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NO-DIG INSPECTION TECHNOLOGIES FOR UNDERGROUND PIPELINES

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ABSTRACT

Inspection through diagnosis of pipe defects is the essential work of underground pipeline maintenance and rehabilitation. To avoid excavation, a No-dig inspection is commonly executed by manually interpretation on closed circuit television (CCTV) images, but this approach seems inefficient because of human's fatigue, subjectivity, and time-consumption. To solve this problem, several automated diagnosis systems have been developed to attempt to assist general staffs in diagnosin g pipe defects. In addition, many researchers pointed out that CCTV image quality would also influence accuracies of manually interpretation or automated diagnosis systems. Therefore, a procedure of inspection through pipe defect diagnosis is proposed and applied to sewer inspection. This paper briefly introduces a series of inspection technologies involving image quality assessment, morphological feature extraction of pipe defects, and radial basis network (RBN)-based automated diagnosis system. The experimental results show that the proposed image quality index is useful in assessing CCTV image quality and the overall diagnosis accuracies of above 90% can be obtained by the automated diagnosis system.

Key words: No-dig inspection, diagnosis of sewer pipe defects, CCTV image quality assessment, radial basis network (RBN).

1. INTRODUCTION

Inspection is the first step and has the greatest impact on efficacy of underground pipeline maintenance and rehabilitation. To avoid excavation, a No-dig inspection is commonly executed. Either closed circuit television (CCTV) or scanner evaluation technology (SET) mounted on robots is the most popularly inspection equipment to record defects for underground pipelines (Iyer & Sinha 2005; Sinha & Fieguth 2006). CCTV technology compared to SET system is more popular due to its low setup cost and technical requirement (Yang *et al*. 2010). Traditionally, pipe defects are generally detected and classified by human interpretation on inspection images, but this approach would result in incorrect or subjective inspection results (Iyer & Sinha 2005; Yang & Su 2008; Yang & Su 2009). Sewer system is one of the major underground pipelines in modern cities. Thus, several diagnosis systems of sewer pipe defects based on artificial intelligence had been developed to assist the technician-s in interpreting or classifying sewer pipe defects (Wirahadikusumah *et al*. 1998; Xu *et al*. 1998; McKim & Sinha 1999; Gokhale & Graham 2004; Iyer & Sinha 2005; Shehab & Moselhi 2005; Sinha & Fieguth 2006; Yang & Su 2008; Yang & Su 2009).

2. INSPECTION TECHNOLOGIES

The experimental results of the above diagnosis systems concluded that good image quality is the prerequisite for accurate interpretation. Recently, a systematic evaluation approach of CCTV image quality has been presented and applied to the CCTV images before diagnosis of pipe defects (Yang *et al*. 2010). Once the CCTV images are qualified and accepted, morphology segmentation are implemented on them to extract the morphologies of the pipe defects. If a pipe defect is successfully segmented by comparing with its ideal morphology based on the morphological features, including area, major axis length, minor axis length, eccentricity (between 0 and 1), and ratio of major axis length to minor are measured. As for the pipe defects failing to be segmented, the measurement of morphological features is skipped and the major failure cause is researched. Based on the measured morphological features, the automated diagnosis system is able to classify the pipe defects. Finally, the diagnosis accuracies, including producer's accuracy, user's accuracy, and overall accuracy are also assessed. The scheme of the proposed inspection technologies is illustrated as Fig. 1 by integrating image quality assessment, morphological feature extraction of pipe defects, and radial basis network (RBN)-based automated diagnosis system. The above technologies are briefly introduced as follows.

2.1 Quantification of Image Quality

With a value range between 0 and 1, an image quality index is calculated by multiplying luminance (L) similarity with contrast (C) similarity between reference and assessed images for the quantification of image quality (Yang *et al*. 2010).

Let X and Y be the reference and assessed images, respectively. Also, $x = \{x_i \mid i = 1, 2, \ldots, N\}$ and $y = \{y_i \mid i = 1, 2, \ldots, N\}$ express the gray values between 0 and 255, and N represents the number of pixels. Both with a value range of [0 1], L and C represent the luminance and contrast similarities, respectively (Franti 1998; Strasburger *et al*. 2002; Wang & Bovik 2002; Li & Bovik 2010).

