the transmitter antenna covers the entire borehole.

The amplitude attenuation is mainly affected by the conductivity of the medium and the propagation time is mainly affected by the dielectric constant of the medium. Therefore, the distribution of conductivity and dielectric constant of the subsurface medium can be obtained by completely inverting the waveforms of the amplitude and time information of the direct wave. The reflected signals of electromagnetic waves from different media interfaces contain information about the propagation time of electromagnetic waves in both directions from emission to reflection and reception. When they encounter a media interface, cracks that are initially undetectable can also be detected due to changes in reflection geometry compared to single-aperture reflectometer methods. For reflected signals, a reverse time offset can be used to map the media interface.

3.2 Tunnel Inspection

This paper argues that tunnel testing is mainly to detect the tunnel cross-section size, clearance width, height, tunnel lining thickness whether to meet the design standards, to prevent the lining strength reduction due to insufficient thickness. Using rebound method, core method for lining concrete strength testing, to ensure that the concrete strength meets the requirements. Using radar scanning technology, the distribution of reinforcement and the thickness of the protective layer are tested to measure the durability of the lining structure. In addition, we test the performance of waterproofing materials such as tunnel flashing and waterstop. We can also detect environmental factors such as harmful gases, humidity and temperature in tunnels, and assess the structural stability of tunnels through numerical simulation and monitoring methods to prevent structural instability due to changes in geological conditions and loading effects.

Currently, the commonly used inspection methods include ruler measurement, observation, ultrasonic wave, X-ray, radar scanning, numerical simulation and so on. Tunnel is a relatively closed space with certain safety risks. Regular tunnel inspection can detect potential safety hazards inside tunnels in time to ensure the safety of personnel and vehicles. It serves as an engineering structure that requires frequent testing for structural integrity and stability. Geological deformation, water infiltration, earthquakes and other factors may affect the structure of the tunnel, which, if not detected and repaired in a timely manner, may lead to structural damage or collapse of the tunnel, threatening the safety of people's lives and property. Therefore, the environmental pollution of tunnels should be monitored and corresponding measures should be taken to reduce the adverse impact on the surrounding environment.

Geo-radar uses high-frequency electromagnetic waves for tunnel anomaly detection, the amplitude of the reflected wave reflects its characteristic changes, and the position is calculated based on the travel time:

$$g = \frac{\sqrt{V^2 S^2 - A^2}}{2} \tag{1}$$

$$V = \frac{D}{\sqrt{\alpha_t}} \tag{2}$$

Where g is the burial depth, s is the travel time, and A is the send/receive distance. The relative differences in physical properties in common geologies are shown in Table 1:

Table 1: Physical data for common geologies

	Relative permittivity	Velocity of electromagnetic wave	Attenuation
Air	1	0.3	0
Water	78.5	0.023	0.1
Limestone	6-8	0.11	0.5
Silty sand	4-28	0.06	20
Granite	5-7	0.12	0.03
Concrete	4-16	0.12	/
Metal	1-10	0.02	100000000

Radar wave reflection is enhanced if the difference in dielectric constants becomes large:

$$X = \frac{\sqrt{\alpha_1} - \sqrt{\alpha_2}}{\sqrt{\alpha_1} + \sqrt{\alpha_2}} \tag{3}$$

The tunnel inspection process must be integrated with the inspection content and processed with an antenna of appropriate frequency. When implementing the data acquisition process in the field, parameter acquisition modes, time windows, gain methods and sizes, and filtering need to be determined. Parameters are calibrated for wave speed prior to actual data acquisition and proper calibration and distance measurement work is performed during distance acquisition.

3.3 Waveform Recognition

The waveform recognition algorithm is based on the principles of signal processing and pattern recognition, and realizes the non-contact detection of the internal structure of the tunnel through feature extraction, classification and recognition of the waveform signals collected by the geo-radar. Common waveform recognition techniques include frequency domain analysis based on Fourier transform, time-frequency analysis based on wavelet transform, and pattern recognition based on machine learning. Fourier transform converts the signal from the time domain to the frequency domain, and then analyzes the characteristics of different frequency components in the signal. The wavelet transform analyzes the time-frequency characteristics of signals at different scales. In tunnel detection, it can identify changes in the formation structure and the location of anomalies more finely.

