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RESEARCH ARTICLE

Sewer pipe defects diagnosis assessment using multivariate analysis on CCTV video imagery

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ABSTRACT
Closed circuit television (CCTV) technology has been commonly used to inspect underground pipe defects, and high CCTV image quality is a prerequisite for accurate defect diagnosis. An acceptance criterion for CCTV inspection videos is critical for ensuring accurate diagnosis and preventing disputes between employers and contractors. This paper used multivariate statistical methods to evaluate the overall quality of CCTV images and to define an acceptance criterion for CCTV videos. Numerous CCTV images from a sewer inspection project were assessed and their quality, consisting of similarity in luminance and contrast distortions, was calculated by comparing a set of ideal images. Principal component analysis (PCA) and redundancy analysis (RDA) grouped the CCTV videos into homogeneous segments with similar image quality and provided a visual acceptance criterion for CCTV inspection videos. Furthermore, RDA triplot indicated that the contrast improvement of CCTV images can effectively enhance image quality and increase the diagnosis efficiency.

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Closed circuit television (CCTV); image quality; luminance; contrast; principal components analysis (PCA); redundancy analysis (RDA)

1. Introduction

Sewer maintenance plays a pivotal role in hydraulic infrastructures and water reuse for environmental protection and wastewater management. However, implementing sewer rehabilitation, which involves inspecting sewers, and determining rehabilitation methods and substitution materials, is often difficult because sewer systems are buried underground (Yang and Su 2006, Lin *et al.* 2015). The condition of stormwater pipes is commonly divided into structural and hydraulic condition to recognize two different deterioration processes and consequences (Micevski *et al.* 2002). The former deterioration in most cases is a result of physical impacts, such as overloads and soil pipe interaction, whose ultimate result is pipe collapse accompanied with traffic disruption. The latter is caused by the gradual reduction of the sectional diameter of pipes due to tree roots or debris which eventually results in flooding (Tran *et al.* 2006). On the other hand, acid attack caused by low pH industrial waste discharged into the sewer, such as sulphide corrosion or hydrogen sulphide (H_2S) corrosion (Parande *et al.* 2006), is the most serious affecting factor contributing to the creation of cracks. In addition to sulfuric acid attack, other external environmental factors also result in pipe cracks, including depth, slope, soil type, and intrusion of trees around the pipe (Wirahadikusumah *et al.* 1998).

However, monitoring and rehabilitating sewer systems are difficult because of low visibility. One of the non-destructive inspection techniques, closed circuit television (CCTV) mounted on robots, is the most common inspection method for recording underground pipeline conditions to diagnose defects (Su *et al.* 2011, Plihal *et al.* 2016). In real pipe diagnosis of sewers, CCTV inspection projects provide video streams comprising thousands of frames of field CCTV video images. Several diagnostic systems have been developed to interpret automatically the sewer defects shown in individual CCTV images and, thus, overcome human subjectivity as well as save time (Wirahadikusumah *et al.* 1998, Shehab and Moselhi 2005, Yang *et al.* 2011a). However, the accuracy and efficiency of diagnosing defects through CCTV inspection depend mainly on CCTV image quality and the experience of inspectors. In general, the pipe condition is assessed by inspectors visually and manually that is highly dependent on the experience of the inspectors. To enhance the assessment process with robustness and automation, establishing a machine learning process for pipe condition assessment is essential. Before pipe condition assessment, the quality of the CCTV image has to be assured so that a process to objectively evaluate the CCTV image quality needs to be developed.

CCTV image quality depends on external environmental effects, the camera-object distance, and the relative camera-object velocity (Hertel and Chang 2007). A perfect image requires no loss in fidelity with the original scene so that measuring the image similarity or fidelity of CCTV images against a perfect reference image is a popular approach for image quality assessment (Wee

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et al. 2010). Based on this concept, an approach for assessing the quality of individual images by considering luminance and contrast distortions (or similarity with ideal images) was proposed to define an index of image quality for different pipe defects (Yang *et al.* 2011b). Although an approach for evaluating the quality of individual frames of CCTV images was proposed in our previous study (Yang *et al.* 2011b), a proper acceptance criterion for the image quality of CCTV videos would facilitate efficient defect diagnosis and sewer system rehabilitation (Selvakumar *et al.* 2012), but has not yet been established.