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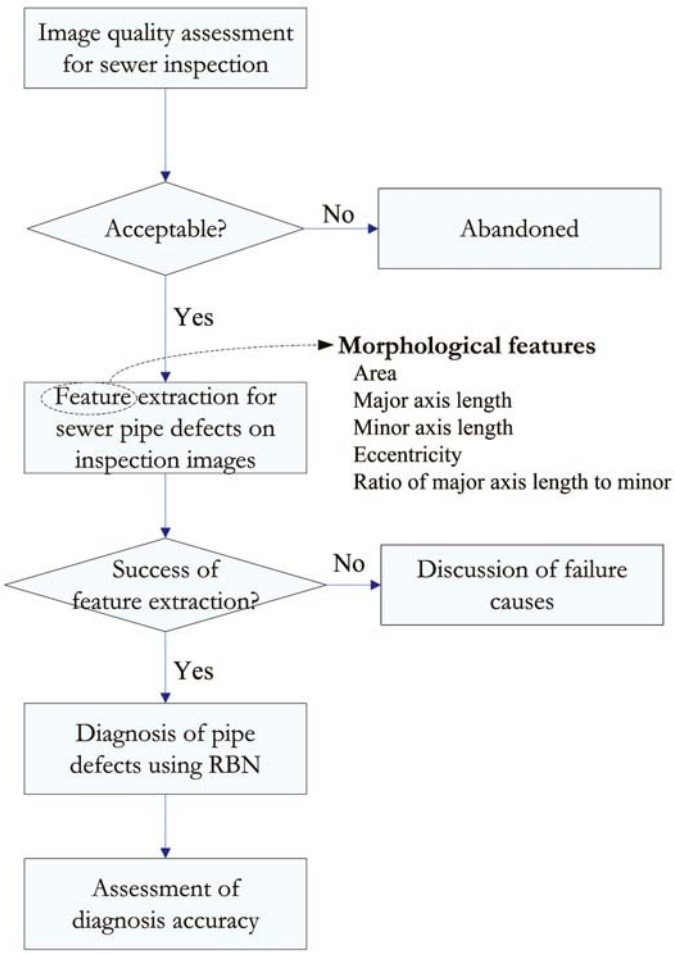


Fig. 1 The scheme of the operations of the proposed inspection technologies

$$L = \frac{2\bar{x}\,\bar{y}}{(\bar{x})^2 + (\bar{y})^2} , \qquad \bar{x} = \frac{1}{N}\sum_{i=1}^{N} x_i \ , \ \bar{y} = \frac{1}{N}\sum_{i=1}^{N} y_i \ , \tag{1}$$

$$C = \frac{2\sigma_x \, \sigma_y}{\sigma_x^2 + \sigma_y^2} , \tag{2}$$

$$\sigma_x^2 = \frac{1}{N-1}\sum_{i=1}^{N}(x_i - \bar{x})^2 \ , \ \sigma_y^2 = \frac{1}{N-1}\sum_{i=1}^{N}(y_i - \bar{y})^2 \ .$$

An assessed image with an image quality index approaching to 1 has a high similarity of luminance and contrast, respectively, to the ideal image and represents good image quality. The calculation of the image quality index and the detailed process of the image quality assessment are described in the literature of Yang *et al*. (2010).

Morphological feature extraction of pipe defects morphology-based segmentation is considered as an effective approach to segment out the pipe defects from CCTV images. A series of the morphology-based segmentation works including opening operation, image binary, and measurements of morphological features was proposed by Yang & Su in 2009. Opening operation, in which erosion immediately followed by dilation, is applied to a gray-level image using the same structuring element to well distinguish the pipe defect on a CCTV image (Parker 1997; Gonzalez & Woods 2002). Due to its non-parametric, unsupervised, and automatic characters, Otsu's technique is the most popular image binary method to find an optimal threshold for the opening operated gray-level image to segment the pipe defect (Sinha & Fieguth 2006). The details of opening operation, image binary, and measurements of morphological features are available in the literature of Yang and Su (2009).

