Location distribution detection of urban drainage pipeline based on deep learning feature

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Abstract: In order to improve the accuracy and efficiency of drainage pipeline location distribution detection, a new urban drainage pipeline location distribution detection method based on depth learning feature is proposed in this paper. Firstly, the main contents of drainage pipeline location data are analysed, and the drainage pipeline data are collected by acoustic detection method. Secondly, the dual tree complex wavelet method is used to extract the location distribution characteristics of urban drainage pipelines. Finally, the deep convolution neural network is used to train the location distribution characteristics to complete the detection results of urban drainage pipeline location distribution. The experimental results show that compared with the traditional detection methods, the detection accuracy of this method is higher and the time is shorter.

Keywords: deep learning features; urban drainage belt; position distribution detection.

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1 Introduction

Drainage pipeline is an indispensable part of urban pipe network system. As a basic urban facility, drainage pipeline undertakes the real-time discharge of sewage, urban rainfall and other drainage needs (Wang et al., 2019). With the development of urbanisation in China, the construction of drainage pipeline system has also developed rapidly, and the overall structure is more perfect (Junaidi et al., 2018). However, with the complexity of urban construction, the layout of drainage pipelines is more complex, and urban construction is often divided into old urban areas and new urban areas, which are built in time (Dobrescu, 2021; Bai, 2018; Kndler et al., 2019). Whenever it is necessary to optimise the drainage pipeline structure and detect congestion, the location of urban drainage pipeline should be determined first. However, with the age of old urban areas and the complicated distribution of drainage pipelines, the location distribution of drainage pipelines is more complex and difficult to detect. Therefore, it is of great practical significance to study the location distribution detection method of drainage pipeline.

Liu and Yuan (2019) proposes a method for detecting the location distribution of drainage pipelines based on CCTV method. This method first uses CCTV pipeline endoscope technology to collect the layout of drainage pipelines, and obtains the location distribution results of urban pipelines through three-dimensional simulation software. Although this method can obtain more accurate detection results of drainage pipeline position distribution, it takes a long time due to the need for overall pipeline layout, so it is easy to be limited in practical application. Peng et al. (2021) proposes a method for detecting the location distribution of urban drainage pipelines based on improved convolution neural network. This method detects the location distribution based on pipeline image recognition, constructs the objective function of pipeline recognition, and solves the objective function according to the distribution characteristics to complete the detection of location distribution. However, the location distribution feature extraction accuracy of the drainage pipeline based on this method is insufficient, resulting in the low detection accuracy of the final location distribution. Guo et al. (2021) proposed the location distribution detection results of urban drainage pipelines based on scenario simulation. In this method, the network distribution model of urban drainage pipelines is constructed through scenario simulation method, different key detection points are set, and the location distribution results of the whole drainage pipeline are obtained through the location distribution of different detection points. However, because the method obtains the overall pipeline position distribution results through discontinuous detection points, the detection accuracy is insufficient.

In order to solve the problems of low detection accuracy and long detection time of the above traditional methods, a location distribution detection method of urban drainage pipeline based on depth learning feature is proposed. The overall research technical route of this method is as follows:

1 The type of drainage pipeline position data is analysed, and the acoustic detection method is used to collect the drainage pipeline position data.

2 Based on the collected data, the double tree complex wavelet method is used to extract the location distribution characteristics of urban drainage pipeline. According to the extracted location distribution characteristics, the deep convolution neural network is used for training and processing, and the output result is the detection result of urban drainage pipeline location distribution.

3 Experimental verification, taking the extraction accuracy of drainage pipeline distribution characteristics and the detection accuracy of drainage pipeline position distribution as the experimental comparison index, the comparative verification experiment is carried out.

2 Location and distribution detection of urban drainage pipeline

2.1 Acoustic data acquisition based on urban drainage pipeline

The collection of urban drainage pipeline data is the basis of location distribution detection. The urban drainage pipeline data to be collected in this study mainly includes the following contents:

1 Topographic data, topographic data on both sides of the centre line of the drainage pipeline, road name, sideline and ownership data, and nearby topographic map, etc.

2 Diameter, length, construction time, construction unit of drainage pipeline, as well as pit conditions upstream and downstream of the pipeline, etc.

3 Coordinate data, well cover height and specification data of pipeline cellar well, including well cover size, well depth and bottom falling form (Magana et al., 2020; Ying et al., 2018; Yang et al., 2018).

