Automation model of sewerage rehabilitation planning

M.D. Yang and T.C. Su

Department of Civil Engineering, National Chung Hsing University, 250 Kuo Kuang Road, Taichung, Chinese Taiwan

Abstract The major steps of sewerage rehabilitation include inspection of sewerage, assessment of structural conditions, computation of structural condition grades, and determination of rehabilitation methods and materials. Conventionally, sewerage rehabilitation planning relies on experts with professional background that is tedious and time-consuming. This paper proposes an automation model of planning optimal sewerage rehabilitation strategies for the sewer system by integrating image process, clustering technology, optimization, and visualization display. Firstly, image processing techniques, such as wavelet transformation and co-occurrence features extraction, were employed to extract various characteristics of structural failures from CCTV inspection images. Secondly, a classification neural network was established to automatically interpret the structural conditions by comparing the extracted features with the typical failures in a databank. Then, to achieve optimal rehabilitation efficiency, a genetic algorithm was used to determine appropriate rehabilitation methods and substitution materials for the pipe sections with a risk of mal-function and even collapse. Finally, the result from the automation model can be visualized in a geographic information system in which essential information of the sewer system and sewerage rehabilitation plans are graphically displayed. For demonstration, the automation model of optimal sewerage rehabilitation planning was applied to a sewer system in east Taichung, Chinese Taiwan.

Keywords Automation model; genetic algorithm; geographic information system; image processing; neural network; sewerage rehabilitation

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Introduction

As in other developed and developing countries, several major cities in Taiwan have been devoted to construct new sewer systems in recent years. So far, the invested budget for the new infrastructures of sewerage has been raised up to 353 million USD in 2005 (Construction and planning agency, 2005). In addition to new infrastructure constructions, maintenance is the other big issue for a sewer system because of the ease of getting cracks and defects due to corrosive wastewater inside and complex surroundings outside as well as the difficulty of inspection and rehabilitation due to underground allocation (Yang *et al.*, 2005) In order to keep sewer systems in a good structure and performance condition, regular rehabilitation of sewerages is necessary (Hernebring *et al.*, 1998).

Aboveground inspection, flow monitoring, flow measurement, manhole and sewer inspection, simulation, cleaning of pipes, and internal inspection should be performed before undertaking a construction plan of sewerage rehabilitation (Gupta *et al.*, 2001). After the implementation of the prior tasks, the external and internal conditions of sewer pipes can be revealed and then the identification of appropriate rehabilitation methods is the most important consideration affecting the cost-effectiveness of a rehabilitation plan (Ouellette and Schrock, 1981).

In the UK, rehabilitation strategy for urban sewer systems is to systematically rehabilitate only critical sewers which have the highest economic consequences of failure. Water Research Centre (WRC) concluded that critical sewers represented about 20% of the entire network but accounted for 90% of the rehabilitation costs (Fenner and Sweeting, 1999). The UK policy of selective rehabilitation is merely focused on the criteria of

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economic consequences of failure rather than the integral capacity of a sewer system. Furthermore, many failures such as blockage and collapse keep occurring on the non-critical pipes which are usually smaller diameter pipes (Fenner and Sweeting, 1999). An advanced rehabilitating strategy should offer more reliable sewer systems than systematically rehabilitating critical pipes (Ariaratnam and MacLeod, 2002). An efficient rehabilitation strategy considering both critical and non-critical pipes should be developed to benefit local sewer networks.

Moreover, currently optimal sewerage rehabilitation planning greatly relies on experts' effort. For a sewer system with a great amount of pipes, the rehabilitation planning becomes inefficient and time-consuming. Thus this paper proposes an automation sewerage rehabilitation model and presents how the model assists general staffs in efficiently planning optimal sewerage rehabilitation for a local sewer network in east Taichung, Taiwan.

