Automation in Construction 15 (2006) 73 – 83
AUTOMATION IN CONSTRUCTION
www.elsevier.com/locate/autcon

Neuro-fuzzy network for the classification of buried pipe defects

Sunil K. Sinha [a,*], Paul W. Fieguth [b]

[a] Department of Civil and Environmental Engineering, Pennsylvania State University, University Park, PA 16802, USA
[b] Department of Systems Design Engineering, University of Waterloo, ON N2L3G1, Canada

Accepted 4 February 2005

Abstract

Pipeline infrastructure is decaying at an accelerating rate due to reduced funding and insufficient quality control resulting in poor installation, little or no inspection and maintenance, and a general lack of uniformity and improvement in design, construction and operation practices. The current practice that is being followed to inspect the conditions of pipes is usually time consuming, tedious and expensive. It may also lead to diagnostic errors due to lack of concentration of human operators. Buried pipe defect classification is thus a practical and important pattern classification problem. These defects appear in the form of randomly shaped cracks and holes, broken joints and laterals, and others. This paper proposes a new neuro-fuzzy classifier that combines neural networks and concepts of fuzzy logic for the classification of defects by extracting features in segmented buried pipe images. A comparative evaluation of the K-NN, fuzzy K-NN, conventional backpropagation network, and proposed neuro-fuzzy projection network classifiers is carried out. Among the five neural methods implemented and tested, the proposed neuro-fuzzy classifier performs the best, with classification accuracies around 90% on real concrete pipe images.

Keywords: Pipeline infrastructure; Automated inspection; Image processing; Segmentation; Features; Neural network; Backpropagation network; Neuro-fuzzy projection network

1. Introduction

Feature extraction and object classification are important areas of research and of practical applications in a variety of fields including pattern recognition, artificial intelligence, statistics, cognitive psychology, vision analysis, and medicine [1–8]. Over the last 25 years, extensive research has taken place in the development of efficient and reliable methods for the selection of features in the design of pattern classifiers, where the features constitute the inputs to the classifier. The quality of this design depends on the relevancy, discriminatory power and ease of computation of various features. Another important issue in object classification is the choice of an appropriate classifier. There are at least two types of classifiers: traditional classifiers (e.g., linear discriminant, maximum likelihood, k-nearest neighbor, etc.) [9] and neural based classifiers (e.g., backpropagation, projection network, self-organizing map, adaptive resonance theory, etc.) [10].

Given a digitized pipe image containing several objects, the pattern recognition process consists of three major phases, as shown in Fig. 1. The goal of this paper is to apply methods of feature extraction and several classifications to buried pipes, a problem of considerable practical and research interest [11]. Chae and Abraham [14] employed image preprocessing, classification through a neural network, and defect identification using a fuzzy estimator. Moselhi and Shehab-Eldeen [12,13] classified pipe defects through a conventional backpropagation neural network trained with feature vectors as inputs. Automated real-time pavement distress detection using fuzzy logic and neural networks was studied using fuzzy homogeneity for image enhancement and feature extraction [15]. A methodology for automated pavement crack detection [16] demonstrated the potential of using neural network for classification and quantification of cracking on

* Corresponding author. Tel.: +1 814 865 9433; fax: +1 814 863 7304.
E-mail addresses: sunil@engr.psu.edu (S.K. Sinha), pfieguth@uwaterloo.ca (P.W. Fieguth).

0926-5805/$ - see front matter © 2005 Elsevier B.V. All rights reserved.
doi:10.1016/j.autcon.2005.02.005

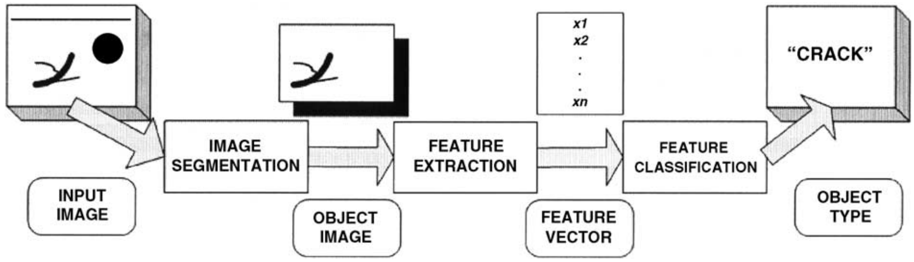

Fig. 1. The three phases of pattern recognition.

pavement, and it requires further improvement of the image segmentation.