From the above contents, some data can be obtained by consulting relevant materials, and the actual location of the drainage pipeline is the focus of this data acquisition. Therefore, the acoustic detection method is used to accurately collect the data of the location of the drainage pipeline. The specific process is as follows.

The sound wave p_i is injected into the pipe S_1, when the incident sound wave encounters the acoustic load, it will generate a reflected wave and a transmitted wave in the pipe, which are respectively represented by p_r and p_t (Kumar et al., 2018). Obviously, there is a certain correlation between the above three kinds of sound waves, and the correlation occurs at the interface where the pipeline interface changes. Therefore, the correlation can be expressed as the continuous relationship of sound pressure and the relationship of volume velocity. The specific expression of the two correlation relationships is as follows:

$$p_i + p_r = p_t \tag{1}$$

$$S_1\left(v_i + v_r\right) = S_2 v_t \tag{2}$$

In formula (2), v_i, v_r and v_t represent the volume velocities of incident wave, reflected wave and transmitted wave respectively.

In urban drainage pipelines, there are differences in the acoustic principles between tee fittings and ordinary pipes, so the tee fittings in the drainage network will affect the data collection accuracy of acoustic detection technology. In the tee, the expression for the acoustic impedance is:

$$Z_b = R_b + jX_b \tag{3}$$

In the formula, Z_b represents the cross-sectional area of the tee, R_b represents the acoustic resistance, and X_b represents the acoustic reactance (Kimia et al., 2018).

In urban drainage pipeline, the correlation expression between sound pressure and volume velocity at the connection between main pipeline and tee pipe is as follows:

$$p_i + p_r + p_t = p_b \tag{4}$$

$$\frac{s_{p_i}}{\rho_0 c_0} - \frac{s_{p_r}}{\rho_0 c_0} = \frac{s_{p_t}}{\rho_0 c_0} + \frac{p_b}{z_b} \tag{5}$$

In the formula, p_t represents the transmitted wave of sound wave in the tee.

Combined with dual tree complex wavelet, the acoustic test results of drainage pipeline are filtered to improve the accuracy of data acquisition. The expression of dual tree complex wavelet is:

$$\psi_c(t) = \psi_h(t) + i\psi_g(t) \tag{6}$$

In the formula, $\psi_h(t)$ represents the real part of the wavelet, $\psi_g(t)$ represents the imaginary part of the wavelet, i represents the complex unit, h represents the real part filter and g represents the imaginary part filter.

As the name suggests, dual tree complex wavelet is a wavelet transform composed of two wavelet transform structures. Therefore, the principle of wavelet transform is also applicable to dual tree complex wavelet. Calculate the wavelet coefficients and scale coefficients of the real part of dual tree complex wavelet:

$$dI_j^{\mathrm{Re}}(n) = 2^{j/2} \int_{-\infty}^{+\infty} x(t)\psi_h\left(2^j t - n\right) dt,\ j = 1, 2, \ldots, J \tag{7}$$

$$cI_J^{\mathrm{Re}}(n) = 2^{J/2} \int_{-\infty}^{+\infty} x(t)\psi_h\left(2^J t - n\right) dt \tag{8}$$

Similarly, the wavelet coefficients and scale coefficients of the imaginary part of the dual tree complex wavelet can be calculated:

$$dI_j^{\mathrm{Im}}(n) = 2^{j/2} \int_{-\infty}^{+\infty} x(t)\psi_g\left(2^j t - n\right) dt,\ j = 1, 2, \ldots, J \tag{9}$$

$$cI_J^{\mathrm{Im}}(n) = 2^{J/2} \int_{-\infty}^{+\infty} x(t)\psi_h\left(2^J t - n\right) dt \tag{10}$$

Add the above formula to construct the overall wavelet coefficient and scale coefficient of dual tree complex wavelet transform:

$$d_J^{\varphi}(n) = dI_j^{\mathrm{Re}}(n) + jdI_j^{\mathrm{Im}}(n),\ j = 1, 2, \ldots, J \tag{11}$$

$$C_J^{\varphi}(n) = cI_J^{\mathrm{Re}}(n) + icI_J^{\mathrm{Im}}(n) \tag{12}$$

In the sound field of urban drainage pipeline, it is set that there is a volume element V_0, the initial volume of the volume element is ρ_0, the medium density at the volume element of the sound field is P_0, and the pressure at the volume element is. Since the sound wave propagates from a section of the drainage pipe, the volume element will vibrate to a certain extent with the propagation of the sound wave. Therefore, set the kinetic energy as ΔE_k, the variation range of pressure in the vibration process as $P_0 \to P_0 + p$, and the potential energy in the vibration process as ΔE_p. Combined with the above parameters, the acoustic energy of volume element is calculated:

