Abstract—Ground Penetrating Radar (GPR) has been widely used in pipeline detection and underground diagnosis. In practical applications, the characteristics of the GPR data of the detected area and the likely underground anomalous structures could be rarely acknowledged before fully analyzing the obtained GPR data, causing challenges to identify the underground structures or anomalies automatically. In this article, a GPR B-scan image diagnosis method based on learning in the model space is proposed. The idea of learning in the model space is to use models fitted on parts of data as more stable and parsimonious representations of the data. For the GPR image, 2-Direction Echo State Network (2-DESN) is proposed to fit the image segments through the next item prediction. By building the connections between the points on the image in both the horizontal and vertical directions, the 2D-ESN regards the GPR image segment as a whole and could effectively capture the dynamic characteristics of the GPR image. And then, semi-supervised and supervised learning methods could be further implemented on the 2D-ESN models for underground diagnosis. Experiments on real-world datasets are conducted, and the results demonstrate the effectiveness of the proposed model.

Index Terms—2-Direction echo state network, B-scan image, ground penetrating radar, learning in the model space.

I. INTRODUCTION

MORERN cities are facilitated by a large number of urban roads and subsurface facilities. Unlike above-ground buildings, the health of some urban roads and facilities requires exploration of the medium beneath the ground to be effectively estimated. Without proper diagnosis and maintenance, some aging roads or facilities might suffer from various abnormal modes, mainly including subsurface cavities, moisture damage, and loose media, bringing urban hazards such as moisture damage, land subsidence, and infrastructure collapse [1]. Therefore, detecting subsurface anomalies under urban roads is one of the major undertakings in urban operation. As one of the most suitable means for imaging the subsurface, Ground Penetrating Radar (GPR) makes the use of the transmission and reflection of the electromagnetic (EM) waves to detect dielectric properties’ changes in host materials [2], [3]. In real-world applications, GPR could be combined with positioning means, such as Global Positioning System (GPS), odometer, etc., to detect and locate subsurface objects or anomalies. When an object or anomaly is identified from the GPR image, their position and range could be located through the corresponding positioning data. Considerable efforts have been devoted to interpreting GPR B-scan images, which could be roughly divided into two categories: identifying and fitting hyperbolic characteristics on B-scan images and detecting non-hyperbolic features.

The hyperbolic characteristic in the B-scan image is generated by linear cylinder objects where GPR has moved across. The radius and depth of the object could be estimated by identifying and fitting the hyperbolic characteristic [4]. Graphic methods [5], [6], [7], machine learning methods [8], [9], [10], and some methods that combine multiple approaches [11], [12], [13], [14] have been employed to extract and fit hyperbolic features from noisy GPR B-scan images.

Besides hyperbolic characteristics generated by linear cylinder objects, non-hyperbolic features might be more common and realistic targets in GPR B-scan images when imaging the subsurface. These features could be formed by different kinds of subsurface media or targets, including subsurface cavities, moisture damage, loose media, etc. Different subsurface media or targets would generate different characteristics of the image. Even the same kind of underground target could form different detail features on B-scan images due to differences in its composition, size, and surrounding media [15]. For example, the moisture-damaged area would form as a continuous or discontinuous highlight area in GPR B-scan images, while the water content and whether the surrounding is hollow will feasibly affect the bright changes and edges of the area in the obtained B-scan images [16]. Some dielectric-constant-based methods [17], [18] and signal processing algorithms [19], [20] have been proposed to localize the subsurface objects. Recently, Convolutional Neural Network (CNN) methods [21], [22], [23], [24], [25], [26], [27] have also been utilized in recognizing objects on the image.

In order to identify anomalies in the data, model-space-based methods have been proposed and used for data classification and diagnosis [28], [29], [30], [31], [32]. As shown in Fig. 1, the
model-space-based methods map the data from the data space to the model space by fitting the data with models, and then use the models that could describe the dynamic characteristics\textsuperscript{1} of the data to represent the data or data clusters. In \textsuperscript{28}, temporal signal data was segmented and mapped from signal space to model space. The Cycle topology with Regular Jumps (CRJ) \textsuperscript{33}, \textsuperscript{34} was utilized to fit the signal segments. The fitted CRJ model for each data segment was further classified in the model space. Subsequently, in \textsuperscript{29} and \textsuperscript{30}, the framework of learning in the model space was utilized in the fault diagnosis of the Barcelona water network and the Tennessee Eastman Process. In \textsuperscript{31} and \textsuperscript{32}, time-series data was mapped into the model space and then classified. The above model-space-based methods aim to handle data with contextual relationships. However, the GPR B-scan image not only has the continuity of detection time or position in the horizontal direction but also correlates in the vertical direction due to the continuity of the underground medium and EM waves. The fitting models used in the above model-space-based methods are constructed by the traditional Echo State Network (ESN) \textsuperscript{35}, which might not be able to capture the dynamics of two-dimensional image data. Therefore, there is a need for a designed model that can fit or describe two-dimensional image data \textsuperscript{36} to capture the dynamic characteristics of the GPR B-scan image and map the image into the model space with a proper size for further processing.

