TSINGHUA SCIENCE AND TECHNOLOGY
ISSN 1007-0214 60/67 pp375-380
Volume 13, Number S1, October 2008

Imagery Enhancement and Interpretation for Remote Visual Inspection of Aging Civil Infrastructure

Wei Guo, Lucio Soibelman**, James H Garrett

Department of Civil and Environmental Engineering, Carnegie Mellon University, 5000 Forbes Avenue, Pittsburgh, PA 15213, USA

Abstract: In this paper, we describe an image enhancement and interpretation methodology to enhance and recognize surface defects and critical patterns from remote imagery of sewer pipeline inspection. The objective is to provide inspectors and professionals with better tools to allow them to examine the imagery for condition assessment. We present initial results of a collaboration with a robotic company through a case study on computer-assisted processing and interpretation of sewer pipeline inspection imagery. In the mean time, the described enhancement and interpretation methodology can also be applied to sewer pipeline condition assessment in an offline mode, where this methodology can support professionals' examination of acquired sewer condition imagery.

Key words: remote visual inspection; infrastructure assessment; image processing and analysis; defects; region of interest; detection; classification

Introduction

Currently, visual inspection is still widely used for condition assessment of many civil infrastructure systems, such as bridges, highways, and sewer pipelines. Sewer pipelines are particularly difficult to access by human-entry approach for visual inspection. Video based inspection using closed-circuit television (CCTV) has been the predominant nondestructive method used for remote visual inspection of sewer pipelines in the United States[1]. Through an inspection console, an inspector can access the live imagery for remote inspection. A software package called Wincan[2] has been embraced by most inspection contractors, utilities and other maintenance professionals. It allows recording, analyzing, and reporting defects through a graphical user interface. An inspector examines a remotely captured live video which provides pipe condition information, and recognizes defects and useful pipe features from the survey video for further analysis and maintenance decision making. However, the current practice of CCTV inspection suffers at times from being ineffective and error-prone due to inspector fatigue or boredom. Moreover, the image quality acquired from CCTV surveys is affected by the poor imaging conditions. For example, low contrast imagery caused by poor illumination during a video inspection can cause an inspector to miss some critical defects during a lengthy video inspection process.

An image processing and analysis based methodology in support of inspection and condition assessment of sewer pipelines is the focus of this paper. Inspectors or professionals, with the aid of computer enhancement and interpretation, can examine the imagery for surface defects and patterns of interest. In our research, an image enhancement and interpretation methodology was investigated and developed to highlight and identify surface defects. For example, the proposed approach emphasizes image features, such as cracks and corrosion, from remote visual inspection imagery of a sewer pipeline surface. In this paper, we present the initial results of a collaboration with RedZone

Received: 2008-05-31
** To whom correspondence should be addressed.
E-mail: lucio@andrew.cmu.edu

Robotics Inc. RedZone develops robotic sewer inspection mobile platforms, such as a device that is inserted into a sewer, and acquires high quality video and images of sewer pipelines that can be displayed on an inspection console manned by an inspector[3]. We describe a framework for automatic image enhancement and interpretation, and also illustrate it using experimental test results from real remote visual inspection data acquired by the RedZone robotic platform.

1 A Hierarchical Approach for Infrastructure Assessment

The Pareto Principle (80/20 rule) observes that a majority of results are caused by a minority of inputs[4]. In the domain of infrastructure assessment and asset management, a hierarchical approach for evaluating and managing those assets, based on this Pareto Principle, can help us to focus on the problem assets or assets of interest that most likely lead to failure and make the major contribution to the managerial and financial decisions. Considering the sewer pipeline infrastructure which is our focus in this paper, the hierarchical approach can be applied to strategically focus sewer inspection and assessment in those areas that most likely need attention. The fundamental idea of the hierarchical approach is described as follows. Problematic regions or regions of interest (ROIs) are identified by inspectors and/or engineers from CCTV inspection videos or images. Further attention is given to those ROIs, instead of the entire network. Additional or more sophisticated condition assessment techniques can then be selected and employed to the ROIs. Based on this second level of assessment, regions that have critical defects and are most likely to fail are extracted from the ROIs and can be further examined to acquire multi-faceted condition data for more comprehensive analysis. Furthermore, a maintenance strategy can be determined, for example, where rehabilitation is needed, what rehabilitation method is to be used, and so on.