Automation model of sewerage rehabilitation planning

Sewerage rehabilitation includes four major steps, such as processing sewer inspections, assessing structural conditions of pipe sections, identifying failure lengths, and determining rehabilitation methods and substitution materials (see Figure 1) (WRC, 1993; Ouellette and Schrock, 1981). Sewer inspection is used to monitor structural conditions and identify the lengths and locations of failures. Based on the inspection images, the grade of structural condition for each pipe can be assigned according to the regulations

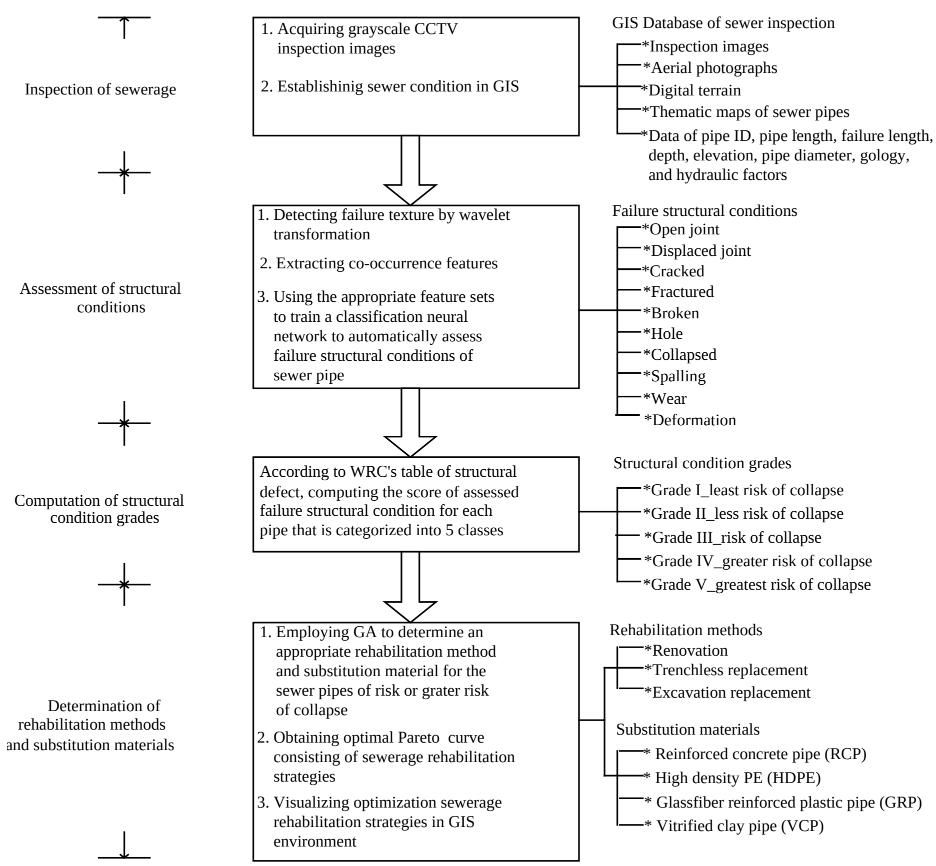


Figure 1 Flowchart of sewerage rehabilitation

of the Manual of Sewer Condition Classification (WSA and FWR, 1993). The structural condition grades provide a quantitative assessment of pipe condition as a reference of sewerage rehabilitation planning.

Sewer inspection

Sewer inspection consists of inner sewer wall surface inspection and within pipe wall and bedding condition inspection (Makar, 1999). Failure Observation on inner sewer wall surface such as pipe deformations, cracking, and missing bricks is the standard approach to sewer inspection and provides the basic information to determine the need for sewer rehabilitation (WRC, 1993). Although there are five available inspection approaches, such as stationary CCTV systems, mobile CCTV systems, laser-bedding condition, ultrasonic inspection (sonar), and computer aided CCTV, in inspecting inner sewer wall surface systems, nowadays closed circuit television (CCTV) systems are the most common approaches because of their economy (Makar, 1999). By moving forward a mobile CCTV system with a mounted video camera inside sewer pipes less than 1500 mm diameters, engineers are allowed to remotely inspect the entire pipe between a pair of manholes. In this model, a database was established in a geographic information system (GIS) in which aerial photographs, digital terrain, inspection images, thematic maps of sewer pipes and manholes, and data of pipe section ID, pipe length, failure length, pipe diameter, depth, geology, elevation, and hydraulic factors, were included.