$$\begin{aligned} \Delta E = \Delta E_k + \Delta E_p &= \frac{1}{2}\left(\rho_0 V_0\right) v2 + \left(-\int_0^p p dV\right) \\ &= \frac{V_0}{2}\rho_0\left(v2 + \frac{1}{\rho_0^2 c_0^2}\right)p^2 \end{aligned} \tag{13}$$

Then the calculation formula of energy density per unit volume in the drainage pipeline can be constructed:

$$\varepsilon = \frac{\Delta E}{V_0} = \frac{1}{2}\rho_0\left(v2 + \frac{1}{\rho_0^2 c_0^2}\right)p^2 \tag{14}$$

In the drainage pipeline, the propagation mode of sound wave is plane wave, so the instantaneous value of sound energy density is calculated by the following formula:

$$\Delta\tilde{E} = \frac{V_0}{2}\rho_0\left[\frac{p_a^2}{\rho_0^2 c_0^2}\cos^2(wt - kx)\right] + \frac{p^2 a}{\rho_0^2 c_0^2}\cos 2(wt - kx) \tag{15}$$

Taking the average value of the calculation results of formula (15), the average time value of acoustic energy density in the drainage pipeline can be obtained:

$$\overline{\Delta\tilde{E}} = \frac{1}{T}\int_0^T \Delta E dt = \frac{1}{2}V_0 \frac{p_a^2}{\rho_0^2 c_0^2} \tag{16}$$

Calculate the average sound energy density in the drainage pipeline as the location distribution characteristics of urban drainage pipeline:

$$\tilde{\varepsilon} = \frac{\overline{\Delta\tilde{E}}}{V_0} 2\frac{p_a^2}{\rho_0^2 c_0^2} = \frac{P_e}{\rho_0 c_0^2} \tag{17}$$

2.2 Location distribution detection of urban drainage pipeline based on deep learning feature

After extracting the location distribution features of urban drainage pipelines, the depth neural network is used to supervise the learning and training of the location distribution features. The deep convolutional neural networks (CNNs) with more hidden layers have a more complex network structure. Compared with the traditional machine learning methods, they have stronger ability of feature learning and expression, and can improve the effectiveness of urban drainage pipeline location distribution detection. The location distribution detection process is shown in Figure 1.

Based on the collected data, the location distribution features of urban drainage pipelines are extracted, and trained in the feature space to get the final location distribution detection results.

The location distribution characteristics of urban drainage pipes extracted in Subsection 2.1 can be directly used as input layer data without pre-processing the data. Level by level training can improve the accuracy of location distribution detection (Luo and Hu, 2020; Zheng et al., 2020). The principle of training the position distribution characteristics of drainage pipeline by deep convolution neural network is shown in Figure 2.

Figure 1 Location distribution detection process

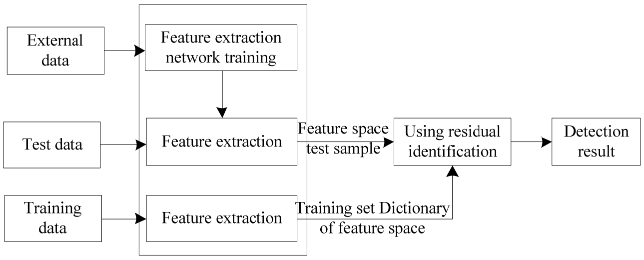
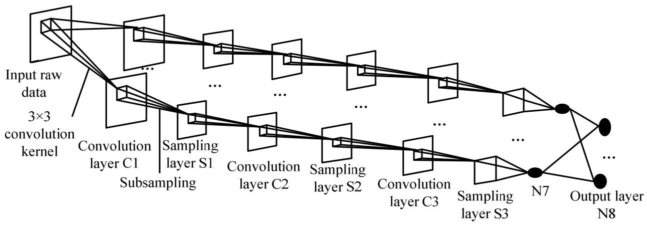


Figure 2 Principle of deep learning feature extraction



From the training principle shown in Figure 2, it can be seen that the deep convolution neural network consists of input layer, convolution layer, down sampling layer and feature vector layer. The parameters of each hierarchy are shown in Table 1.