In this article, a GPR B-scan image diagnosis method based on learning in the model space is proposed. A sliding window is constructed and swiped across the obtained GPR image. The GPR image segments in the sliding window are mapped into the model space with the proposed 2-Direction Echo State Network (2D-ESN). Specifically, the 2D-ESN is a model that considers both current information and historical information in two different directions. In GPR images, each point is correlated with surrounding points in the horizontal and vertical directions. Different underground structures will show different variation laws in the horizontal and vertical directions in the GPR B-scan image, that is, the dynamic characteristics. By constructing the connections between the points on the image in both the horizontal and vertical directions, the 2D-ESN could effectively capture the dynamic characteristics of the GPR image. As a result, GPR image segments of similar structures would be mapped to similar 2D-ESN models. On the contrary, the 2D-ESN models fitted from GPR image segments generated by different underground structures would have large differences in the model space due to the different dynamic characteristics. Moreover, the 2D-ESN is a model that could fit B-scan images without iterative training, enabling real-time underground diagnosis. Subsequently, the distance measuring method for 2D-ESN models is modified in the constructed model space. Based on the constructed model space and distance measuring method, supervised and semi-supervised algorithms could be utilized to identify or classify anomalies on GPR B-scan images in the model space. The procedure of the proposed method is visualized in Fig. 2.

The main contribution of this paper could be summarized as follows:

1) In the proposed 2D-ESN, both detection position and time continuity in the horizontal direction and medium continuity in the vertical direction of the GPR B-scan images are taken into account to capture the dynamic characteristics of the B-scan image effectively.

2) For an image with the depth (length of a column) of $M$, the proposed 2D-ESN with $N$ hidden layer units could fit a model of size $2N$ instead of an $M \times N$ model obtained by the traditional ESN, which could effectively reduce the memory usage and enable the proposed diagnosis method to run efficiently on a personal computer for real-time processing.

3) The proposed diagnosis method could perform real-time diagnosis of GPR images without sufficient prior knowledge and data and further classify different types of abnormal data in the constructed model space.

The rest of this paper is organized as follows. Some background work is presented in Section II. The 2D-ESN is discussed in Section III, by which the GPR B-scan image segment could be mapped into the model space. Section IV provides the diagnosis in GPR images based on learning in the model space. Experiments are conducted and analyzed in Section V. Finally, conclusions are drawn in Section VI.

II. BACKGROUND

Ground Penetrating Radar (GPR) has become increasingly important as a nondestructive tool to estimate the healthy operation of some urban roads and underground facilities. The GPR transmitter and antenna emit electromagnetic energy into the ground. When the energy encounters a buried object or a boundary between materials having different permittivity, it would be reflected or scattered back to the surface. A receiving

\textsuperscript{1}Dynamic characteristics refer to the manner in which the data values change. Especially, in this article, dynamic characteristics refer to the way in which gray values in the GPR B-scan image change as a function of depth and sensor location.
Fig. 2. Procedure of the proposed method. A sliding window is constructed and swiped across the obtained GPR image. Among them, the normal window data means that there is no abnormal underground structure in the sliding window, and the abnormal window data means that there exist abnormal underground structures in the sliding window. The GPR image in each sliding window is mapped into the model space by the proposed 2D-ESN. Supervised and semi-supervised algorithms are then utilized to identify or classify anomalies on GPR B-scan images in the model space.

Fig. 3. Figure shows the generation of a B-can image. The left side of the figure is a B-scan image. The abscissa in the left B-scan picture is the detection position, and the ordinate is the time (the time from emission to reception of the electromagnetic wave). The right side is a received wave in the left B-scan image. The bottom of the right side shows that different gray values correspond to different magnitudes. The gray value of each pixel represents the corresponding amplitude at this position and time.

Antenna would then record the variations in the return waves. By arranging the received waves horizontally according to a temporal or spatial relationship, and using the corresponding gray value to represent the wave intensity, a GPR B-scan image could be obtained [3] as presented in Fig. 3. Afterwards, the subsurface situation or existing objects could be estimated by interpreting different shapes or characteristics on the obtained GPR B-scan image [37]. However, due to the refraction and reflection of EM waves, the various shapes on the GPR image are not actually the same as the actual objects. Besides, the system noise, the heterogeneity of the medium, and mutual wave interactions also make it challenging to automatically cope with the GPR images obtained in the detection area [2]. Published methods for interpreting GPR B-scan images could be roughly divided into two categories: identifying and fitting hyperbolic features on B-scan images and detecting non-hyperbolic features. The hyperbolic features in the B-scan image are generated by linear cylinder objects where GPR has moved across. In practical applications, the obtained B-scan images could be noisy. Some graphic methods [5, 6, 7] and machine learning methods [8, 9, 10] have been proposed to identify hyperbolic shapes on the GPR image. Combinations of the above methods [11, 12, 13, 14] have also been utilized to obtain more accurate and reliable results.

Apart from hyperbolic features, non-hyperbolic features could be formed by different kinds of subsurface media or targets, including subsurface cavities, moisture damage, loose media, etc. Some existing studies relied on the dielectric constant method with the air-coupled antenna to localize the subsurface objects [17, 18], where the dielectric constant value was assumed to be the same along the vertical direction within the road layer and calculated based on the reflectance amplitude of the GPR wave [38]. However, the dielectric constant could be sensitive and easily affected by material constituents, air void content, pavement density, and layer thickness [39]. Thus the use of this kind of method generally requires knowledge of the basic conditions of the underground medium in advance, and its effect could be affected by the user’s experience. There are also some published works that identify underground objects from GPR data by signal processing or image recognition methods. In [19], the frequency-domain-focusing (FDF) technology of synthetic aperture radar (SAR) was utilized to aggregate scattered GPR signals for acquiring testing images, where a low-pass filter was designed to denoise primordial signals, and the profiles of detecting objects were extracted via the edge detection technique based on the background information. Subsequently, in [20], a...
formula was conducted to relate the hidden crack width with the relative measured amplitude. Likewise, methods based on data or signal characteristics generally require prior knowledge or examples of subsurface conditions or structures.