Assessment of structural conditions

After finishing sewer inspection, inspectors categorize the structural failures into 9 classes, such as open joint, displaced joint, cracked, fractured, broken, hole, collapsed, spalling, wear, and deformation. However, the human examination seems tedious and inefficient to reveal all structural failures of pipeline on thousands of CCTV inspection images. Moreover, visual inspection being subjective in nature inspectors could result in mistaken judgements as to the degree of seriousness of sewer failure (Wirahadikusumah *et al.*, 1998; Makar, 1999). Thus, computer aided artificial intelligence should be employed in image inspection to increase process efficiency and reduce mistaken manual interpretations (Moselhi and Shehab-Eldeen, 1999; Chae and Abraham, 2001). In this paper, a computed-aided model combining techniques of digital image processing and neural network was developed for automatically assessing sewer pipeline conditions. This model adopts digital image processing techniques such as wavelet transformation and co-occurrence features that were proven to be efficient in texture failure detection (Latif-Amet *et al.*, 2000). Also, neural network as a supervised classification was established to automatically classify pipeline failures.

First of all, failure textures were detected on every frame of the acquired grayscale CCTV inspection images by wavelet transformation that decomposed each gray level image into one approximation image and three detail textured images in vertical, horizontal and diagonal directions, respectively. Secondly, co-occurrence features including angular second moment (ASM), entropy (ENT), contrast (CON), homogeneity (HOM), dissimilarity (DIS), correlation (COR), and cluster tendency (CLS) in 0°, 90°, and 45° and 135° directions were extracted from three detail textured images of horizontal, vertical, and diagonal directions. The correlations of the features were examined to eliminate redundancy between dependent features thus increasing the accuracy of texture description and decreasing the difficulty of pattern recognition. Finally, the appropriate feature sets were input into a classification neural network to automatically assess the structural conditions of pipe sections.

Computation of structural condition grades

After finishing assessment of structural conditions, structural condition scores were computed that can be classified into five categories (Grade I through V) for each pipe section. Being designed by WRC (1993), a structural defect scores table, which assigns properly the relative score to each structural failure, was adopted to quantify the structural condition. The definitions of different structural condition grades are also described in Figure 1. If the assessment result of the classification neural network reveals a pipe section with least (Grade I) or less risk (Grade II) of collapse, the rehabilitation method will be assigned as no rehabilitation (or renewal) so that the rehabilitation cost can be substantially reduced. Otherwise, the rehabilitation methods and substitution materials of the pipe sections with risk (Grade III), greater risk (Grade IV), or greatest risk (Grade V) of collapse remain to be determined appropriately (Ouellette and Schrock, 1981). An optimization process needs to be established in the automation model to decide rehabilitation methods and substitution materials.

Determination of rehabilitation methods and substitution materials

Previous researches indicate that both the rehabilitation method and substitution material affect rehabilitation cost and service life during sewerage rehabilitation (Ouellette and Schrock, 1981; Reyna, 1993; Gupta *et al.*, 2001). In this paper, three rehabilitation methods, i.e. renovation, excavation replacement, and trenchless replacement, and four substitution materials, i.e. reinforced concrete pipe (RCP), high density PE (HDPE), glassfiber reinforced plastic (GRP), and vitrified clay pipe (VCP), were considered to be alternatives in a sewerage rehabilitation plan. Trenchless replacement cost is much higher than excavation replacement cost, but social cost resulting from trenchless replacement is much lower than excavation replacement. Furthermore, the longer the service life of substitution material is, the higher its cost is. Thus, an appropriate rehabilitation method and a substitution material for each failure pipe section to reach the least cost and the longest service life for the entire sewer system is the trade-off problem remaining to be solved.

Genetic algorithm (GA), is considered as a robust and powerful evolutionary optimization technique (Balla and Lingireddy, 2000; McCrea and Navon, 2004). The GA-based optimization model for sewerage rehabilitation was first to encode a chromosome by integer numbers representing two decision variables, including rehabilitation method and substitution material, and to randomly generate an initial population presenting the size of solution space. The length of chromosome of GA can be flexibly changed with the number of failure pipe sections. Then, the fitness value of each chromosome can be estimated by the estimation results of rehabilitation cost and service life. Finally, a trade-off curve (Pareto curve) of rehabilitation cost vs. service life reaches the upper left region representing less rehabilitation cost and longer service life. Through the repeated steps of a new population, crossover, and mutation generation by generation, GA operation was terminated when the trade-off curve has no further improvement of rehabilitation cost and service life. The gene information of the chromosomes on the final trade-off curve is composed of the best rehabilitation plans with the appropriate rehabilitation methods and substitution materials for the failure pipe sections.