Table 1 Hierarchy and parameters of deep convolution neural network

Layer number	*Type*	*Number and size of characteristic drawings*	*Convolution kernel*
0	Input layer X0	1 and 48 × 48	-
1	Convolution layer C1	100 and 46 × 46	3 × 3
2	Down sampling layer S1	150 and 23 × 23	2 × 2
3	Convolution layer C2	150 and 20 × 20	4 × 4
4	Down sampling layer S2	150 and 10 × 10	2 × 2
5	Convolution layer C3	250 and 8 × 8	3 × 3
6	Down sampling layer S3	250 and 4 × 4	2 × 2
7	Full connection layer N7	200 and 1 × 1	4 × 4
8	Feature output layer N8	32 and 1 × 1	-

The specific steps of using depth neural network to detect the location distribution of urban drainage pipeline are as follows:

1 Network learning: The $f(y)$ of CNN is extracted from external learning data, and the feature training sample $X = \{X_1, X_2, \ldots, X_l, \ldots, X_C\}$ is mapped. The mapping expression is:

$$X_1' = f(X_i) \tag{18}$$

After the mapping process is completed, the training dictionary $\{X_1', X_2', \ldots, X_i', \ldots, X_C'\}$ of the feature space of the deep neural network is obtained.

2 Input layer: The 48 × 48 mapping template is directly used as the training input of the deep neural network.

3 Convolution layer: After receiving the characteristic image $X_{l-1,j}$ and convolution kernel $k_{l,x} \times k_{l,y}$ input from the input layer, the convolution layer obtains the characteristic $X_{l,j}$ in the convolution l layer through the convolution combination operation. The expression is:

$$X_{i,j} = f\left(\sum_{i \in M_j} X_{l-1,j} * w_{l,i,j} + b_{l,j}\right) \tag{19}$$

In the formula, M_j represents the set composed of the input layer characteristic diagram $X_{l-1,j}$, $w_{l,i,j}$ represents the weight of convolution calculation, and $b_{l,j}$ represents the bias parameter.

4 Downsampling layer: In the downsampling layer, the convolution result is downsampled through the downsampling function:

$$X_{l,i} = f\left(\beta_{l,i} down\left(X_{l-1,j}\right) b_{l,j}\right) \tag{19}$$

In the formula, $down(.)$ represents the downsampling function and $\beta_{l,i}$ represents the multiplicative bias parameter.

5 Position distribution detection output: Calculate the expression coefficient of urban drainage pipeline location distribution:

$$\hat{\alpha}' = \arg\min_{\alpha'} \left\| y' - X'\alpha' \right\|_2^2 + \lambda \alpha_1' \tag{20}$$

The distribution expression of the pipeline is constructed according to the location of the pipeline, and the calculation result is expressed as follows:

$$identity = \arg\min_{i'} \left\| y' - X_i' \hat{\alpha}_i' \right\|_2^2 \tag{21}$$

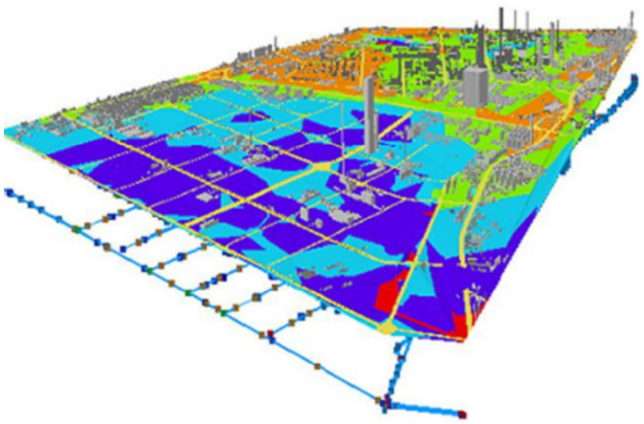
3 Experimental verification

In order to verify the detection performance of the proposed location distribution detection method of urban drainage pipeline based on deep learning feature, simulation and comparative verification experiments are carried out.

Taking the drainage pipeline in the city as the research object, the location distribution of drainage pipeline is detected. The three-dimensional simulation diagram of urban drainage pipeline is shown in Figure 3.

According to the urban drainage pipeline shown in Figure 3, the acoustic detection method is used to collect the location distribution data of the drainage pipeline, and the collected data is stored in MySQL database as the experimental sample data. The total amount of data is 3 GB.