Recently, Convolutional Neural Network (CNN) methods have been utilized in recognizing objects in GPR B-scan images. Tong et al. [21,22] conducted a CNN structure to automatically localize several kinds of targets in GPR data, which used the GPR signals as an input value to import into the CNNs. In [23, 24], YOLO (You-Only-Look-Once) [40] was utilized to detect potholes and crackings beneath the roads. In [41], a mixed deep CNN model combined with the ResNet-based network was proposed to detect the moisture damage in GPR data. Liu et al. [25] proposed a method for combining the YOLO series with GPR images to recognize the internal defects in asphalt pavement. In real-world applications, when detecting the underground objects in a certain area or along a road, it is difficult to ensure that the existing training B-scan images obtained from other areas or datasets are consistent with the underground situation in the area or road to be detected. Moreover, collecting enough training data and training a suitable CNN for the detecting area or road could be time-consuming.

In this article, a model-space-based approach for GPR B-scan image diagnosis is proposed. A sliding window is built, which slides over the obtained GPR images. The GPR images in each sliding window would be mapped into the model space by the proposed 2D-ESN with the “next item prediction” task. Subsequently, the distance measurement method of the 2D-ESN models is modified in the constructed model space. Based on the above, supervised and semi-supervised algorithms are utilized to identify or classify underground anomalies in the constructed model space.

III. 2-DIRECTION ECHO STATE NETWORK

In order to map the data into the model space, the model used to fit the data should adequately capture the dynamic characteristics of the data. Meanwhile, in the process of real-time diagnosis, newly collected data needs to be processed constantly, which also puts forward requirements for the solution and the memory occupation of the model. In this section, the 2-Direction Echo State Network (2D-ESN) is proposed to satisfy the above requirements. The Echo State Network (ESN) is briefly introduced in advance, and the 2D-ESN is then detailed.

A. A Brief Introduction to Echo State Network (ESN)

A traditional ESN [35] could be considered as a recurrent discrete-time neural network that processes sequential data with context. To capture the dynamic characteristics of sequential data, the ESN takes into account not only the impact of current input but also the impact of historical information. As shown in Fig. 4, an ESN consists of an input layer with \( K \) units, a hidden layer with \( N \) units, and an output layer with \( L \) units. The input value, hidden state, and output value at time step \( n \) could be represented as \( x(n) = (x_1(n), \ldots, x_K(n))^T \), \( h(n) = (h_1(n), \ldots, h_N(n))^T \), and \( y(n) = (y_1(n), \ldots, y_L(n))^T \), respectively. The iteration and prediction formulas of the ESN are defined as:

\[
\begin{align*}
\mathbf{h}(n) &= g(\mathbf{W}^{hh} \mathbf{h}(n-1) + \mathbf{W}^{hx} \mathbf{x}(n)), \\
\mathbf{y}(n) &= \mathbf{W}^{yh} \mathbf{h}(n) + \mathbf{a},
\end{align*}
\]

where \( \mathbf{W}^{hx} \in \mathbb{R}^{N \times K} \) is the input weight between the input layer and the hidden layer, \( \mathbf{W}^{hh} \in \mathbb{R}^{N \times N} \) is the reservoir weight in the hidden layer, \( \mathbf{W}^{yh} \in \mathbb{R}^{L \times N} \) is the output weight between the hidden layer and the output layer, \( g \) is the activation function (typically \( \tanh \)), and \( \mathbf{a} \) is the bias vector of the output model.

As a simplified Recurrent Neural Network (RNN), the input and reservoir weights in the ESN are first randomly generated and fixed. Additionally, the ESN has the “memory” feature like the RNN. According to (1), during the iterative process of the hidden layer, the hidden state \( \mathbf{h}(n) \) is affected by the current input value \( \mathbf{x}(n) \) and the previously processed hidden state \( \mathbf{h}(n-1) \). Therefore, the reservoir will iteratively retain historical information by taking into account both the current input and the previous processed hidden states [42]. Besides, the reservoir in this kind of network should have the Echo State Property (ESP) [42], which means that the reservoir would asymptotically wash out the effect of the historical information over time to ensure the stability of the ESN. In ESN, the reservoir weight \( \mathbf{W}^{hh} \) is scaled as:

\[
\mathbf{W}^{hh} \leftarrow \frac{\alpha \mathbf{W}_{\text{initial}}^{hh}}{\lambda_{\text{max}}},
\]

where \( \mathbf{W}_{\text{initial}}^{hh} \) is the randomly initialized weight of the reservoir, \( \lambda_{\text{max}} \) is the maximum of the absolute values of \( \mathbf{W}_{\text{initial}}^{hh} \)’s eigenvalues, and \( 0 < \alpha < 1 \) is the scaling parameter. Thus for \( \mathbf{W}^{hh} \), \( \alpha \) serves as the spectral radius. Among them, the spectral radius of a matrix refers to the maximum of the absolute values of its eigenvalues. In the ESN, the effect of historical information on the current hidden state is related to the spectral radius of the reservoir weight [42]. The reservoir with a larger spectral radius could retain more memory. Conversely, a smaller spectral radius

\[\text{The reservoir is the component of the hidden layer and is utilized to process historical information.}\]
would cause the reservoir to forget more historical information. In this article, the spectral radius of the reservoir weight is set from 0 to 1 to satisfy the ESP.