In order to take advantage of and make effective use of sewer inspection data, meaningful information from the imagery needs to be extracted. For example, in an inspection video, problematic regions or ROIs can be detected automatically, and further attention can be focused only on those detected regions. In addition, the detected defects or patterns in the ROIs can be classified according to their types and severity levels. To achieve the detection and classification tasks described above using an automatic means, recent techniques in digital image processing, pattern recognition and computer vision can be used.

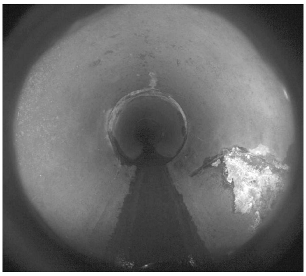
In Section 2, we describe a computer-assisted image processing and analysis methodology for enhancing and interpreting surface defects/patterns in sewer inspection imagery. Image enhancement algorithms support an inspection process by correcting artifacts due to various imaging conditions (e.g. inevitably inconsistent and poor illumination, camera settings, and source of lighting) and highlighting image features that are characteristics of surface defects/patterns. Image interpretation algorithms can make it feasible to automatically examine and analyze large volumes of inspection imagery so that inspectors can concentrate on imagery suggestive regions.

2 Computer-Assisted Image Enhancement and Interpretation

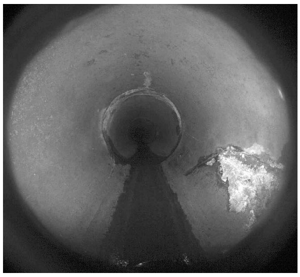
The processing and analysis of sewer inspection imagery involve enhancing, recognizing, and quantifying various objects in an image. Objects in inspection images may be any defect or pattern which is distinguishable in an image and is critical for condition assessment and subsequent decision making. Digital image processing and analysis have already been widely used in many applications including medical imaging, aerospace engineering, remote sensing, and semiconductor manufacturing[5,6]. In the following subsections, we describe the use of digital image processing and analysis methods for image enhancement and interpretation for sewer inspection imagery.

2.1 Computer-assisted image enhancement

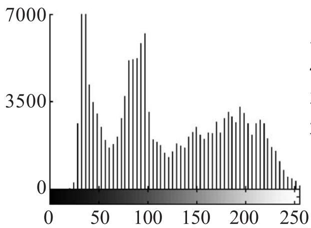
Digital image processing can serve as a prelude to visual inspection, including both manual and automated approaches. For example, sewer inspection imagery can be enhanced, making critical features more distinguishable to human eyes and computational algorithms. An image enhancement process is typically carried out to achieve both better human visual perception and computerized interpretation. For example, a bilateral denoising filter or unsharp masking process can be implemented for enhancing sewer images. A bilateral denoising filter smoothes an image without blurring the edges[7]. The unsharp masking algorithm involves a filtering process to remove image noise and a histogram adjustment process to enhance image contrast and illumination[8]. A graphical illustration is shown in Fig. 1. The image showing in Fig. 1a was enhanced, and the resultant image is shown in Fig. 1b. The histograms of the original image and the resultant image are shown in Fig. 1c and Fig. 1d, respectively.



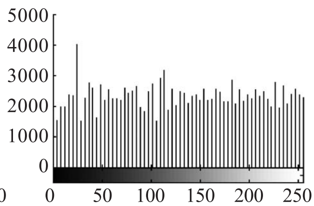
(a) Original image



(b) The resultant image after unsharp masking



(c) Histogram of (a)



(d) Histogram of (b)

Fig. 1 Example of image enhancement by unsharp masking (image from RedZone)

An image histogram is a histogram of the pixel intensity values in a digital image. To enhance the contrast and illumination of the original image, we can equalize its histogram so that the pixels are distributed evenly over the entire intensity range[5]. As shown in Fig. 1c, the histogram of the original image shows the number of pixels at each intensity value in that image. Resulting from the histogram equalization operation, the histogram as shown in Fig. 1d is flattened, and the contrast of the resulted image is essentially improved. This enhancement using an unsharp masking technique is useful for two reasons: (1) it provides a better visual presentation for humans, and (2) it adjusts contrasts and illuminations of different images used for image analysis tasks. Thus, the detailed information (e.g., edges and other image features) in the original image can be highlighted through image enhancement operations, while image noise is reduced through filtering.