We have previously demonstrated morphological [17] and statistical [18] approaches to segmenting images of underground concrete pipes, an important precursor step to this paper. The proposed morphological approach is effective at segmenting joints, laterals and pipe background, as in Fig. 2, and the statistical approach is effective at segmenting cracks from pipe images, as in Fig. 3.

Although the developed methods were effective at segmentation, they did not assess the severity or extent of distress, a more subtle question, but one of crucial importance in pipe infrastructure assessment. The purpose of this paper is to propose and develop a neuro-fuzzy classifier which is able to classify the severity of distress in cracks, holes, laterals, joints, and pipe collapse. Our approach combines a fuzzy membership function with a projection neural network where the former handles feature variations and the latter leads to good learning efficiency.

2. Feature extraction

Feature extraction is an important stage for any pattern recognition task, especially for pipe defect classification, since pipe defects are highly variable and it is difficult to find reliable and robust features. Trained operators mainly rely on five criteria [19] in the visual interpretation of images: intensity, texture, size, shape, and organization. Intensity corresponds to spectral features, which can generally be extracted easily. Textural features are those characteristics such as smoothness, fineness, or coarseness associated with an image [20], reflecting local spatial properties. Other features such as size, shape, and organization associate with large scale or global spatial distribution.

Shape and textural features are most commonly used in the material/pavement classification field [16]. Some of these common shape features include area, length, roundness, and morphology. Textural features distinguish objects by using statistical measures such as gray-scale co-occurrence matrices [21] and variants, such as gray-scale difference vectors, moment invariants, and gray-scale difference matrices. The salient features of the data can also be extracted through a mapping, such as Fourier transform, Hough transform, Karhunen–Loeve transform, or principal components [22], from a higher dimensional input space to a lower dimensional representation space. Because pipe-image texture is largely dominated by pipe discoloration and background patterning, which are largely

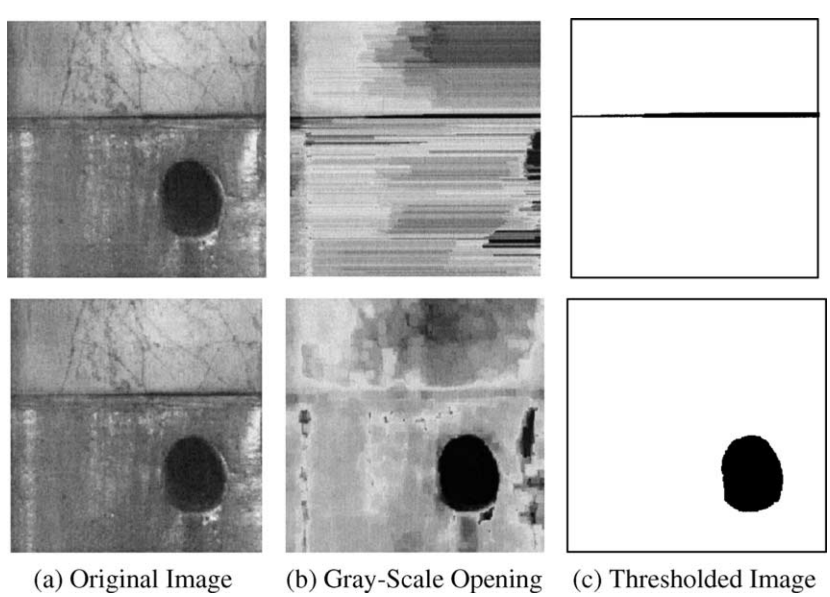

Fig. 2. An illustration of morphological segmentation, from [17], identifying a joint (top) and lateral (bottom).