The optimization of waveform recognition technology is mainly reflected in the two aspects of algorithm improvement and data processing. On the one hand, the generalization ability and robustness of the model are improved through continuous optimization of the algorithm structure, so that it can adapt to the waveform recognition tasks in different tunnel environments. The model structure combining convolutional neural network and recurrent neural network is adopted to realize the effective extraction and classification of reflected waveforms inside the tunnel. On the other hand, the improvement of data processing technology has also greatly enhanced the accuracy of waveform recognition. By preprocessing, denoising and enhancing the acquired radar data, the effects of environmental noise and interference signals are eliminated and the signal quality is improved. Meanwhile, wavelet transform and spectrum analysis are used to further extract the key feature information in the waveform. The full-waveform inversion method is improved by using alternating iterations for the simultaneous inversion of dielectric constant and conductivity, and the dielectric constant is updated as follows:

$$\alpha_{\mathrm{u}} = \alpha - \tau_{\alpha} \cdot S_{\alpha} \tag{4}$$

Updating the conductivity as follows:

$$\beta_{\mathrm{u}} = \beta - \tau_{\beta} \cdot S_{\beta} \tag{5}$$

The initial model uses the results of the full waveform inversion in the Laplace domain and imposes inequality constraints based on the parameter vectors during the inversion process.

4. Results and Discussion

4.1 Tunnel Waveform Identification

Gradient-optimized datasets were randomly generated with 2, 3, and 4 layers of wave velocity models and error models, 1000 wave velocity models per layer. Each model undergoes ten rounds of inversion iterations for both virtual and real detectors and stores the inversion gradients, generating a total of 10,000 gradient optimization datasets (real detector gradients, virtual detector gradients). A gradient optimized dataset was created by randomly selecting 1% of the data as a validation set and 1% as a test set to achieve full waveform inversion for deep learning. The parameters of the full waveform version have a great influence on the inversion results, and in order to obtain better target gradients optimized for the full waveform version, this paper describes the experience of the full waveform version optimized for the inversion parameters. The experiments compare the effect of different sampling times on the inversion power of the whole waveform according to the arrangement of the virtual detector observation method. 1000 inversions are performed at Reke wavelet frequencies of 40Hz, 80Hz, 120Hz, 160Hz and 200Hz and the best optimization function is selected.

4.2 Gradient Optimization Network Comparison Experiment

In the experiments, both U-Net and ResGradNet were trained using Adam Optimizer with a learning rate of 0.0001, starting at every 200 steps and decreasing exponentially until it reaches 0. Considering the cost and efficiency of the network training, the experiments defined the amount of training data used for each network parameter update as batch size = 30, and the rounds of network parameter iterations as 500.

4.3 Analysis of Results

A grid of wave speed values was created using rand to simulate the output of the full waveform inversion, and then the isosurface function was used to plot an isosurface of the wave speed data that represents a constant wave speed value in three dimensions, as shown in Figure 2. The Lights and Illumination function is used to add illumination effects to the 3D plot to enhance the visualization.