2.2 Computer-assisted image interpretation

Automatic image interpretation is a difficult problem. It is also task specific. Regarding the sewer inspection task, it is important to detect objects of interest automatically to assist human inspection and assessment processes. Techniques in computer vision and pattern recognition can assist human inspectors and engineers in interpreting large data sets, for example, to detect defects from hours of inspection videos and thousands of still images. The general architecture of the automatic image interpretation method for inspection and condition assessment of sewer infrastructure is shown in Fig. 2.

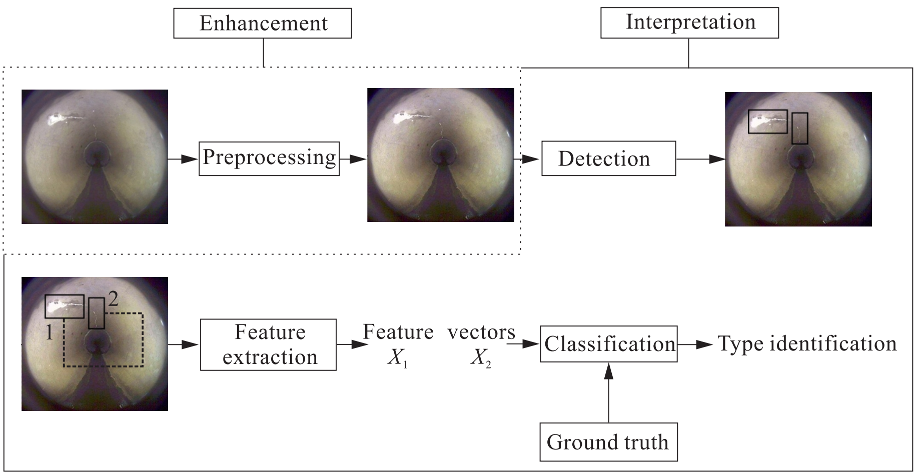


Fig. 2 Approach for automatic image enhancement and interpretation for sewer inspection (image from RedZone)

A preprocessed, enhanced inspection image is fed into the interpretation process. The interpretation process includes three main steps, which are detection, feature extraction, and classification. The first step of the interpretation process is the detection of defects and critical patterns, which are used for making engineering and management decisions, in an input image. The following step is feature extraction. The underlying concept of feature extraction is to represent image as vector, which is a suitable format for computers to handle[6]. Feature extraction can be considered as a function to achieve this image-to-vector process. Features could be the geometric characteristics of defects/patterns, color features, texture features, histogram features, and spectral features. An appropriate set of features should be selected. One important consideration when selecting appropriate features is the robustness of a feature. A robust feature can usually provide consistent recognition results. Features can be extracted from the whole image or from specific regions of an image. In fact, the feature extraction process can also be part of image preprocessing process and detection process, since features (e.g., color and intensity of each pixel) are needed to be extracted and used for some image enhancement and detection algorithms. Once features are extracted, an image can be analyzed computationally. The last step of the process is classification. The objective of a classification process is to identify the defects/patterns that are detected in an image or a video. Automatic defect classification from sewer images has been investigated recently, and some common patterns including cracks and joints can be identified[9]. So far, few studies have investigated the detection process, so the rest part of this section describes in more detail the step of detection and is customized for the domain of sewer inspection and condition assessment.

Detection is the task of determining whether an image contains defects/patterns or not (presence), and localizing them if they are present (location). The detection approaches can be grouped into two classes: holistic knowledge-based approaches and local bottom-up approaches.

2.3 Holistic knowledge-based approach

One of the major approaches to deal with detection problems is the use of prior knowledge about the defects/patterns, which exists in sewer inspection images. A common method using prior knowledge for detection analyzes an image by matching features (e.g., texture, color, and size) of objects that are to be detected with those in the image to determine the regions most likely contain the objects[8,10]. According to the pipeline assessment and certification program (PACP)[11], there exist a large number of types of defects in sewer pipes, and each defect may be of various shapes, colors, poses and sizes under different pipe conditions. Therefore, it is not feasible to use the common method described above to detect a variety of defects/patterns in sewer pipes, mainly because such common method cannot deal effectively with variations in pose, shape, and size[10].