Model application

Study site

The sewer system at the 9th district of Taichung city in central Taiwan was selected as the study site for demonstration. In ten sewer subsystems, subsystem A through J in this district, the diameters of most pipelines are 300 mm and 85% of pipes are made of VCP. The other pipelines with diameters larger than 350 mm are made of RCP. A CCTV

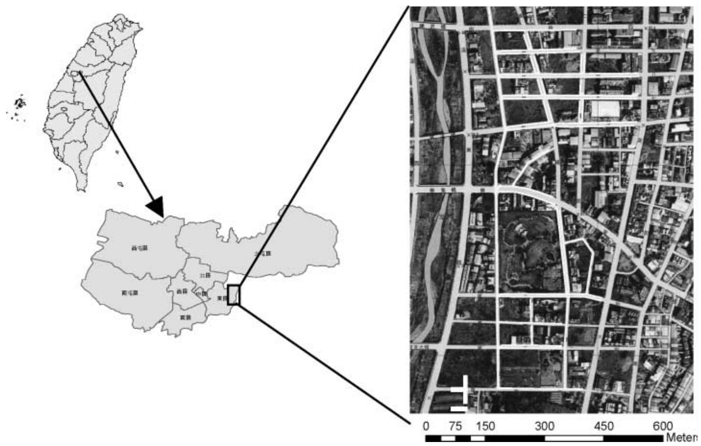


Figure 2 Layout of subsystem G

inspection for these sewerages was executed in 2002 by Taichung city government. Those inspection records reveal that most failures were found in subsystem G which was chosen to be the study case for the model of sewerage rehabilitation planning. Figure 2 is the layout of subsystem G consisting of 152 pipe sections. 291 CCTV inspection images of subsystem G were acquired that provide the distribution and patterns of sewerage failures. A statistical analysis of those images also reveals that open joint, wear, cracked, and broken are the typical failure structural conditions.

Results and analysis

Through the series steps of producing the detail textured images by wavelet transformation (see Table 1), extracting the co-occurrence features from the detail textured images, and testing the correlation of the co-occurrence features, five feature sets, including [CON, CLU], [HOM, CLU], [DIS, CLU], [ASM, COR, CLU], and [ENT, COR, CLU], were found to be more robust in texture description. Consequently, these five feature sets were used to train a classification neural network which has three, eight, and four perceptrons in input, hidden, and output layers, respectively. According to the training results, the classification accuracies of [CON, CLU], [HOM, CLU] and [DIS, CLU] were

Table 1 Detail textured images of typical failures

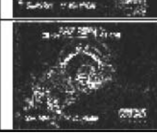
Typical failure	Approximation	Horizontal detail	Vertical detail	Diagonal detail
Open joint				
Wear				
Cracked				
Broken				

Table 2 Recognition result of typical failures in subsystem G

Typical failure	No. of images	No. of recognized images	Recognition rate of recognition
Open joint	107	70	0.65
Wear	56	30	0.54
Cracked	112	76	0.68
Broken	16	13	0.81
Total	291	189	0.65

between 55% and 60%, and those of [ASM, COR, CLU] and [ENT, COR, CLU] were between 65% and 70%. Therefore, both [ASM, COR, CLU] and [ENT, COR, CLU] are recommended to be the appropriate feature sets for the classification neural network. Table 2 shows the classification accuracies of the four typical failure structural conditions.

Through the assessment of the structural failures by the classification neural network, 105 pipe sections in subsystem G have structural condition grades less than or equal to grade II which were suggested to be rehabilitated just by renewal including chemical grouting or cement grouting. The other 47 pipe sections remain to be determined for one of three alternative rehabilitation methods and one of four alternative substitution materials. The computation time of this automation model was about 500 seconds on Pentium IV 1.3G PC to obtain the Pareto curve for determining optimal sewerage rehabilitation plans. The optimal Pareto curve consists of the best plans and ranges from 18.51 to 18.59 million NTD (1 USD≅ 33.3 NTD) for a complete rehabilitation. Compared with about 20 million NTD which is an experts' quotation made by Taichung city government in 2003, the cost estimated by the model has about 7.5% reduction. Moreover, the model provides multiple optimal rehabilitation plans consisting of the Pareto solutions varying with service life and rehabilitation cost (see Figure 3). The service life of sewerage is rapidly increased by the increase of the total rehabilitation cost at lower capita as shown in Figure 3. Over 18.55 million NTD, the rehabilitation effectiveness increases considerably slowly with the increase of total rehabilitation cost. Based on this Pareto curve, the municipal authority and engineers can determine the rehabilitation budget under a planned service life of sewerage. Applying this optimization model and displaying the results of this optimization model in GIS, decision-makers can clearly realize and adopt the appropriate rehabilitation methods and substitution materials for the failure pipes (Figure 4).