2.2 Automated Diagnosis System

Yang and Su (2008) employed three common neural networks, *i.e.* back-propagation neural network (BPN), radial basis network (RBN), and support vector machine (SVM), to diagnose pipe defects based on the textural features on CCTV images. The test results indicate that BPN needs the longest computation time but with the lowest accuracy. SVM and RBN have better classification accuracy, but SVM needs to determine the best parameters within the kernel functions a prior based on heuristics at present (Seo 2007). Thus, RBN technique is suggested to be used to diagnose pipe defects based on their morphological features on CCTV images. The application of RBN to the diagnosis of pipe defects also can be found in the literature of Yang and Su (2009).

3. APPLICATION AND DISCUSSIONS

Four CCTV inspection video streams (I, II, II, and IV) were acquired from sewer inspection to represent the CCTV image quality of the four construction projects (project 30, project 31, project 32, and project 34) for connection house in Taichung city, which is the largest city in the central Taiwan, as shown in Fig. 2. Most of the underground sewer pipes are made of either vitrified clay pipe (VCP) or polyvinyl chloride (PVC) pipe in Taichung city. The information of the tested CCTV videos is listed on Table 1. The experimental results of the three inspection technologies applied to the sewer inspection and rehabilitation project are shown as follows:

3.1 Inspection Image Quality Assessment

In this paper, the inspection images within each CCTV inspection video stream were assessed against the six specific reference images as Fig. 3 (UK water industry engineering and operations committee 1994). Table 2 is the statistic of the inspection image quality analysis for the four video streams. Most CCTV video streams have great quality with a mean image quality index of above 0.85, except for Video II provided by project 31 with a mean image quality index of only 0.7. The quality assessment of the tested CCTV images varying with defect patterns is listed on Table 2 that illustrates "Crack" images have the least similarity against the ideal image. Also, according to the variation analysis of image quality including maximum, minimum, and mean values, in Fig. 4, Video III provided by project 32 has a significant quality variation in all six patterns of pipe defects, while Video I has the steadiest quality. Table 3 and Fig 5 show the distribution of image quality indices for all four video streams. Figure 6 also shows that the CCTV images of about 20% have an image quality index less than 0.6 for video II that may consider to be abandoned. As to the other CCTV images in the video stream II with an image quality below the average needs to be improved. Noticeably, the video stream III has the highest image quality identified by 48.9% CCTV images with an image quality index of above 0.9. According to this result, it is suggested that a CCTV video stream with a mean quality index of above 0.8 approximately can be considered acceptable. Those CCTV images with a quality index of below 0.7 needs to be enhanced and less than 0.6 should be abandoned.

3.2 Morphological Features of Pipe Defects

Opening operation and image binary using Otsu's technique were applied to the accepted inspection images in order to segment the morphologies of the pipe defects on the images. In our experiment, there were 291 CCTV inspection images including 107 samples of "open joint", 112 samples of "crack", 16 samples of "broken pipe", and 56 samples of "fracture". The experimental result shows that 33 of 107 samples of "open joint", 22 of 112 samples of "crack", and 5 of 16 samples of "broken" pipe were successfully segmented. Compared the success cases with failure cases, the major failure was caused by the intense light reflected from pipe wall that interfered the reflected light by pipe defects so to result in failure segmentation. Subsequently, for the 60 successfully segmented cases the morphological features were measured and found that the areas of "broken" pipe or "open joint" are much larger than those of cracks. The eccentricities of "crack" are almost above 0.9, so eccentricity can be regarded as the significant feature of crack.

Table 1 The tested CCTV video streams

Video ID	Project No.	Material	Frame number	Pipeline length (m)
I	30	VCP	16,573	35.6
II	31	PVC	4,498	44.1
III	32	PVC	3,613	5.7
IV	34	VCP	28,899	59.3