Multivariate statistical techniques, such as principal component analysis (PCA), logistic regression, and redundancy analysis (RDA), were useful in grouping data, reducing the dimensionality of data, identifying data variation, and predicting the infrastructure's future performance (Ana and Bauwens 2010, Zeilhofer *et al.* 2010, Arora and Reddy 2013, Tsai *et al.* 2016). For example, Huang *et al*. (2015) used an integrated PCA method to determine the causes of toxicity in a seashore area. The influence of the sewer's physical properties on the structural deterioration of the Leuven sewers was investigated using logistic regression (Ana *et al.* 2009). RDA can identify correlations among response and explanatory variables, and was usually applied to causal identification in environmental and biological systems (Zhao *et al.* 2010). Huang *et al*. (2015) and Franceschini and Turina (2012) were two of the few studies to apply RDA to interpret the causal relationships between toxicity, geochemical conditions, and derived byproducts in groundwater (Huang *et al.* 2015) and to identify a small set of critical indicators for the performance evaluation of sewage service companies (Franceschini and Turina 2012), respectively. Therefore, the image quality may be improved to enable the inspection of defects by evaluating the variation of image quality through multivariate statistical techniques.

Moreover, to prevent disputes between employers and contractors, a direct and quick method for determining the image quality of CCTV videos is essential for the acceptance of CCTV video streams. The goal of this research was to assess the quality of CCTV video images by (1) using descriptive statistics, (2) applying the PCA technique, and (3) screening the dominant factor contributing to the quality of CCTV images by using the RDA method. Finally, 13 CCTV video tapes comprising 166,943 frames provided by CCTV inspection projects in Taichung City, Taiwan were evaluated and demonstrated in this study.

2. Methodology

2.1. Image data acquisition and quality assessment

Thirteen CCTV inspection video tapes were acquired from four construction projects (no. 30, no. 31, no. 32, and no. 34) for house connection in Taichung City, which is the largest city in Central Taiwan (Figure 1). In these sewer systems, most of the buried sewer pipes (Table 1) are either vitrified clay pipes (VCPs) or polyvinyl chloride (PVC) pipes. These two types of sewer pipe can exhibit eight typical pipe defects, namely multiple fractures, holes, collapse, open joints, breakage, sewer deformation, large