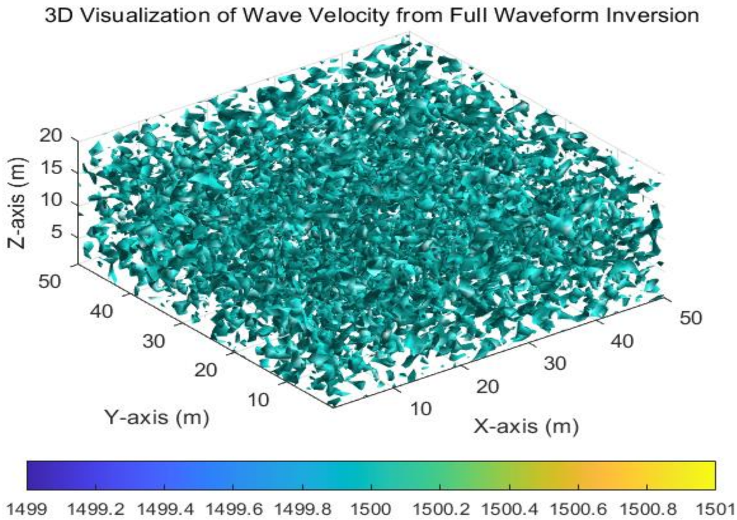

Figure 2: 3D view of wave speed values from full waveform inversion results

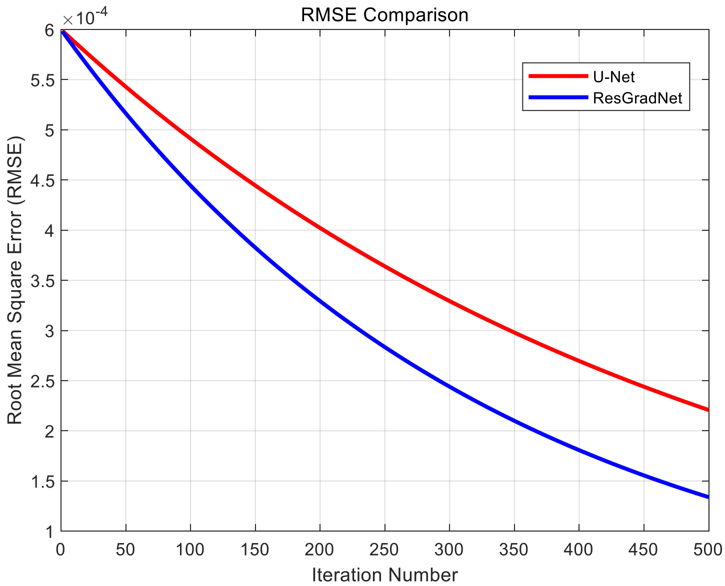

Figure 3: Comparison of network loss functions

As shown in Figure 3, U-Net and ResGradNet are used to train the dataset. The total number of iteration rounds is 500, and comparing and analyzing the training prediction results from the loss function point of view, it can be seen that both of the proposed networks can converge effectively and guarantee a certain accuracy. Compared with ResGradNet, the U-Net network performs poorly in terms of convergence speed, prediction accuracy, etc., which indicates that there is a certain shortcoming in the performance of the U-Net network.

5. Conclusion

In recent years, with the rapid development of artificial intelligence and machine learning technology, the waveform recognition algorithm has been greatly optimized and improved. Intelligent waveform recognition technology realizes automatic analysis and processing of geological radar data by introducing advanced algorithms such as deep learning and machine learning. This paper takes geo-radar technology as the starting point, analyzes the principle of radar detection, and applies this to tunnel detection. Subsequently, this paper discusses the waveform recognition method, through the tunnel waveform recognition, gradient optimization network comparison experiments, and get the corresponding data results. In a critical area of the tunnel, the geo-radar waveform recognition technology showed a clear signal of reflected wave. After further data processing and analysis, we successfully extracted the amplitude, frequency and phase of the reflected wave using advanced waveform recognition algorithms, identifying safety hazards such as voids, cracks and loose bodies inside the tunnel. Radar waves are affected by multiple reflections and scattering during propagation, resulting in complex and variable received waveform signals. Most waveform recognition algorithms are based on statistical learning and pattern recognition methods, which are often difficult to achieve the desired results when dealing with complex and variable tunnel environments. Therefore, this paper will develop more advanced waveform recognition algorithms and models for tunnel environments.

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References

[1] Jian Huang, Xi Yang, Feng Zhou, Xiaofeng Li, Bin Zhou, Song Lu, Sergey I. Ivashov, Iraklis Giannakis, Fannian Kong, Evert C. A deep learning framework based on improved self-supervised learning for ground-penetrating radar tunnel lining inspection. Comput. Aided Civ. Infrastructure Eng. 39(6): 814-833 (2024)

[2] Mahmut Nedim Alpdemir, Mehmet Sezgin. A reinforcement learning (RL)-based hybrid method for ground penetrating radar (GPR)-driven buried object detection. Neural Comput. Appl. 36(14): 8199-8219 (2024)

[3] Krishnendu Raha, K. P. Ray. Ground Penetrating Radar Model and its Validation using Developed Prototype. Wirel. Pers. Commun. 135(2): 1233-1244 (2024)

[4] Pang-jo Chun, M. Suzuki, Y. Kato. Iterative application of generative adversarial networks for improved buried pipe detection from images obtained by ground-penetrating radar. Comput. Aided Civ. Infrastructure Eng. 38(17): 2472-2490 (2023)

[5] Xin Wang, Duan Zhao, Yikun Wang. Nondestructive Detection of Coal-Rock Interface under Mining Environment Using Ground Penetrating Radar Image. Int. J. Pattern Recognit. Artif. Intell. 37(8): 2354009:1-2354009:22 (2023)

[6] Wei Yao, Xu Zhou, Guanghua Tan, Shenghong Yang, Kenli Li. GCNet: Ground Collapse Prediction Based on the Ground-Penetrating Radar and Deep Learning Technique. Int. J. Pattern Recognit. Artif. Intell. 37(16): 2350032:1-2350032:22 (2023)