Table 2 The quality index of the tested CCTV images versus defect patterns

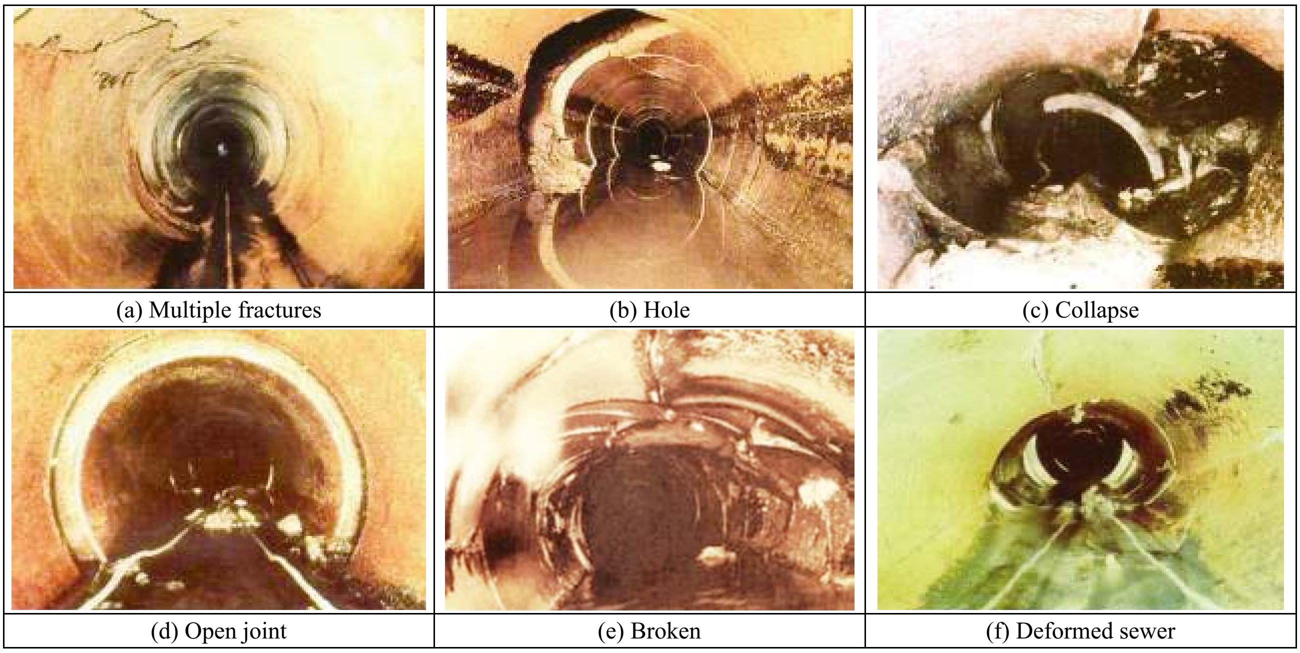
Video ID	Reference image						Average
	FM	H	C	OJ	B	DS	
I	0.8866	0.8938	0.7888	0.8552	0.8177	0.9220	0.8607
II	0.7289	0.7647	0.6131	0.6999	0.6418	0.7811	0.7049
III	0.8754	0.8858	0.7937	0.8532	0.8327	0.9194	0.8601
IV	0.8781	0.8843	0.7810	0.8425	0.8140	0.9155	0.8526

PS: FM = Multiple fractures; H = Hole; C = Collapse; OJ = Open joint; B = Broken; DS = Deformed sewer

Table 3 Statistic of the image quality analysis

Video ID	Image quality index							
	0.2-0.3	0.3-0.4	0.4-0.5	0.5-0.6	0.6-0.7	0.7-0.8	0.8-0.9	0.9-1.0
I	0.0%	0.0%	0.0%	0.0%	1.8%	18.3%	50.2%	29.7%
II	0.0%	0.0%	3.7%	5.1%	24.0%	64.2%	1.5%	1.5%
III	0.2%	0.2%	0.2%	1.4%	7.8%	13.5%	27.8%	48.9%
IV	0.0%	0.0%	0.0%	0.1%	3.1%	28.5%	33.5%	34.7%