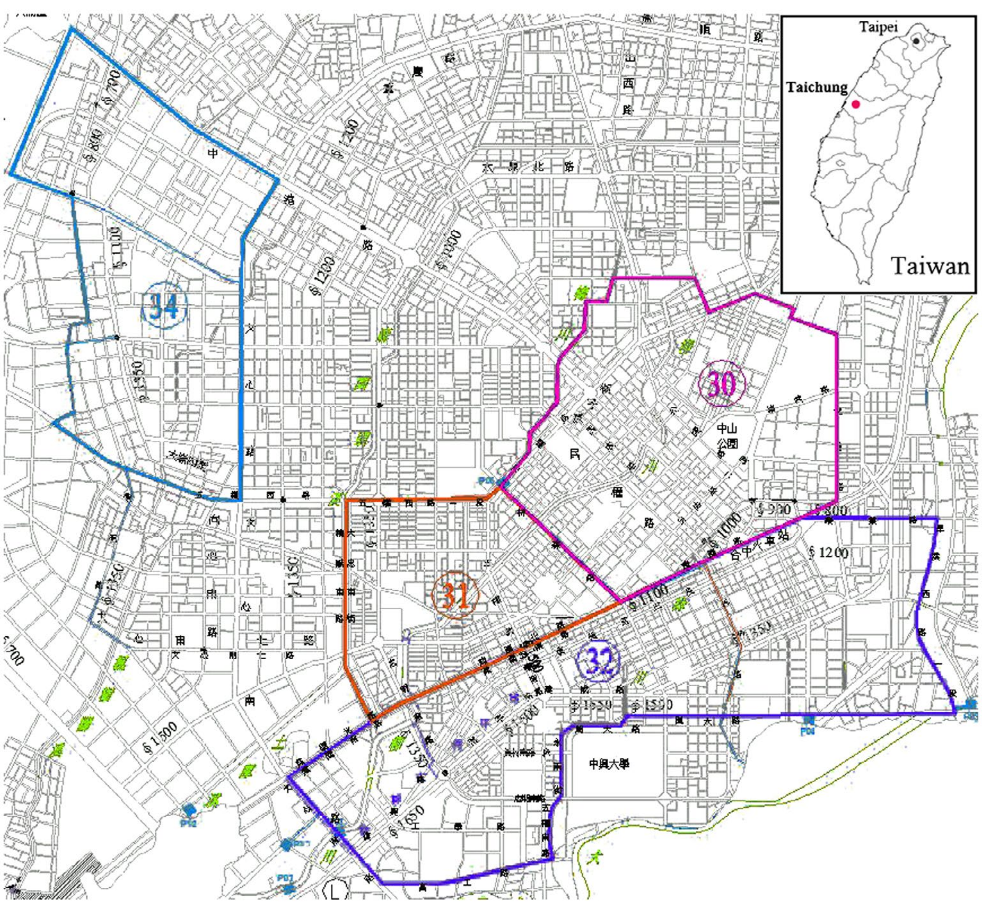

Figure 1. Location of four sewer CCTV inspection projects in the study case.

Table 1. Quality index of CCTV videos varying with various pipe defects.

					Quality index								
Video ID	Project NO.	Material	L[a]	C[b]	FM[c]	H[d]	C[e]	OJ[f]	B[g]	DS[h]	SL[i]	D[j]	Mean
30-1	30	VCP	0.962	0.887	0.886	0.893	0.788	0.855	0.817	0.922	0.766	0.904	0.854
30-2		VCP	0.957	0.862	0.855	0.865	0.749	0.817	0.779	0.894	0.739	0.909	0.826
30-3		VCP	0.959	0.865	0.894	0.951	0.825	0.874	0.869	0.933	0.776	0.906	0.879
31-1	31	PVC	0.958	0.756	0.728	0.764	0.613	0.699	0.641	0.781	0.647	0.919	0.724
31-2		PVC	0.960	0.744	0.719	0.761	0.607	0.695	0.633	0.769	0.622	0.903	0.714
31-3		PVC	0.957	0.769	0.750	0.784	0.639	0.725	0.663	0.793	0.631	0.895	0.735
31-4		PVC	0.977	0.859	0.850	0.894	0.764	0.828	0.797	0.894	0.742	0.947	0.840
32-1	32	PVC	0.956	0.891	0.875	0.885	0.793	0.853	0.832	0.919	0.775	0.891	0.853
32-2		PVC	0.951	0.889	0.877	0.869	0.760	0.837	0.798	0.939	0.782	0.896	0.845
34-1	34	VCP	0.962	0.880	0.878	0.884	0.781	0.842	0.814	0.915	0.760	0.909	0.848
34-2		VCP	0.955	0.880	0.874	0.873	0.764	0.839	0.787	0.909	0.774	0.902	0.840
34-3		VCP	0.954	0.870	0.861	0.863	0.750	0.825	0.775	0.900	0.761	0.902	0.830
34-4		VCP	0.962	0.857	0.849	0.865	0.746	0.816	0.778	0.893	0.735	0.915	0.825
Ref	–	–	1	1	1	1	1	1	1	1	1	1	1

[a]Luminance; [b]Contrast; [c]Fractures multiple; [d]Hole; [e]Collapse; [f]Open joint; [g]Broken; [h]Deformed sewer; [i]Spalling Large; [j]Debris.

spalling, and debris. Thousands of CCTV images were retrieved from the CCTV inspection video streams by using video stream processing software (Yang *et al.* 2011b). Luminance (L) and contrast (C) similarities were adopted to assess the image quality and are defined in Equations (1) and (2) (Wang and Bovik 2002). Let X and Y be the reference and assessed images, respectively. In addition, $x = \{x_i | i = 1, 2, ..., N\}$ and $y = \{y_i | i = 1, 2, ..., N\}$ express the gray values for a sample image and reference image, respectively, and N represents the number of pixels.

$$L = \frac{2\bar{x}\bar{y}}{(\bar{x})^2 + (\bar{y})^2} \tag{1}$$

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

$$\bar{x} = \frac{1}{N}\sum_{i=1}^{N} x_i, \quad \bar{y} = \frac{1}{N}\sum_{i=1}^{N} y_i,$$