[7] Teddy Ort, Igor Gilitschenski, Daniela Rus. GROUNDED: A localizing ground penetrating radar evaluation dataset for learning to localize in inclement weather. Int. J. Robotics Res. 42(10): 901-916 (2023)

[8] Ejup Hoxha, Jinglun Feng, Diar Sanakov, Jizhong Xiao. Robotic Inspection and Subsurface Defect Mapping Using Impact-Echo and Ground Penetrating Radar. IEEE Robotics Autom. Lett. 8(8): 4943-4950 (2023)

[9] Rik Bähnemann, Nicholas R. J. Lawrance, Lucas Streichenberg, Jen Jen Chung, Michael Pantic, Alexander Grathwohl, Christian Waldschmidt, Roland Siegwart. Under the Sand: Navigation and Localization of a Micro Aerial Vehicle for Landmine Detection with Ground-Penetrating Synthetic Aperture Radar. Field Robotics 2(1): 1028-1067 (2022)

[10] Iraklis Giannakis, Antonios Giannopoulos, Craig Warren. A Machine Learning Scheme for Estimating the Diameter of Reinforcing Bars Using Ground Penetrating Radar. IEEE Geosci. Remote. Sens. Lett. 18(3): 461-465 (2021)

[11] Federico Lombardi, Hugh D. Griffiths, Maurizio Lualdi, Alessio Balleri. Characterization of the Internal Structure of Landmines Using Ground-Penetrating Radar. IEEE Geosci. Remote. Sens. Lett. 18(2): 266-270 (2021)

[12] Alexander Weinrauch, Daniel Mlakar, Hans-Peter Seidel, Markus Steinberger, Rhaleb Zayer. A Variational Loop Shrinking Analogy for Handle and Tunnel Detection and Reeb Graph Construction on Surfaces. Comput. Graph. Forum 42(2): 309-320 (2023)

[13] Sim Kuan Goh, Narendra Pratap Singh, Zhi Jun Lim, Sameer Alam. Interpretable Tracking and Detection of Unstable Approaches Using Tunnel Gaussian Process. IEEE Trans. Aerosp. Electron. Syst. 59(3): 2658-2671 (2023)

[14] Min Xue, Huaicheng Yan, Meng Wang, Hao Shen, Kaibo Shi. LSTM-Based Intelligent Fault Detection for Fuzzy Markov Jump Systems and Its Application to Tunnel Diode Circuits. IEEE Trans. Circuits Syst. II Express Briefs 69(3): 1099-1103 (2022)

[15] Naotake Ishikura, Daishi Kondo, Vassilis Vassiliades, Iordan Iordanov, Hideki Tode. DNS Tunneling Detection by Cache-Property-Aware Features. IEEE Trans. Netw. Serv. Manag. 18(2): 1203-1217 (2021)

[16] Yujiao Wu, Jianping Dong, Zulin Fang, Gexiang Zhang, Haina Rong. Speaker recognition with global information modelling of raw waveforms. J. Membr. Comput. 6(1): 42-51 (2024)

[17] Zeliang An, Tianqi Zhang, Yuqing Xu, Gert Frølund Pedersen, Ming Shen. Multimodality-Aided Multicarrier Waveform Recognition in Low SNR Regimes Based on Denoised Cyclic Autocorrelation Transformation. IEEE Trans. Aerosp. Electron. Syst. 59(5): 5859-5875 (2023)

[18] Chunjun Zheng, Chunli Wang, Ning Jia. A two-channel speech emotion recognition model based on raw stacked waveform. Multim. Tools Appl. 81(8): 11537-11562 (2022)

[19] Thien Huynh-The, Van-Sang Doan, Cam-Hao Hua, Quoc-Viet Pham, Toan-Van Nguyen, Dong-Seong Kim. Accurate LPI Radar Waveform Recognition with CWD-TFA for Deep Convolutional Network. IEEE Wirel. Commun. Lett. 10(8): 1638-1642 (2021)

[20] Thien Huynh-The, Cam-Hao Hua, Van-Sang Doan, Quoc-Viet Pham, Dong-Seong Kim. Accurate Deep CNN-Based Waveform Recognition for Intelligent Radar Systems. IEEE Commun. Lett. 25(9): 2938-2942 (2021)

[21] Weijian Si, Chenxia Wan, Chunjie Zhang. Towards an accurate radar waveform recognition algorithm based on dense CNN. Multim. Tools Appl. 80(2): 1779-1792 (2021)