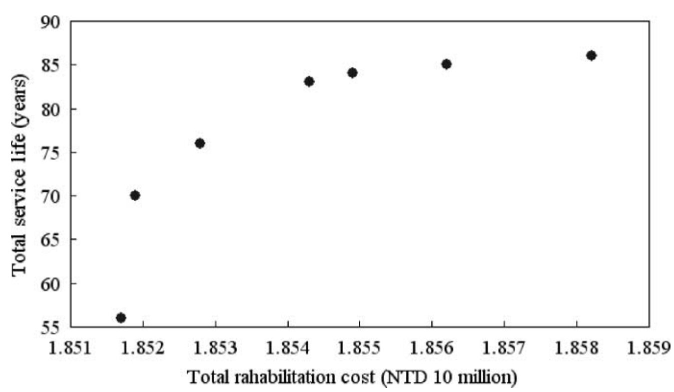
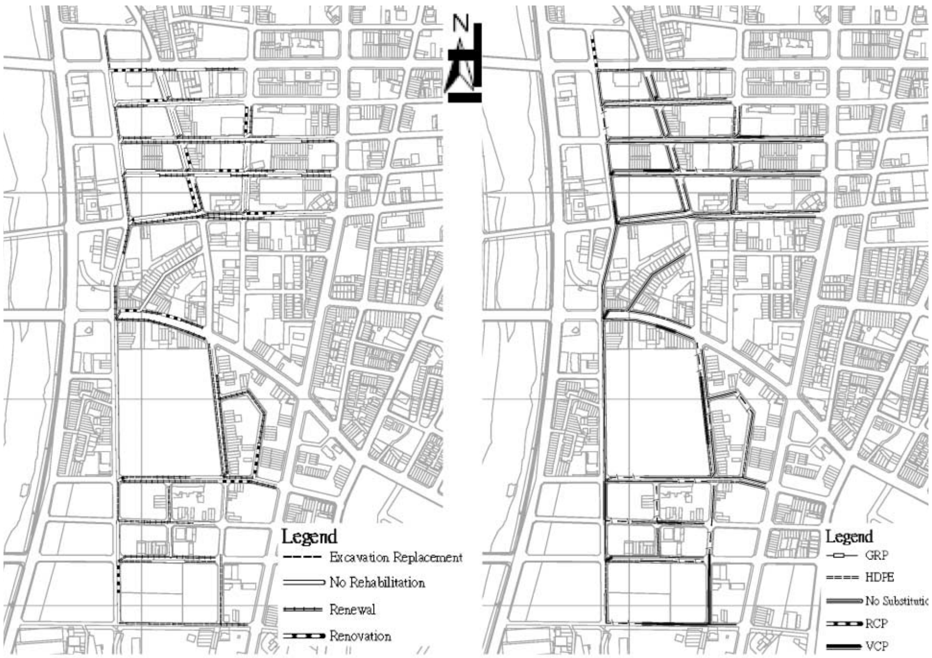


Figure 3 Optimal Pareto curve of sewer rehabilitation



(a) Layout of rehabilitation methods   (b) Layout of substitution materials

Figure 4 Displays of optimization results in GIS

Conclusions

The combined techniques of image processing, neural network, GA, and GIS integrated in the automation model of sewerage rehabilitation planning can assist engineers in determining the appropriate rehabilitation method and substitution material for each failure pipe section to reach the optimal rehabilitation efficiency. Using the appropriate feature sets trains a classification neural network that could expedite the procedure of assessing structural conditions. Both [ASM, COR, CLU] and [ENT, COR, CLU] are recommended to be the appropriate feature sets for the classification neural network. Moreover, the GA-based optimization model for sewerage rehabilitation significantly reduced the rehabilitation cost for a complete rehabilitation of the 9th district sewerage system, and provided multiple optimal rehabilitation plans by searching the Pareto solutions. In the future enlarging the failure database and improving classification ability will be continued before such an automation model of planning optimal sewerage rehabilitation strategies can be broadly applied to other sewer systems.

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