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

Eight typical defects shown in Figure 2 and proposed by the Manual of Sewer Condition Classification (UK water industry engineering and operations committee 1994) were adopted as the ideal reference for CCTV images. All sample images were converted into gray-level images, and the similarity in the luminance (L) and contrast (C) between the sample and ideal reference CCTV images was determined. An image quality index (Q) is calculated as follows:

$$Q = L \times C = \frac{1}{M}\sum_{j=1}^{M} \frac{4\overline{(x)}_j\bar{y}_j(\sigma_x)_j\sigma_y}{[(\sigma_x^2)_j + \sigma_y^2][\overline{(x)}_j^2 + (\bar{y})^2]} \tag{3}$$

where M represents the number of sample images. If the image quality index of a CCTV image frame approaches one, then the luminance and contrast of that image are highly similar to those of the ideal image, representing excellent image quality. The processes for calculating the image quality index and assessing image quality are detailed in Yang *et al.* (2011b).

The flowchart of sewer pipe defects diagnosis assessment on CCTV video imagery is shown in Figure 3. First, the CCTV inspection images for a sewer pipe are collected. The L and C of each CCTV image against the reference image are calculated, and then the Q for each CCTV video can be obtained as the image quality index of CCTV videos. The descriptive statistics, PCA and RDA, are applied to create visualized charts and to determine an acceptance criterion of the CCTV inspection video. Also, the RDA can further determine the dominant factor contributing to the quality of the video image.

2.2. Multivariate analysis

PCA is used in data reduction to identify lower numbers of independent principal components that retain maximum variation in representing a dataset. In this study, PCA was conducted by using the orthogonal transformation method with varimax rotation to determine the eigenvalues of the variance matrix of the original variables (Jolliffe 2005). RDA is an extension of PCA. RDA explicitly models response variables as a function of explanatory variables and an extension of multiple linear regression based on PCA (Van Den Wollenberg 1977). The linear relationships between independent variables (X) and response variables (Y) identified using Eigen analysis can be expressed as (Kim *et al.* 2010):

$$(S_{YX}S_{XX}^{-1}S'_{YX} - \lambda_k I)u_k = 0 \tag{4}$$

where S_{YX} is the covariance matrix among response and explanatory variables; $S^{-1}{}_{XX}$ represents the inverse covariance matrix among standardized explanatory variables; I denotes a unit matrix; λ_k represents the eigenvalues of the corresponding axis k; and u_k denotes normalized canonical eigenvectors. The RDA iterative algorithm can be solved using an eigenvalue equation and a couple of matrix multiplications (for details, see Legendre and Legendre (2012)). Because RDA is a series of multiple linear regression steps, more observations than explanatory variables are required. Finally, the RDA ordination diagram (triplot) is obtained. In this diagram, the cosine of the angles between factors indicates their relationship, and the vector length in the triplot represents the importance of this factor within this model. The axes of the ordination diagrams represent the