When fitting an ESN model, we send the input data into the hidden layer iteratively, and the corresponding hidden states are then obtained. The output weights \( W^{yh} \) could be calculated by the ridge regression [43] as:

\[
W^{yh} = (H^T H + \lambda^2 I)^{-1}H^T Y, \tag{3}
\]

where \( I \) is the identity matrix, \( Y \) is a vector of the target values, \( H \) is a vector of the corresponding hidden states, and \( \lambda > 0 \) is a regularization factor.

With the ESN, sequential data with context could be mapped from the data space into the model space for further analysis. But there exist some limitations with ESN. The association of data in the ESN is unidirectional, while relationships in multiple directions within the data could not be captured. Moreover, the size of the ESN model increases linearly with the number of output units according to (3). In GPR data processing, the input data could be the two-dimensional B-scan image. Suppose there is a GPR image, and its vertical direction (depth) contains \( M \) pixels. The size of the obtained ESN’s output weights \( W^{yh} \) would be \( M \times N \). Therefore, if the ESN is directly utilized for fitting image data, the parameter dimension of the output layer would be too large, which is not conducive to further analysis in the model space.

B. 2-Direction Echo State Network (2D-ESN)

As aforementioned, the GPR B-scan image not only has the continuity of detection time or position in the horizontal direction but also correlates with the vertical direction due to the continuity of the underground medium. Different underground structures will show different variation laws (dynamic characteristics) in the horizontal and vertical directions in the GPR B-scan image. To capture the dynamic characteristics of an image, the 2D-ESN correlates each point in the image with the left and upper points and builds memory for the upper left points that have been processed. Moreover, the 2D-ESN reduces the number of parameters in the output layer by order of magnitude compared to the ESN methods used in existing model-space-based methods.

The processing flow of the 2D-ESN for image data is shown in Fig. 5. The 2D-ESN starts from the initial point (1, 1) in the image and gradually sends points column by column into the reservoir for iteration, where each column is processed from top to bottom. Similar to the ESN shown in Fig. 4, the 2D-ESN consists of the input layer, the hidden layer, and the output layer. The input layer indicates the gray value of the current point in the image. The output layer is the predicted value of the current point. The hidden layer combines the input and the hidden states of upper and left points to generate the hidden state of the current point. Among them, the input layer and hidden layer parameters do not need to be trained, and only the output layer parameters need to be solved.

During the iteration of the 2D-ESN, for each point, the current hidden state is not only influenced by the current input but also by the hidden states of the upper and left points. For point \((i, j)\), the 2D-ESN hidden layer iteration is illustrated in Fig. 6. The iteration formula is defined as:

\[
y(i, j) = g(W^{hhi}h(i - 1, j) + W^{hh}h(i, j - 1) + W^{hx}x(i, j)), \tag{4}
\]

where \( h(i, j) \in \mathbb{R}^{N \times 1} \) is a hidden state of point \((i, j)\) in the image, \( x(i, j) \in \mathbb{R}^{1 \times 1} \) is the gray value of point \((i, j)\) in the image, \( W^{hhi}, W^{hh} \in \mathbb{R}^{N \times N} \) are the reservoir weights in the hidden layer, \( W^{hx} \in \mathbb{R}^{N \times 1} \) is the input weight. Among them, the input weight \( (W^{hx}) \) and reservoir weights \( (W^{hhi}, W^{hh}, W^{hx}) \) in the 2D-ESN are randomly generated. And the reservoir should satisfy the ESP. According to the iteration formula of 2D-ESN that is given in (4), the hidden state \( h(i, j) \) of the current point \((i, j)\) is not only influenced by the input value \( x(i, j) \), but also by the hidden states \( h(i - 1, j) \) and \( h(i, j - 1) \) of the surrounding processed points in the horizontal and vertical directions. As a result, 2D-ESN correlates each point in the GPR image with the left and upper points, therefore building memory for the upper left points that have been processed in both the horizontal and vertical directions.

In order to map the image data into the model space through the 2D-ESN, the “next item prediction” task is accomplished and shown in Fig. 7, that is, to construct the mapping between the target value and its upper and left hidden states. For point \((i, j)\), the 2D-ESN prediction formula is defined as:

\[
y(i, j) = W^{yh1}h(i - 1, j) + W^{yh2}h(i, j - 1) + a, \tag{5}
\]

where \( y(i, j) \in \mathbb{R}^{1 \times 1} \) is the output value of point \((i, j)\) in the image, \( h(i - 1, j), h(i, j - 1) \in \mathbb{R}^{1 \times 1} \) are the hidden state of upper and left points of current point \((i, j)\) in the image, and \( a \) is the bias vector of the output model. \( W^{yh} = [W^{yh1}, W^{yh2}] \) is the output weight of the 2D-ESN, where \( W^{yh1}, W^{yh2} \in \mathbb{R}^{1 \times N} \) could be obtained by the ridge regression as (3). According to
the above prediction formula (5) and the ridge regression (3), the 2D-ESN provides the output weight of size $2N$ instead of the output weight of size $M \times N$ provided by the ESN, where $M$ is the number of vertical pixels (depth) of the image.