Figure 3 Three dimensional simulation diagram of urban drainage pipeline (see online version for colours)

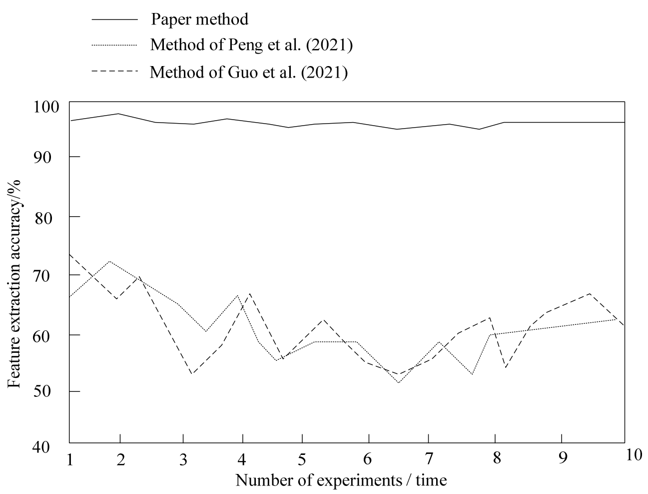


After the selection of experimental objects and the collection of data, the simulation comparison and verification experiment is started. Before the experiment, in order to reduce the experimental error and improve the reliability of simulation and verification, the method in this paper is compared with the methods in Peng et al. (2021) and Guo et al. (2021), taking the extraction accuracy of drainage pipeline distribution features and the detection accuracy of drainage pipeline position distribution as the actual comparison indexes.

3.1 *Accuracy of feature extraction of urban drainage pipeline distribution*

A key step in the drainage pipeline position distribution detection method is to extract the distribution characteristics of urban drainage pipelines. Therefore, the extraction accuracy of drainage pipeline distribution characteristics of this method is verified. The comparison results of this method with those of Peng et al. (2021) and Guo et al. (2021) are shown in Figure 4.

Figure 4 Extraction accuracy of distribution characteristics of drainage pipeline



From the comparison results of the extraction accuracy of drainage pipeline distribution features shown in Figure 4, it can be seen that among the three comparison methods, the extraction accuracy of drainage pipeline distribution features of this method is the highest, and the fluctuation range is small, which is always stable at about 96%. However, the accuracy of drainage pipeline distribution feature extraction by Peng et al. (2021) and Guo et al. (2021) fluctuates greatly, and the level is low, with a maximum of more than 80%.

3.2 *Detection accuracy of location distribution of urban drainage pipeline*

Through the above experiments, the accuracy of drainage pipeline position distribution feature extraction is verified. In this part, the detection accuracy of drainage pipeline position distribution by different methods is compared and verified. The detection accuracy results of drainage pipeline position distribution by the three methods are shown in Table 2.

Table 2 Location distribution and detection accuracy of urban drainage pipeline

Number of experiments/ time	*Detection accuracy of drainage pipeline position distribution/%*		
	Paper method	*Peng et al. (2021) method*	*Guo et al. (2021) method*
1	95.2	72.5	62.6
2	95.2	70.6	62.8
3	95.2	69.5	62.9
4	99.5	71.1	62.4
5	99.5	71.3	62.8
6	99.5	72.2	62.9
7	92.7	70.1	64.1
8	92.7	71.7	61.4
9	97.1	71.9	61.8
10	97.2	73.1	62.7

By observing the comparison results of the detection accuracy of drainage pipeline position distribution shown in Table 2, it can be seen that there is a large gap in the detection accuracy results of the three methods under multiple experiments. The detection accuracy of drainage pipeline position distribution of this method is more than 92%, the detection accuracy of Peng et al. (2021) method is about 70%, and the detection accuracy of Guo et al. (2021) method is about 60%.

4 Conclusions

In order to improve the detection accuracy of urban drainage pipeline position distribution and provide technical support for pipeline laying and maintenance, an urban drainage pipeline position distribution detection method based on deep learning feature is proposed. The performance of the method is verified from both theory and experiment. When detecting the location distribution of urban drainage pipeline, this method can accurately extract the location distribution characteristics of pipeline and improve the detection accuracy of pipeline location distribution. Specifically, compared with the method based on improved convolution neural network, the feature extraction accuracy of this method is significantly improved and is always stable at about 96%; compared with the method based on situation simulation, the position detection accuracy of this method is significantly improved, reaching more than 92%.

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