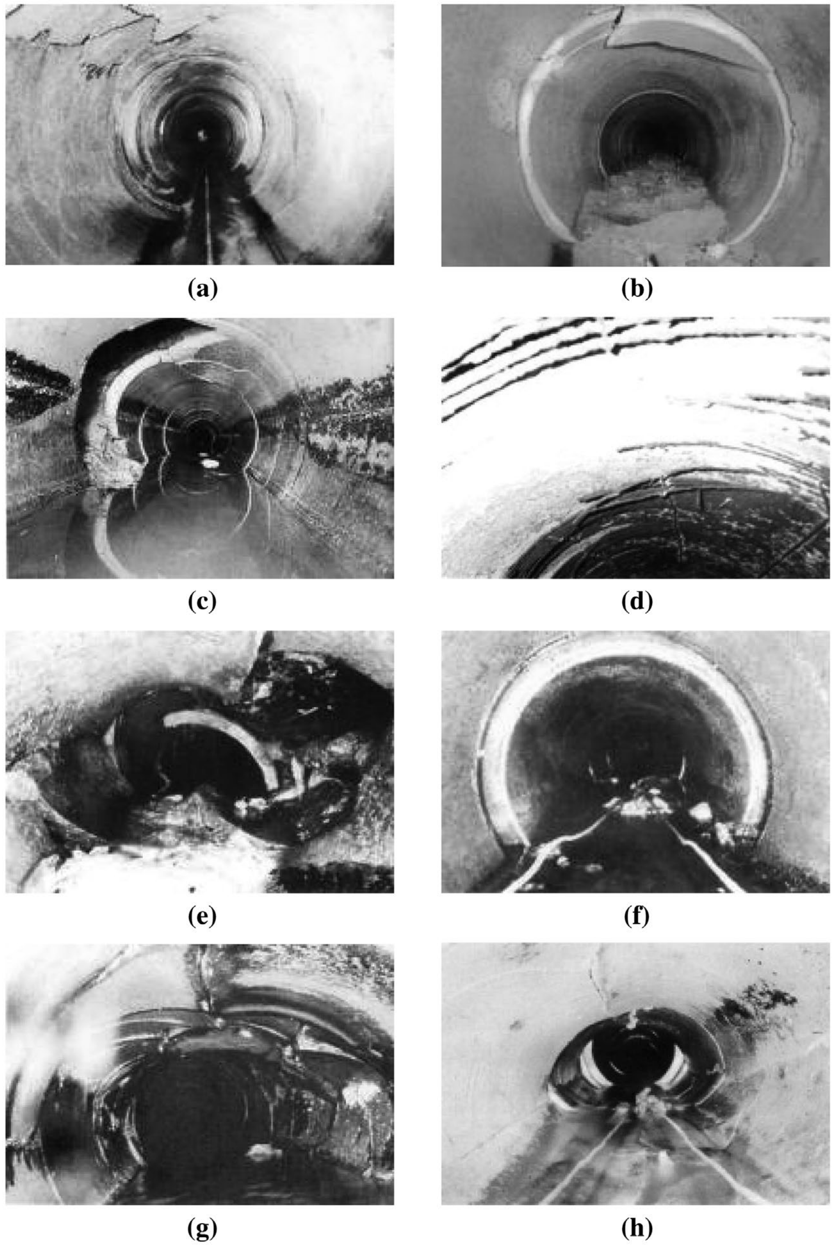

Figure 2. Ideal reference images of typical sewer defects cited from the Manual of Sewer Condition Classification. (a) Fractures multiple; (b) Debris; (c) Hole; (d) Spalling Large; (e) Collapse; (f) Open joint; (g) Broken and (h) Deformed sewer.

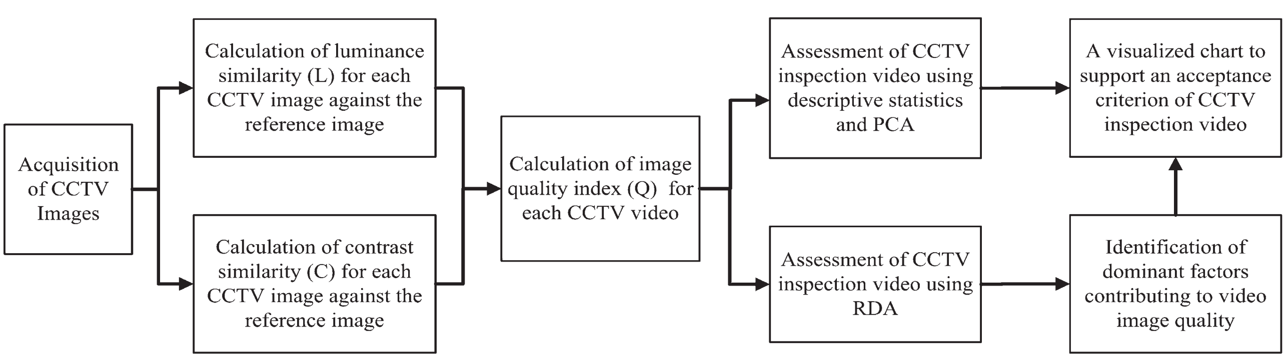

Figure 3. Flowchart of CCTV video imagery assessment in this study.

weighted sums of the independent explanatory variables, and a positive correlation is expected when the arrows point in the same direction (Michalsen *et al.* 2007). In the current study, the response variables were the Q value of the CCTV video for eight typical pipe defects, namely multiple fractures, debris, holes, large spalling, collapse, open joint, breakage, and sewer deformation (Table 1). The explanatory variables in the model were CCTV luminance, CCTV contrast, and pipe material. All RDA tests were performed using the Canoco® software for Windows 4.5, and the graphics were generated in CanoDraw for Windows 4.1® (ter Braak and Smilauer 2002). Options in Canoco software in this paper were "focus scaling" on inter-species correlations, species scores divided by standard deviation, and centering by species.