When 2D-ESN processes the point in the image with (4) and (5) in the sequence shown in Fig. 5, it actually establishes a connection between the currently processed point and all the previous upper left points to capture the dynamic characteristics of the image horizontally and vertically. With 2D-ESN, each segment of GPR B-scan images could be mapped from the data space to the model space by the “next item prediction” task. The predictive model fitted through a GPR B-scan image segment indicates the mapped point of this image segment in the model space. Intuitively, differences between the fitted 2D-ESN models reflect differences in dynamic characteristics between the corresponding training data. The method to measure the difference between the models in the model space would be introduced in the next section.

From the perspective of practical application requirements, real-time diagnostic results could aid in the localization and repair of subsurface anomalies. In 2D-ESN, only $W_{yh1}, W_{yh2} \in \mathbb{R}^{1 \times N}$ need to be solved by ridge regression when fitting a model, ensuring the speed and efficiency of the process of mapping data into the model space. Also, the memory occupied by 2D-ESN is limited, which is helpful for performing real-time diagnostics on a personal computer in on-site applications.

IV. Diagnosis in GPR Images Based on Model Space

In this section, the distance measuring method for 2D-ESN models is modified in the constructed model space. Based on the constructed model space and distance measuring method, learning methods in the model space, including semi-supervised and supervised algorithms, are introduced for underground diagnosis.

A. Measure the Distance Between Two 2D-ESNs

After mapping GPR B-scan images into the model space via 2D-ESN, the distance between the fitted 2D-ESN models should be defined to measure the difference between models. The $m$-norm distance [28] between models $f_1(x)$ and $f_2(x)$ ($f_1, f_2 : \mathbb{R}^{N \times 2} \rightarrow \mathbb{R}$) could be defined as follows:

$$L_m(f_1, f_2) = \left( \int_C D_m(f_1(x), f_2(x))d\mu(x) \right)^{1/m},$$

where $D_m(f_1(x), f_2(x)) = \|f_1(x) - f_2(x)\|_m$ is a function that measures the difference between $f_1(x)$ and $f_2(x)$, $\mu(x)$ is the probability density function of the input domain $x$, and $C$ is the integral range. In this article, we adopt $m = 2$ and first assume that $x$ is uniformly distributed.

For two different 2D-ESN models, $f_1(x)$ and $f_2(x)$ could be represented by the following equation:

$$\begin{cases} f_1(h) = W_{yh1}h + a_1, \\ f_2(h) = W_{yh2}h + a_2, \end{cases}$$

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where $h = [h(i-1,j), h(i,j-1)]^T$ is the hidden states of the upper and left points, $W^{gh} = [W^{gh1}, W^{gh2}]$ is the output weight, and $a$ is the bias vector of the output model.

Substituting (7) into (6), the following equation could be obtained:

$$L_2(f_1,f_2) = \frac{1}{3} \| W_1^{gh} - W_2^{gh} \|^2 + \| a_1 - a_2 \|^2,$$

where $L_2(f_1,f_2)$ is the obtained distance between two 2D-ESNs. Through (8), the distance between any two 2D-ESNs could be measured. Thus the distance-based algorithms could be utilized in the model space for classification.

B. Model Diagnostics in the Model Space

In practical applications, the characteristics of the obtained GPR data of the detected area and the likely underground anomalous structures could be rarely acknowledged before analyzing the obtained GPR data. In this case, semi-supervised learning (one-class learning) is utilized for real-time underground diagnosis in the model space. In this article, One-Class SVM (OCSVM) [44] is used to find a hyperplane that has the greatest distance from the origin in the kernel feature space with the given training samples, that is the fitted models, falling beyond the hyperplane. Specifically, several normal GPR B-scan image segments are mapped to the model space via the 2D-ESN, and a normal OCSVM classifier is trained. Then, for the subsequently fitted models, the OCSVM classifier trained from normal models\(^4\) is continuously used for classification, and the model classified as abnormal is put into the abnormal set. The models fitted by abnormal data could be further trained by incremental one-class learning [28]. Fig. 8 illustrates one-class learning and incremental one-class learning.

For supervised classification tasks, that is when there is already data similar to the underground environment that can be used for model space mapping or training, the classification algorithms like K-Nearest Neighbors (KNN) [45], Random Forest [46], and Support Vector Machine (SVM) [47] could be utilized in the constructed model space.

\(^4\)The normal model refers to the model fitted by normal data.

V. EXPERIMENTAL STUDY

In this section, experiments on real-world datasets are conducted. After that, the analysis of the experimental results and some comparative works are presented.

A. Experimental Settings on Real-World Datasets

To evaluate the effectiveness of the proposed model, experiments\(^5\) are conducted on GPR images collected from three different types of roads, including cement, asphalt, and non-paved roads. 10 groups of GPR B-scan images are obtained along these roads by GSSI-SIR30 GPR. The GSSI SIR-30 GPR is deployed along the roads, coupled with GPS to record the corresponding positions. The utilized devices and detection are shown in Fig. 9.

The collected data has been manually classified, and some locations with part of underground anomalies were excavated and repaired. To eliminate the noise and highlight the subsurface structures, some operations are conducted on the obtained GPR B-scan images, which consist of three tasks: 1) Eliminating the undesired presence of the ground surface echo; 2) Reducing noise; 3) Compensating propagation losses. First, the reflectance of the ground surface is eliminated in advance. This work is supported by the Matgpr [48] which is a freeware Matlab package for the analysis of common-offset GPR data. Then a filtering step based on the standard median filter is performed [49] to reduce the electromagnetic noise and interferences. Finally, concerning the compensation of the propagation losses caused by the medium attenuation and the signal energy radial dispersion, a nonlinear time-varying gain [50] is applied to the received signal. The above operations have been introduced and evaluate in our

\(^5\)The experiments are conducted on a laptop with CPU: AMD Ryzen 7 5800H, and GPU: NVIDIA GeForce RTX 3060.
previous work [14] and [51] with considerable denoising effect. Thus, they are not expanded in this article.