However, to solve this particular detection problem in the sewer infrastructure domain, we found that prior knowledge about a healthy or normal pipe can be used as a reference to differentiate the defected regions from the healthy regions. By adopting the change detection method[12,13], changes or ROIs are identified from a difference image yielded by subtracting two images. We have considered two feasible methods to generate the difference image for ROI detection from sewer inspection imagery. One is image-to-mean comparison. A mean image of a set of inspection images or a video clip can be calculated as a reference to be used for image subtraction. Each image to be examined is subtracted by the mean image to produce a difference image. This method requires a relatively large number of images to yield a good mean image for comparison, and is particularly suitable for an offline analysis. Another is image-to-reference comparison. A pre-selected reference image is used for image subtraction. A reference is usually needed to be chosen for different pipe segments. Regarding CCTV on-site inspections, this method is suitable since an inspector can easily point out a reference image to be used by the automatic ROI detection algorithm shortly after the inspection starts.

2.4 Local bottom-up approach

Different from the knowledge-based approach as described above, a bottom-up approach for detection does not require prior knowledge about pipe features, but rather tries to cluster an image into homogeneous regions and to classify each region as either belonging to a defect/critical pattern or not. To cluster a sewer image into regions, we adopted a commonly used clustering algorithm, called *k*-means clustering. The fundamental concept of *k*-means clustering is to minimize intra-cluster variance based on similarity between data points. The k-means clustering approach partitions image pixels into homogeneous groups that have similar feature properties through an optimization process[6]. The objective function that we attempted to optimize (minimize) is shown in Eq. (1), where Φ is the objective function, C_i represents clusters or groups, $i = 1, 2, 3, \ldots, k$, $\boldsymbol{X}$ represents features or pre-attentive attributes extracted from each pixel in an image. ϕ_i is the centroid or mean point of all the points in i-th cluster C_i.

$$\Phi(C, X) = \sum_{i=1}^{k} \sum_{x_j \in C_i} \| x_j - \varphi_i \|^2 \quad (1)$$

Given n data points in a cluster, which are represented as a set of feature vectors $\{\boldsymbol{x}_j\}$: $\boldsymbol{x}_1, \boldsymbol{x}_2, \ldots, \boldsymbol{x}_n$, obtained during the pre-attentive processing stage, and assuming the number of clusters is k ($k < n$), we first need to initialize ϕ_i by randomly determining k cluster centroids. Then we assign each $\boldsymbol{x}_j$ to the nearest cluster centroid ϕ_i and recalculate the new cluster centroids, and repeat this process until it can no longer reduce the intra-cluster variance by moving $\boldsymbol{x}_j$ from one cluster to the next.

The k-means method is fast to compute and easy to use. However, the disadvantages of using a k-means method have hindered us from further applying this method for segmentation and visual perception of actual sewer pipe images. A k value has to be specified to initiate k-means clustering algorithm. In a real inspection environment, it is not feasible to correctly predict the number of regions that exist in each image. Moreover, the k-means segmentation results that we computed in our experiments were not stable. For example, the segmentation results using the same image can be very different in different testing trials, as shown in Fig. 3. This is mainly because the k-means method is very sensitive to initial centroids, and hence regions could form differently in different trials[14].