3. Results and discussion

3.1. Image quality assessment using descriptive statistics method

The radar chart in Figure 4a shows the arithmetic mean quality of the assessed CCTV images in different videos. Projects 31 and 32 obviously exhibited the lowest and highest mean quality, respectively. As shown in Figure 4b, videos 31-1, 31-2, and 31-3 rapidly accumulated to 85% at the approximate image quality of 0.7. The closer the accumulation is to 100%, the lower the image quality is. The accumulation curve of video 30-2 was the flattest, indicating relatively high variance and low reliability. Video 30-2 exhibited the second steepest accumulation curve (only more gradual than that of video 30-3) and slowest accumulation (less than 10% for a quality lower than 0.7); both of these results indicate that this video has high quality and reliability. In general, the quality of video 30-3 was considered the most favorable among those of all 13 videos. Although the mean quality of Project 32 was high, its high variance represented low reliability in image quality. Videos 31-1, 31-2, and 31-3 were easily recognized as the lowest quality images, whereas visually distinguishing the other videos was difficult.

3.2. Image quality assessment using PCA

Figure 5 illustrates the results of assessing the image quality through PCA; the PCA1 axis explained approximately 98.3% of the variation in the data quality. Symbols (video tape ID) close to the origin possess an average quality value for all variables. The symbols denoted by green squares, red circles, black stars, orange triangles, and pink diamonds represent Projects 30, 31, 32, 34, and the reference image, respectively. The Euclidean distance between the symbols approximates the dissimilarity in quality, and symbols were grouped into three homogeneous segments with similar quality. The symbols pointing toward the right side of the PCA1 axis, such as the symbol for Project 30-3, which is near the location of the reference image on the far right of the axis, have high image quality. Compared with the videos in Group I, videos 31-1, 31-2, and 31-3 in Group III were

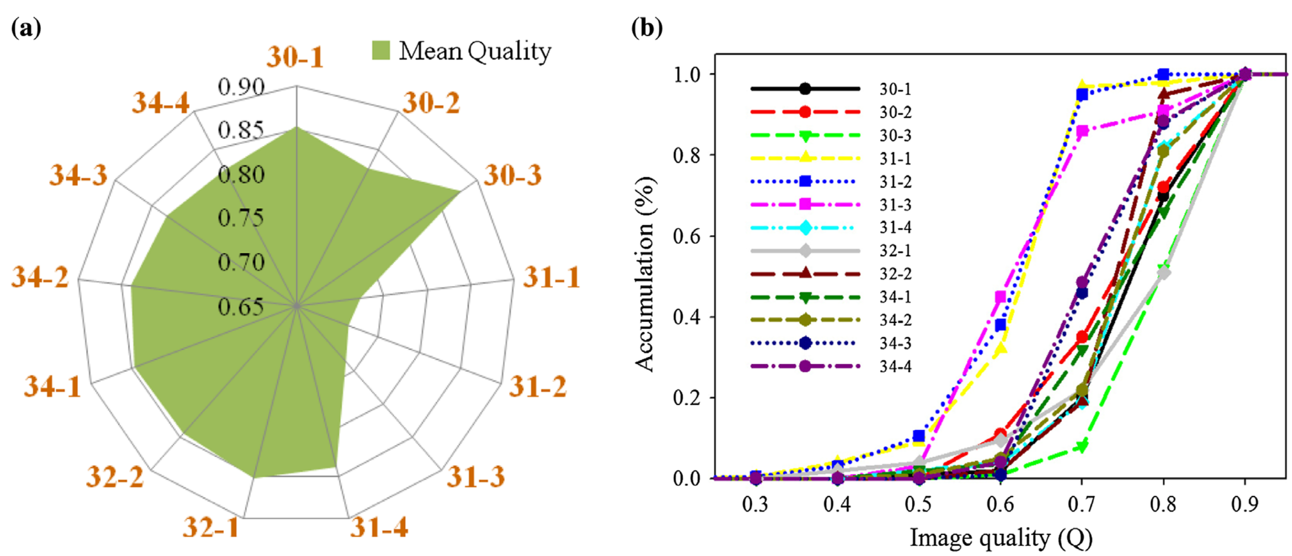

Figure 4. (a) Arithmetic mean quality of the different CCTV images in radar chart; (b) accumulation of image quality of 13 CCTV videos from four sewer CCTV inspection projects.