When mapping GPR data from the data space into the model space, the length of the sliding window is set to be 300 pixels (the distance between every two pixels is about 0.014 m). For the 2D-ESN, since whether there is an abnormality at the current position will not be greatly affected by the long previous road segment, the spectral radius of the reservoir is set to 0.1. After mapping each GPR B-scan image in the window, both the semi-supervised learning task and supervised learning task are conducted.

In our experiments, if there is no recognizable abnormal underground structure existing in the window, the window data is labeled as normal. Otherwise, it is labeled as the type of existing abnormal structure. For a set of processed GPR B-scan image segments, it is assumed that for each type of classified data, the number of correctly classified data in this type is \( N_{tp} \), the number of misclassified data in this type is \( N_{fp} \). Similarly, regarding the data classified into other types as a whole, the numbers of correctly classified and misclassified data are \( N_{tn} \) and \( N_{fn} \), respectively. Then, the Precision, Recall and \( F_1 \) value on this type of data are calculated by (9). The Precision, Recall and \( F_1 \) of the evaluated method are estimated through the mean value of the above evaluation criteria on all types of data.

\[
\begin{align*}
\text{Precision} &= \frac{N_{tp}}{N_{tp} + N_{fp}}, \\
\text{Recall} &= \frac{N_{tp}}{N_{tp} + N_{fn}}, \\
F_1 &= 2 \times \frac{\text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}},
\end{align*}
\]

(9)

B. Semi-Supervised and Supervised Learning Results in the Constructed Model Space

For semi-supervised learning, we conduct experiments for each type of road separately. A part of the normal-road GPR B-scan image with a length of 3000 for each type of road is first selected. Afterwards, the sliding window is utilized on the image with the interval of 20 to generate a series of normal data segments, which are fitted by 2D-ESN. The obtained 2D-ESN models are used to train the OCSVM. The GPR image obtained along the remaining part of the road will be gradually segmented by the sliding window and sent into the 2D-ESN to obtain the corresponding model. Then, the model is classified as normal or abnormal by the trained classifier. Furthermore, if the road has anomalies that can be subdivided, incremental one-class learning is used to classify unknown anomalies.

Fig. 10 shows some results of OCSVM classification after mapping the GPR data obtained along the road from data space to model space. Fig. 11 illustrates some identified abnormalities in the data. In order to intuitively show the classification effect of
The model space, t-distributed Stochastic Neighbor Embedding (t-SNE) \cite{52} is used to reduce the obtained model to three dimensions for visualization. It should be pointed out that the actual model space is far more than three-dimensional. In the model space, it could be observed that the data is clearly divided into normal and abnormal by the blue and red points.

As aforementioned, after performing OCSVM for the same type of abnormal data, we could further classify its mapped values in the model space through incremental OCSVM. A result of incremental OCSVM classification after mapping a GPR image from data space to model space with representative GPR images for each class is illustrated in Fig. 12. Intuitively, the GPR images of different underground structures are clustered into four categories in the model space. After completing the anomaly classification, the overlapping GPR image segments of the same type are merged to obtain the final anomaly GPR image since the length of some anomaly regions in the image exceeds the length of the sliding window. There is a case worth noting that a few different types of GPR image segments appear in a stream of segments that have been classified into the same type of anomaly. In this case, we use a “voting” method to determine the type of these segments. Specifically, we classify the minority of segments that are identified as other types into the majority type, and label the merged GPR image according to the majority type. Fig. 13 shows some of the merged images. Specific results are presented in the following.

Since the collected data in this article has been manually classified and some locations with part of underground anomalies were excavated and repaired. Supervised learning tasks could also be utilized in the conducted model space. In the obtained real-world data, as Fig. 11(a) shows, the GPR images collected along each normal road segment are similar, while the number of anomalies is less than the normal images. For supervised learning, we select a total of about 4000 GPR image segments from the 10 groups, of which about 2500 are normal and about 1500 are generated by subsurface anomalies. Afterwards, the 10-fold cross-validation experiment is carried out. Specifically, the GPR image segments in one of the 10 groups are selected as the test set each time, and the GPR image segments in the remaining 9 groups are used as the training set. Several representative supervised learning methods, including KNN \cite{45}, Random Forest \cite{46}, and SVM \cite{47}, are utilized in the model space. Specific results of semi-supervised and supervised learning tasks in the model space are presented in Tables I and II.

In our experiments, no matter supervised or unsupervised learning, the method proposed in this article does not require many or multiple types of data for training. The wrong classification mainly comes from the window data that has just stepped from the normal part to the abnormal part or is about to leave the abnormal part, as shown in Fig. 14. The data at this kind of window would be mapped to “transition points” in the model space as shown in Fig. 15. These transition points reflect the sensitivity of the model space method to anomalies, but to some extent, this phenomenon would cause confusion when sliding through two or more adjacent anomalies. Therefore, further studies could be performed on the trajectories of points in the model space to improve the accuracy of anomaly classification. Besides, in real-world applications, the positioning data could be erroneous. For example, in the case of tall buildings and trees in urban cities, satellite-based positioning signals of GPS could be blocked \cite{53}. The positioning accuracy of an odometer would degrade when a rough or slippery ground is measured \cite{54}. Thus using a range slightly larger than the anomaly area to locate the subsurface anomaly could help find the real-world anomalies after processing the GPR image.