Fig. 2 The location of four sewer construction projects in Taichung city



(a) Multiple fractures (b) Hole (c) Collapse

(d) Open joint (e) Broken (f) Deformed sewer

Fig. 3 Reference CCTV images

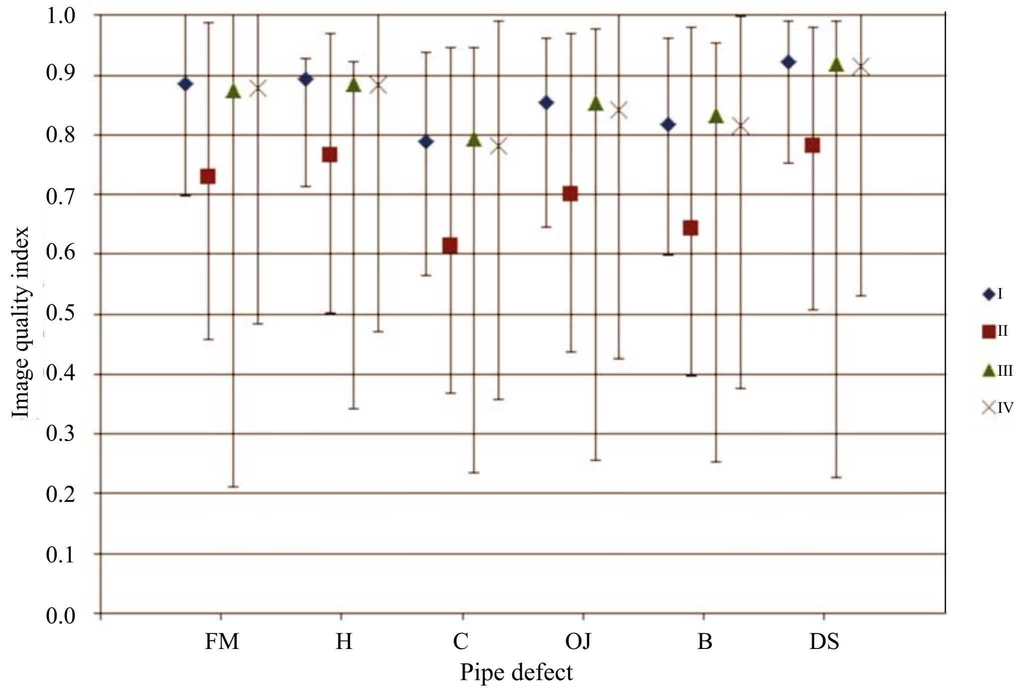


Fig. 4 Variation of CCTV image quality index versus pipe defect

3.3 Automated Pipe Defect Diagnosis by RBN

To train the automated diagnosis system, 30 pipe defect images which were randomly selected from the 60 pipe defect images which were implemented by an expertise-based human diagnosis a priori. Then, all 60 pipe defect images were diagnosed by the automated diagnosis system. Before inputting the morphological features of pipe defects into the automated diagnosis system, the five-dimensional set of data was transformed by PCA (principal component analysis) into a two-dimensional set of uncorrelated variables to represent about 95% information and reduce the computation effort. This two-dimensional set of uncorrelated variables was analyzed by the automated diagnosis system and obtained an overall accuracy of 95.0% (see Table 4).

4. CONCLUSIONS

This paper proposes an integrated procedure of no-dig pipe inspection for sewer defects. These inspection technologies involving image quality assessment, morphological feature extraction of pipe defects, and RBN-based automated diagnosis system, are briefly introduced and applied to sewer inspection in Taichung city. An image quality index considering luminance