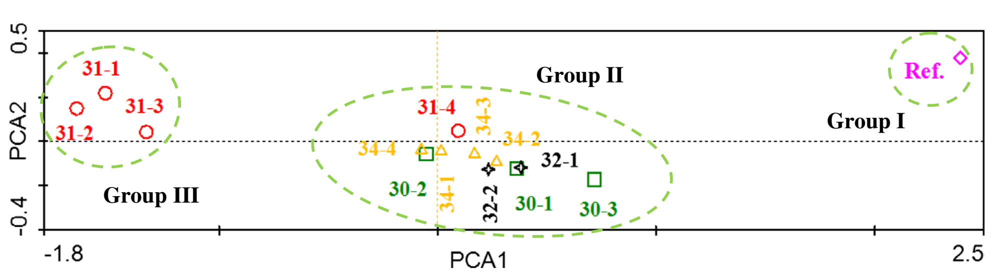

Figure 5. CCTV image quality assessment using PCA method identifying 13 CCTV videos into two groups against the reference group.

considered the videos with the lowest image quality. In other words, these videos must be rejected when contractors submit CCTV inspection videos. By contrast, the videos in Group II had a higher image quality and are suitable for diagnosing pipe defects. This result is consistent with the aforementioned result obtained by using heavy descriptive statistical analysis and indicates that efficient visual discrimination of image quality can be achieved through PCA; therefore, PCA can be used as a systematic acceptance criterion for a pipeline CCTV inspection project. However, although video 31-4 was provided by the same contractor who implemented Project 31, it is not part of the poor Group III (Figure 5); the cause of this cannot be explained by using PCA (Zuur *et al.* 2007). Thus, this causality between variables must be further investigated through RDA analysis.

3.3. Evaluation of contributions to image quality using RDA

RDA is an extension of PCA, and it explicitly models response variables as a function of explanatory variables (Zuur *et al.* 2007). Figure 6 shows the result of assessing the image quality by using RDA. The RDA1 axis explained 99.4% of the variation in data quality. A long projection of the blue arrow on the RDA1 axis indicates variation in video image quality. The projected distance of each symbol (video tape ID) perpendicularly on the blue arrow indicates the corresponding value of image quality (Q). A symbol close to the origin has an average value of Q, and a symbol on the left has an above-average Q value (ter Braak 1986, Lepš and Šmilauer 2003). RDA groups symbols into two segments (Groups A and B) according to similarity in CCTV video image quality. Videos 31-1, 31-2, and 31-3 in Group B opposite to the blue arrows can be considered poor-quality videos that must not be accepted by employers or engineering contractors. This result indicates that RDA provides efficient discrimination of video image quality. The long projection of the blue arrow on the RDA1 axis indicates that breakage and collapse are less frequently diagnosed through CCTV inspection than other defects. By contrast, the debris defect can be easily recognized because of the high Q value and low variance among videos (Table 1). A small angle between the blue arrows indicates a high correlation between defects, and most defects, except for debris, exhibited a high correlation with each other. This result indicates that debris deposited within a sewer can be completely identified because of its obvious difference from sewer pipes. In addition, the overlapped blue arrows representing breakage and collapse may be classified as the same defect in an automated diagnostic model because of the similar gray value of the reference image.

To determine the dominant factor contributing to video image quality, the quantitative and nominal explanatory variables in Figure 6 are represented by red arrows and red triangles, respectively. A longer projection of the red arrow onto RDA1 indicates that contrast dominates the variation of video image quality, and contrast improvement can be applied to enhance the image quality and, thus, increase effectively the efficiency of defect diagnosis. The projection point of the videos in Group B lies in an opposite contrast direction, and the low quality of these videos is attributed to a lower contrast. In addition, most of the low-quality videos provided by Project 31 suggest that this project must devote its focus onto contrast enhancement by using techniques such as high-resolution imaging and post-processing of inspection images. Furthermore, the improvement effects, such as the CCTV shot angle and light intensity for the L value, may not substantially enhance the image quality of CCTV inspection videos. The approximate right angle between the red arrows indicates that contrast and luminance are independent and, thus, can serve as indices for assessing CCTV image quality.