**TABLE I**

| Road          | Precision | Recall | $F_{1}$-score |
|---------------|-----------|--------|---------------|
| Cement Road   | 98.01%    | 98.49% | 98.24%        |
| Asphalt Road  | 98.33%    | 98%    | 98.16%        |
| Non-paved Road| 97.33%    | 98.65% | 97.99%        |

**TABLE II**

| Algorithm      | Precision | Recall | $F_{1}$-score |
|----------------|-----------|--------|---------------|
| KNN            | 98.01%    | 96.11% | 97.05%        |
| Random Forest  | 97.43%    | 96.46% | 96.94%        |
| SVM            | 97.97%    | 95.65% | 96.80%        |
Fig. 14. Schematic diagram of transition stage of GPR image. (a) and (b) are two examples of underground anomalies, in which the blue part of the sliding window is the normal part, the red part is the abnormal part, and the yellow dotted line is the dividing line. The GPR image state transition data shown here are mapped to transition points in the model space.

Fig. 15. Visualization of the transition points in the model space. In the model space, the points in the magenta circle are the part where the sliding window starts to slide to the abnormal part.

C. Comparison and Analysis

In this subsection, comparative work and analysis are conducted, including the comparison between the proposed method and other state-of-art methods, comparison between the ESN and the proposed 2D-ESN based on the framework learning in the model space, analysis of different spectral radii of 2D-ESN, the iterative direction, and the effects of various window sizes.

1) Comparison and Analysis With Other Methods: To evaluate the efficiency and effectiveness of the proposed method, comparison of the proposed method on the supervised learning task against Histograms of Oriented Gradient (HOG) [55], Deep Residual learning (ResNet) [56], and AlexsNet [57] is conducted. The compared methods (HOG+SVM, AlexsNet, ResNet-18) could directly classify GPR B-scan image segments into classes. The proposed method first fits the GPR image segments with 2D-ESN, and then uses KNN to classify the fitted 2D-ESN models in the model space. Specific results of the comparison are presented in Table III.

Fig. 16. Visualization of the window data in the (a) model space and (b) HOG feature space. Compared with the HOG feature space, in the model space, the data has a better clustering result.

| Algorithm       | Precision | Recall | P1 score | Time(s) |
|-----------------|-----------|--------|----------|---------|
| HOG+SVM         | 98.11%    | 92.59% | 95.27%   | 3.08    |
| AlexNet         | 98.96%    | 94.16% | 96.30%   | 620     |
| ResNet-18       | 98.79%    | 93.57% | 95.87%   | 843     |
| Proposed Method | 98.01%    | 96.11% | 97.05%   | 25.79   |

Histogram of Oriented Gradient (HOG) [55] is a feature descriptor used in image processing for object detection. In this article, HOG with the cell of size $32 \times 32$ is utilized to extract the feature of the window data. And then, SVM is used for classification in the HOG feature space. This algorithm counts the number of occurrences of gradient directions in local parts of the image, which mainly focuses on contour information. However, the GPR B-scan image is generated by arranging received EM waves horizontally in a temporal or spatial relationship, and representing the wave intensities with corresponding grayscale values. Thus it not only has the continuity of detection time or position in the horizontal direction but also correlates in the vertical direction due to the continuity of the underground medium and EM waves. The diagnosis in GPR images should regard the GPR image as a whole and take the continuity and changing laws in both the two directions into account, not only limited to the contour information of the image. The proposed method captures the changing regularity, i.e., the dynamic characteristics of GPR images by fitting the image with the designed 2D-ESN model. Fig. 16 shows an example of a comparison between the fitted 2D-ESN models and HOG features. It can be observed that the blue (normal) and black (abnormal1) dots in the HOG are intertwined and difficult to separate. Intuitively, models fitted by different types of GPR images in the model space show larger inter-class distances. As a result, as shown in Table III, HOG has high computational efficiency, but with a limited recall.

For AlexNet and ResNet-18, deep learning methods usually have large-scale parameters, and gradually converge the model through the gradient descent algorithm, putting forward requirements on the quantity, format, and quality of the training data,
along with the non-negligible off-line training time and computing resources. In underground diagnosis, the underground environments could be varying, and it could be difficult, if not impossible, to collect and label sufficient training data in the same or similar underground environment. This leads to a relatively low recall since the network could not be well-trained. However, the proposed method focuses more on the internal dynamic characteristics of the data, and only the ridge regression is utilized to fit the data, coupled with a mature and efficient distance-based classifier such as KNN and SVM in the model space. It could be observed from Fig. 16(a) that the GPR images generated by the same type of underground structures with similar dynamic characteristics are transformed into similar 2D-ESN models. Conversely, models fitted from one type of subsurface anomaly have significant differences from normal ones or other types of anomalies due to their distinct dynamic characteristics.

