Available online at www.sciencedirect.com
ScienceDirect
Expert Systems with Applications 35 (2008) 1327–1337
Expert Systems with Applications
www.elsevier.com/locate/eswa

Automated diagnosis of sewer pipe defects based on machine learning approaches

Ming-Der Yang *, Tung-Ching Su

Department of Civil Engineering, National Chung Hsing University, 250, Kuo Kuang Road., Taichung 402, Taiwan

Abstract

In sewage rehabilitation planning, closed circuit television (CCTV) systems are the widely used inspection tools in assessing sewage structural conditions for non man entry pipes. Currently, the assessment of sewage structural conditions by manually interpretation on CCTV images seems inefficient, especially for several thousands of frames in one inspection plan. Also, the assessment work significantly involves engineers' eye sight and professional experience. With a purpose of assisting general staffs in diagnosing pipe defects on CCTV inspection images, a diagnostic system by applying machine learning approaches is proposed in this paper. This research was first to use image process techniques, including wavelet transform and computation of co-occurrence matrices, for describing the textures of the pipe defects. Then, three neural network approaches, back-propagation neural network (BPN), radial basis network (RBN), and support vector machine (SVM), were adopted to classify pipe defect patterns, and their performances were compared and discussed. The diagnostic system of pipe defects was applied to a sewer system in the 9th district, Taichung City which is the largest city in middle Taiwan. The result shows that the diagnosis accuracy of 60% derived by SVM is the best and also better than the diagnosis accuracy of 57.4% derived by a Bayesian classifier.

Keywords: CCTV images; Sewer pipe defects; Diagnostic system; Textural features

1. Introduction

Sewage rehabilitation plays an important role as sewage construction but is not easily processed due to uncertainty of occurrence of sewer pipe defects. Thus, worldwide engineers pay a greater attention to the proactive and preventive repair strategies than the traditional approach of regular sewer maintenance (Fenner, 2000). Before undertaking sewer rehabilitation, four major series steps of sewer rehabilitation planning including inspection of sewage, assessment of sewage structural conditions, computation of structural condition grades, and determination of rehabilitation methods and substitution materials have to be finished (Yang & Su, 2006, 2007). Various tools or technologies such as closed circuit television (CCTV) cameras mounted on robots, ground piercing radar (GPR), sonar and infrared thermograph, are developed to assist engineers in sewage inspection (Cordes, Berns, Eberl, Ilg, & Suna, 1997; Fenner, 2000; Makar, 1999; Moselhi & Shehab-Eldeen, 1999; Wirahadikusumah, Abraham, Iseley, & Prasanth, 1998). CCTV, one of the most popular inspection tools because of its commercial availability, is usually mounted on robot to be putted inside sewer pipes from a manhole and remotely-controlled outside to acquire images of inner pipe (Makar, 1999). In addition, the advantages of mobile CCTV system include fewer inspectors needed, more safety-ensured to inspectors, and more detailed data of distance and slope possibly recorded (Madryas & Przybyla, 1998).

Traditionally, pipe defects are generally diagnosed by human interpretation on CCTV inspection images. It remains to improve the technology of interpreting an enormous quantity of CCTV inspection images due to human fatigue, expertise-dependence, and inefficiency. To

* Corresponding author. Tel.: +886 4 2284 0440x214; fax: +886 4 2286 2857.
E-mail address: mdyang@dragon.nchu.edu.tw (M.-D. Yang).

0957-4174/$ - see front matter © 2007 Elsevier Ltd. All rights reserved.
doi:10.1016/j.eswa.2007.08.013

overcome these limitations, some computer vision systems based on morphologies or geometries of pipe defects have been tried (McKim & Sinha, 1999; Moselhi & Shehab-Eldeen, 1999; Xu, Luxmoore, & Davies, 1998). Sinha and Fieguth (2006) used mathematical morphology methodology for segmentation of pipe defects including crack/hole, joint, collapse pipe, and lateral, but the method was difficult to classify those defect patterns into various classes based on their severity of defects. It was suggested that the segmented objects have to be further processed to be classified according to the severity of defects by using other shape or textural features. This paper attempts to apply machine learning approaches to develop a diagnostic system with better capacity in diagnosing pipe defects based on textural features instead of morphological or geometrical features.