Angles between the blue and red arrows represent the correlations among response or explanatory variables (Legendre and Legendre 2012). The smaller angle between debris and luminance indicates that images with higher luminance are in favor of diagnosing debris than other defects. The highest Q value in the debris defect for video 31-4, which was shot from the Project 31 contract but not classified into Group B, could be attributed to its images with high luminance. Similarly, images with a higher contrast are more suitable for diagnosing sewer deformation than other defects. The red triangles in Figure 6 represent the pipe material,

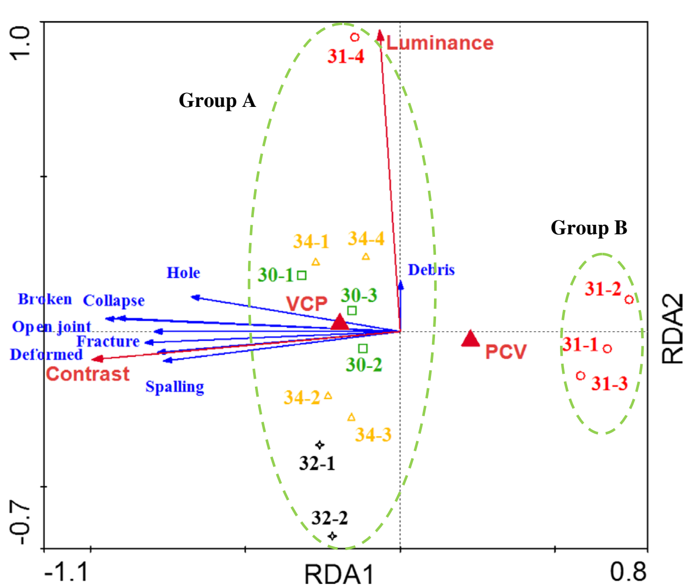

Figure 6. Redundancy analysis ordination triplots of CCTV image quality identifying 13 CCTV videos into two groups with respect to luminance and contrast.

and the Euclidean distance between the symbol and red triangle approximates their correlation. A short distance between PVC and the symbols in Group B implies that CCTV inspection of PVC pipes would provide a low contrast and result in a low image quality. By contrast, CCTV technology is suitable for inspecting VCP pipes because an image shot in a VCP pipe exhibited strong contrast.

By maximizing the difference in quality among CCTV videos to determine whether a CCTV video image is acceptable, PCA can be used to provide a quick approach and a visual figure that can serve as an acceptance criterion. RDA can be used to identify further the dominant factor contributing to CCTV video image quality, and can be useful for improving image quality and the efficiency of defect diagnosis.

4. Conclusion

Inspecting and diagnosing sewer pipe defects are essential for underground pipeline maintenance. Enhancing image quality can improve the validity of pipe defect diagnosis through CCTV inspection. This study proposes a useful approach for determining the image quality of CCTV videos to improve the efficiency of pipe defect diagnosis and establish an acceptance criterion for CCTV videos for acceptance units or inspectors. This study evaluated CCTV video images by using multivariate statistical methods, PCA and RDA, to examine CCTV inspection projects in Taichung City by calculating the similarity in luminance and contrast distortions between the assessed images and reference images. The results showed that PCA and RDA both enable intuitive and visual determination of the quality of CCTV video images and play a key role in acceptance determination of CCTV videos. RDA was conducted to evaluate the factors contributing to overall image quality. The breakage and collapse defects exhibited a tendency to be diagnosed as the same defect, whereas debris was the most easily recognized in CCTV inspections. Contrast was the dominant factor of variation in video image quality, and focusing on contrast enhancement can markedly enhance the image quality and efficiency of defect diagnosis. Furthermore, the reliability of image quality is another condition that must be considered to minimize false detection (Cooper and Schindler 2003, Saraswat and Yadava 2008). Thus, future studies must consider reliability in the quantitative quality assessment of CCTV images. Improving CCTV inspection technology based on the above result would contribute to sewer maintenance and water resource management.

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