2) Comparison Between Learning in the ESN and 2D-ESN Model Space: In order to evaluate the effectiveness of the 2D-ESN compared with original ESN for underground diagnosis in the GPR image, both the ESN and 2D-ESN are performed on the supervised learning task. According to the results in Table IV, 2D-ESN performs better in this task, since it fully captures the dynamic characteristics in both horizontal and vertical directions, more in line with the changing laws in the GPR image. The performance of the ESN gets better with larger reservoirs, but even with larger reservoirs, the classification performance in the ESN model space is not as good as that of the 2D-ESN. Moreover, the size of obtained ESN models increases linearly with the size of the reservoir. The larger reservoir leads to excessive size of the model when processing GPR B-scan images, resulting in a longer running time and taking up much more memory. However, the 2D-ESN processes the data point-by-point to build 2-directional connections within the data, and satisfactory results could be obtained in the fitted 2D-ESN model space with an appropriately sized reservoir. As a result, for underground diagnosis in GPR images, the proposed 2D-ESN can achieve better results in a shorter running time and with a much smaller memory footprint compared with the original ESN.

3) Effects Under Different Spectral Radii of 2D-ESN: In GPR images, continuity exists both in the EM waves and the subsurface media. Nevertheless, anomalies may appear suddenly, and whether an abnormality currently occurs is not greatly affected by the long previously processed data. Therefore, a smaller spectral radius is chosen to ensure that the current processing data is relevant to the nearby, but not greatly affected by the farther data. We also evaluate the effect of different spectral radii on the supervised learning tasks, and the obtained results are presented in Table V.

From the results, it could be observed that for underground diagnosis, a larger spectral radius has a relatively large negative impact on the results. Choosing a smaller spectral radius not only takes into account the continuity existed in the GPR images, but is also more sensitive to sudden anomalies.

4) Analysis of the Iterative Direction in Column-Wise or Row-Wise Ways: In real-world applications, underground detection is carried out along the road. According to Fig. 3, each column of the collected GPR B-scan image is a representation of a received EM wave. Thus, the vertical direction of the GPR image is referred to as the detection at the current moment and position. The horizontal direction of the GPR image refers to the detecting direction, along which the GPR is moved. Therefore, the GPR image is collected column by column. In order to evaluate the effect of the 2D-ESN in row-wise and column-wise ways, the supervised learning tasks are performed respectively. The obtained results are presented in Table VI.

From the results, there is not much difference between the row-wised and column-wise. If we treat each GPR image segment as an independent data sample, no matter which way, 2D-ESN establishes both horizontal and vertical connections within the image. Besides, the column-by-column way is more in line with real-world detection, and it is adopted in our method.

5) Analysis of Different Window Sizes: The size of the sliding window deserves attention in this task. First, the 2D-ESN regards the GPR image in the window as a whole, and fits the data by capturing the dynamic characteristics within the data. Similar to ESN and other reservoir computing methods [28], [33], iterations are required in 2D-ESN to ensure that the dynamic characteristics of the GPR image are fully captured, and to stabilize the model (due to the randomness in the hidden layer). Therefore, the size of the window should not be too short. Second, as Fig. 17 shows, to fully extract GPR images of underground anomalies for subsequent analysis or repair, the final underground anomaly is obtained by merging overlapped image segments that are identified as containing anomalies. Thus
Fig. 17. Fully extract GPR images of underground anomalies for subsequent analysis or repair, the final underground anomaly is obtained by merging overlapped image segments that are identified as containing anomalies. As the window slides from the normal part to the abnormal (or slides away from the abnormal), some windows containing both normal and abnormal parts are identified as abnormal and eventually merged.

### TABLE VII
RESULT OF SUPERVISED TASKS IN THE 2D-ESN MODEL SPACE WITH DIFFERENT WINDOW SIZES

| Window Size | Precision | Recall | \( F_1 \)-score | Time |
|-------------|-----------|--------|-----------------|------|
| 100         | 90.06%    | 93.41% | 90.70%          | 9.64 |
| 200         | 93.00%    | 94.87% | 93.93%          | 17.14|
| 300         | 98.01%    | 96.11% | 97.05%          | 25.79|
| 400         | 97.97%    | 96.05% | 97.06%          | 30.98|
| 500         | 95.85%    | 96.22% | 96.18%          | 38.26|

an excessively long window might result in too large a range of abnormalities after merging. Besides, a larger window will also lead to a longer fitting time.

To evaluate the effect of different window sizes, we conduct supervised learning tasks with different window sizes. The obtained results are presented in Table VII. It could be found that when the window size reaches 300, the precision, recall, and \( F_1 \) score reach a higher level, and would not increase significantly as the window size gets larger.

### VI. CONCLUSION

In this article, a GPR B-scan image diagnosis method based on learning in the model space is proposed. A sliding window is constructed and swiped across the obtained GPR image. The GPR image in each sliding window is mapped into model space by the proposed 2D-ESN. The distance measuring method for 2D-ESN is modified in the constructed model space. Based on the constructed model space and distance measuring method, supervised and semi-supervised algorithms could be utilized to identify or classify anomalies on GPR B-scan images. Both detection position and time continuity in the horizontal direction and medium continuity in the vertical direction of the GPR B-scan image are taken into account in the proposed 2D-ESN. Therefore, the proposed 2D-ESN processes images from the point level, which can effectively reduce the dimension of the fitted model, thereby reducing the memory usage. When applying the proposed method, only a normal GPR image segment of the detection area (i.e., no subterranean anomalies) is required to start the diagnosis. Experiments on real-world datasets are conducted, and both supervised and semi-supervised learning in the model space have achieved considerable results. In future work, we plan to extend 2D GPR B-scan images to multi-dimensional correlated data and design models for these data to achieve efficient mapping from data space to model space. On the other hand, we will study the model change trajectory in the model space (that is, the trajectory of the point in the model space) and design abnormality warning algorithms.

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