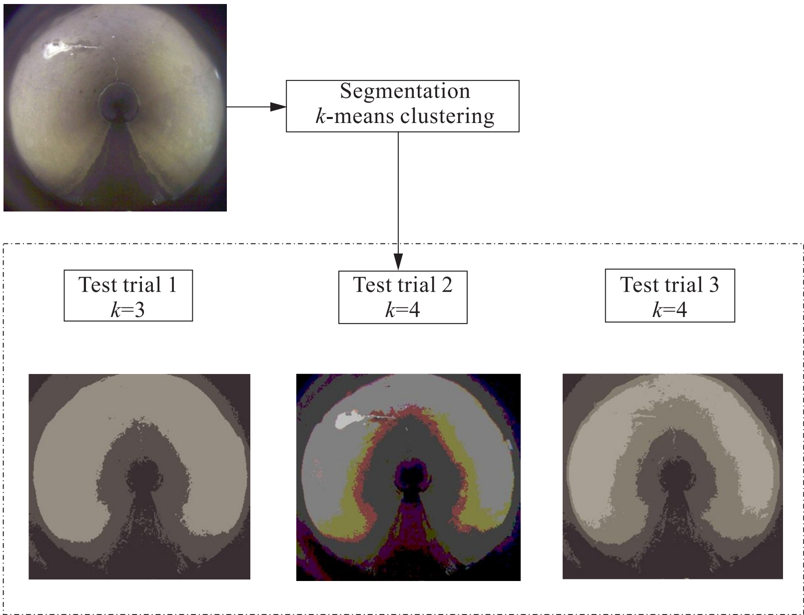


Fig. 3 Different results generated by *k*-means segmentation (image from RedZone)

3 Conclusions and Future Work

Our research efforts are aimed at assisting the current video inspection and condition assessment practice in the domain of civil infrastructure systems, especially with the focus on sewer pipelines. To achieve this objective, we have presented a computer-assisted image enhancement and interpretation method by adopting image processing and computer vision methods. The studies of automatic detection of ROIs and defects have been few to date, but this computer-assisted detection approach could contribute significantly to facilitating sewer inspection activity, and hence is the focus of this paper. Tailored to the domain of sewer infrastructure assessment, we have presented two possible approaches, including a holistic knowledge-based approach, and a local bottom-up approach. As for the knowledge-based approach, we have preliminarily identified that a change detection method can be adopted to detect defects/patterns. Extensive experimental testing is currently being carried out to demonstrate its feasibility and effectiveness. As for the bottom-up approach, we illustrated a *k*-means clustering method in this paper. Future investigation is required to establish a more stable and robust clustering method for segmenting a sewer image into regions for subsequent classification process.

Acknowledgements

The authors wish to thank RedZone Robotics Inc. for providing the datasets for experimental testing and funding for this research. The authors also acknowledge the funding support provided by the Innovative Management & Technology Services - National Aeronautics and Space Administration (IMTS-NASA) grant, and the Pennsylvania Infrastructure Technology Alliance.

References

[1] EPA. Asset management for sewer collection systems. Fact Sheet, United States Environmental Protection Agency (EPA), 2006.

[2] Wincan. http://www.wincan.com, 2008.

[3] RedZone Robotics Inc. http://www.redzone.com/, 2008.

[4] Bookstein A. Informetric distributions, part I: Unified overview. *Journal of the American Society for Information Science*, 1990, **41**: 368-375.

[5] Jahne B. Digital Image Processing. Germany: Springer, 2002.

[6] Forsyth D, Ponce J. Computer Vision—A Modern Approach. London, England: Prentice Hall, 2003.

[7] Jiang W B, M L, Wu Q, et al. Applications of a bilateral denoising filter in biological electron microscopy. *J. of Structual Biology*, 2003, **144**: 114-122.

[8] Amit Y. 2D Object Detection and Recognition: Models, Algorithms, and Networks. USA: MIT Press, 2002.

[9] Sinha S K, Fieguth P W. Neuro-fuzzy network for the classification of buried pipe defects. *Automation in Construction*, 2006, **15**(1): 73-83.

[10] Yang M H, Kriegman D, Ahuja N. Detecting faces in images: A survey. *IEEE Transactions on Pattern Analysis and Machine Intelligence*, 2002, **24**(1): 34-58.

[11] NASSCO. Pipeline Assessment and Certification Program Manual. Pipeline Assessment and Certification Program (PACP), Second Edition Reference Manual. NASSCO, 2001.

[12] Kim S, Pyo H B, Lee S K, et al. Digital image subtraction of temporally sequential chest images byrib image elimination. In: Engineering in Medicine and Biology Society, Proceedings of the 22nd Annual International Conference of the IEEE. Chicago, USA, 2000.

[13] Qu G, Wood S L, Teh C. Wafer defect detection using directional morphological gradient techniques. *Journal on Applied Signal Processing*, 2002, **7**: 686-703.

[14] Bishop C M. Pattern Recognition and Machine Learning. Germany: Springer, 2006.