Like a fingerprint databases, the straightforward approach is to establish a complete databank, which stores an enormous amount of CCTV inspection images collected from many inspection cases. Any inspection image can be classified into one category of sewage structural conditions by comparing the defect characteristic with the stored ones. However, it is almost impossible to establish the databank due to the natural shape irregularities of sewer pipe defects and the complex imaging environment. Therefore, this paper attempts to extract specific principal textural features of pipe defects from CCTV inspection images acquired in one inspection mission to train the diagnostic system and automatically interpret the rest of inspection images based on supervised learning.

Many researches proposed some efficient approaches to extraction of textural features. Wunsch and Laine (1995) concluded wavelet descriptors insensitive to individual shape variations and better than Fourier descriptors in shape representation for handprinted characters. Amet, Ertüzün, and Erçil (2000) used wavelet transform (WT) and co-occurrence matrices to extract the co-occurrence features of defective textile fabrics which are powerful in detecting defects. Moreover, wavelet transform has multiresolution technique, so its sub-band decomposition of tree structure is appropriate for detection of local signal varieties on images. Arivazhagan and Ganesan (2003) presented that co-occurrence features computed from discrete wavelet transformed images are useful for texture segmentation. In this paper, the hybrid use of wavelet transform and co-occurrence matrices is considered as an effective solution for the texture analysis of sewage structural conditions. Based on the extracted co-occurrence features, the diagnostic system could be trained to assign each defect pattern to a correct category.

At present, pattern recognition techniques commonly use multilayer neural network and statistic methods such as Bayesian classifier, maximum likelihood method, and decision tree. Marchant and Onyango (2003) compared a Bayesian classifier with a multilayer feed-forward neural network to a plant/weed/soil discrimination case. The classification result demonstrated that the Bayesian classifier outperform the neural network due to its optimization in the sense of total misclassification error. Unfortunately, in most actual cases there is rarely a complete knowledge about the probabilistic structure of the problem. Thus, the nonparametric methods such as neural networks have been proposed to be widely applied to many actual pattern recognition problems (Duda, Hart, & Stork, 2001). Currently, back-propagation neural network (BPN), radial basis network (RBN), and support vector machine (SVM) are the three commonly used neural networks (Liao, Fang, & Nuttle, 2004) that is adopted in this paper to solve this classification problem of pipe defect patterns. The most efficient neural network technique is commended based on classification performance, and finally the application of this diagnostic system to a sewer system in the 9th district, Taichung City, Taiwan is discussed.

2. Methodology

2.1. Wavelet transform

Wavelet transform (WT) is a linear transform developed from Fourier transform. Unlike Fourier transform whose basis functions are sinusoids, wavelet transform is based on small waves, so-called wavelet, of varying frequency and limited duration so to obtain better resolutions along frequency scale (Chen, Wang, Yang, & McGreavy, 1999; Gonzalez & Woods, 2002). In multiresolution analysis (MRA), a scaling function is to create a series of approximation of a function or an image; additional functions, i.e. wavelet functions, are then used to encode the difference in information between adjacent approximations (Gonzalez & Woods, 2002). A set of wavelet functions is defined as:

$$\psi_{a,b}(x) = 2^{a/2}\psi(2^a x - b) \tag{1}$$

for all $a, b \in \mathbf{Z}$. $\mathbf{Z}$ is a set of integers. The scale parameter a controls stretch or compression of the mother wavelet function; the translation parameter b is an offset along the time axis; $2^{a/2}$ controls its height or amplitude (Chen et al., 1999; Gonzalez & Woods, 2002). Obviously a CCTV image can be regarded as the change of discrete signal along a two-dimensional (2D) scale. Hence, a 2D discrete WT (DWT) was proved to be useful for signal or image processing and pattern recognition (Bashar, Matsumoto, & Ohnishi, 2003; Hwang et al., 2005). The fast wavelet transform was considered as a computationally efficient implementation of the DWT was defined as (Gonzalez & Woods, 2002):

$$\varphi_{a,b}(x) = \sum_b h_\varphi(b)\varphi_{a+1,b}(x), \tag{2}$$

$$\psi_{a,b}(x) = \sum_b h_\psi(b)\varphi_{a+1,b}(x), \tag{3}$$

where $\varphi_{a,b}(x)$ and $\psi_{a,b}(x)$ are computed by convolving $\varphi_{a+1,b}(x)$ with the time-reversed scaling and wavelet vectors, $h_\varphi(b)$ and $h_\psi(b)$. In other words, the original function, $\varphi_{a+1,b}(x)$, is split into a lowpass (approximation compo-