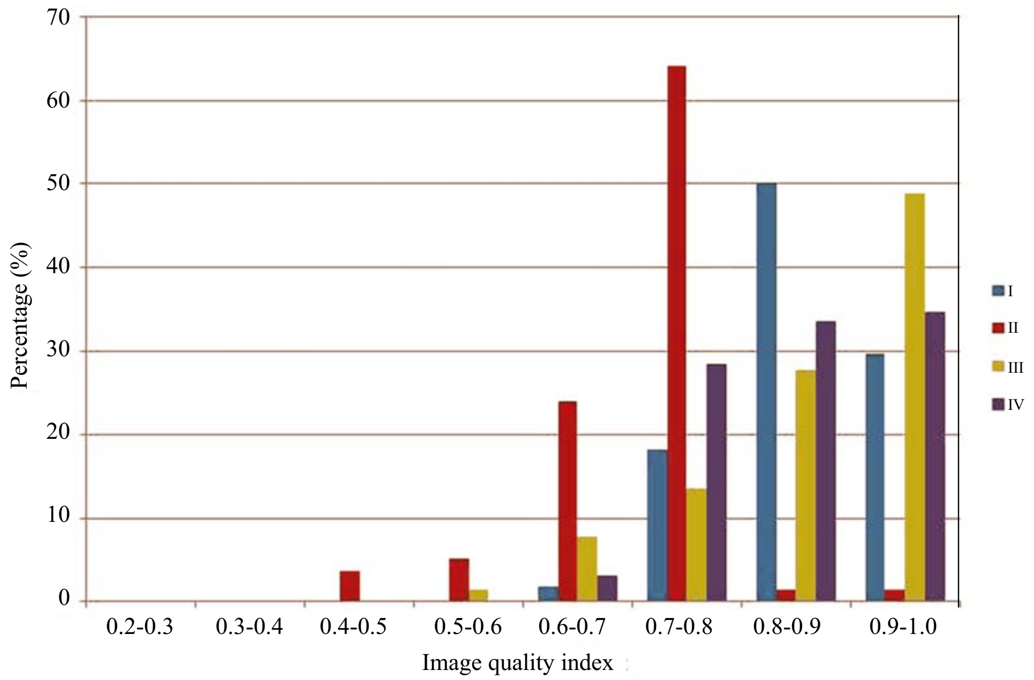


Fig. 5 Distribution of CCTV image quality index for the tested video streams

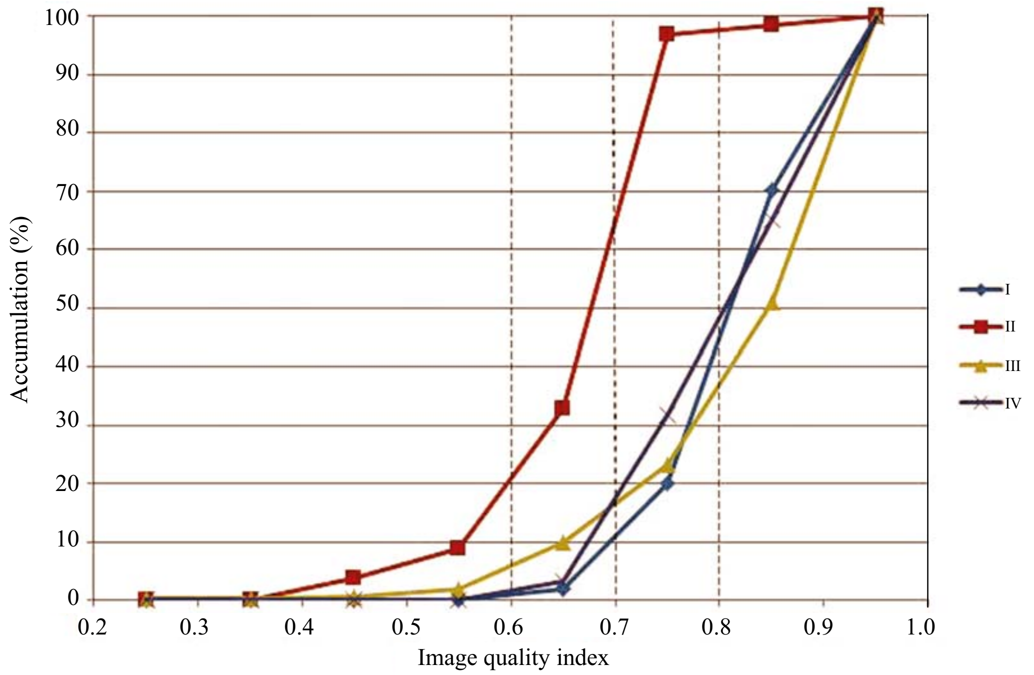


Fig. 6 Accumulation of CCTV image quality index for the tested video streams

Table 4 Classification matrix of sewer pipe defects

Classification data	Reference data			
	Broken pipe	Crack	Open joint	Row total
Broken pipe	3	0	0	3
Crack	0	21	0	21
Open joint	2	1	33	36
Column total	5	22	33	60
	Broken pipe	Crack	Open joint	
Producer's accuracy	60.0% (3/5)	95.5% (21/22)	100.0% (33/33)	
User's accuracy	100.0% (3/3)	100.0% (21/21)	91.7% (33/36)	
Overall accuracy	95.0%			

distortion and contrast distortion is employed to effectively assess inspection image quality by giving a value range between 0 and 1. According to the image quality analysis, a CCTV video stream with a mean quality index of above 0.8 approximately can be acceptable. For the accepted inspection images, a combination of opening operation and Otsu's technique was used for segmenting the morphologies of pipe defects. For the successfully segmented pipe defects including broken pipe, cracks, and open joint, their morphological features were measured and used to classify the pipe defects by the RBN-based automated diagnosis system with an overall accuracy of 95.0%.

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