World Academy of Science, Engineering and Technology
International Journal of Mechanical and Mechatronics Engineering
Vol:2, No:6, 2008

Real-time Laser Monitoring based on Pipe Detective Operation

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***Abstract*—**The pipe inspection operation is the difficult detective performance. Almost applications are mainly relies on a manual recognition of defective areas that have carried out detection by an engineer. Therefore, an automation process task becomes a necessary in order to avoid the cost incurred in such a manual process. An automated monitoring method to obtain a complete picture of the sewer condition is proposed in this work. The focus of the research is the automated identification and classification of discontinuities in the internal surface of the pipe. The methodology consists of several processing stages including image segmentation into the potential defect regions and geometrical characteristic features. Automatic recognition and classification of pipe defects are carried out by means of using an artificial neural network technique (ANN) based on Radial Basic Function (RBF). Experiments in a realistic environment have been conducted and results are presented.

***Keywords*—**Artificial neural network, Radial basic function, Curve fitting, CCTV, Image segmentation, Data acquisition.

I. INTRODUCTION

THE sewer operation is one of the biggest infrastructures of several industrialised countries, reaching 5000 km of sewers per million of persons. Whilst, the total sewer operations in Thailand are predicted to be 170,000 km long. Some sewers are now more than 100 years old, and at least half the total number of sewers is over 50 years old, and around 20% of them are damaged in any reason. According to a study by a Thailand-based company, there are approximately 6,000 collapses and 350,000 blockages per year in the Thailand. Considering that only 0.1 % of the sewer system is replaced every years, these figures are expected to increase by 3% every years. Early detection of pipe defects may prevent severe failures that could involve environmental catastrophes and high economic costs.

Since the small diameter of sewers, humans could not access and directly inspect a large part of pipes in the municipal sewer system. Remotely controlled inspection devices based on mobile robots or wheeled platforms equipped with sensors are used instead. The standard approach is to have a closed circuit television (CCTV) camera fitted on a mobile platform that travels through the pipe recording images onto a videotape. The recorded images are assessed off-line by an engineer. One of the major drawbacks of this technique is the exorbitant amount of information generated, that can reach about 3 hours of video for the inspection of 1 km of line [6].

Standard CCTV is currently used in many pipe inspection applications, such as sewers. This human-based approach is prone to error because of the exorbitant amount of data to be assessed, and smaller anomalies or defects are likely to be overlooked reducing the chance of detection of faults at an early stage. And some research has been carried out in the field of automated sewer inspection. For instance, the Civil and Environmental Engineering group, at Concordia University (Canada), is developing a model for automating the process of identifying surface defects from digitised video images of underground water and sewer pipes, using image analysis, pattern recognition and neural networks [5]. Automatic recognition, rating and classification of pipe defects are carried out by means of artificial intelligence software tools. Images are segmented into potential defect regions and characteristic geometric features. Region classification is performed by a feed-forward, off-line trained neural network classifier. A rule-based system interprets, rates and reports the classified regions as pipe defects [1].

Laser profilers for pipe inspection have been recently proposed to overcome CCTV problems. Positional as well as intensity information, related to potential defects. While single techniques have been used for other types of pipe inspection [9], inspecting the two media (liquid and gas) in sewers is more complex than, for example, gas or water pipelines inspection [7]. The investigation reported in this paper is part of a research program with aiming to develop intelligent autonomous agents, which able to travel inside sewer pipes and inspect them for defect detection. A main research challenge in developing autonomous systems is to create a robust sensor system capable of monitoring the pipe above and below the water line. Two main disadvantages of such camera-based inspection systems are (a) the low quality of the acquired images due to difficult lighting conditions (b) the susceptibility to error during the offline assessment by human operators. This research is aim to overcome these disadvantages and to create an intelligent sensing approach for improved and automated pipe-condition assessment.

Therefore, the time required by the engineer to assess the pipe condition depends on the number of defects. Owing to the variability and the time consumption incurred by the human-based assessment process, automation of this part of the inspection task becomes an important issue.

This research is aim to study and develop multi-sensor systems and to create intelligent sensor fusion and sensor data processing algorithms. It is envisaged that a system based on a laser-profiler and CCD camera measures the surface geometry

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of the drained part of a sewer, while a sonar scanner measures the flooded part. And also is assessment for sampling sewage water leaking from holes around the pipe.

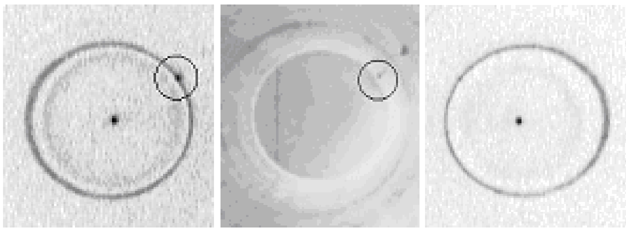
In the development of a micro-robot for inspecting the inside of pipes with an internal diameter of 1 to 3 inches, the author of this paper designed an in-pipe mobile mechanism adaptive to pipe diameter. This paper presents the automated inspection condition assessment of the non-flooded part of the pipe, using a structured light source and a ring-pattern projector. The described method makes use of an intelligent classification stage that provides clear identification of defective pipe segments. The research work presented in this paper mainly aims at the identification of holes. Work to classify other faults such as radial cracks, longitudinal cracks and obstacles is still in the experimental stage and also presents a compact design of the robot's mechanical and electronic systems, and develops a simple for determining the hole position using some characteristics of this in-pipe robot.

The different processing stages such as data acquisition, image processing and classification are described in the following sections. In Section II, the transducer that is used to acquire the images is described. The segmentation of the image into regions of interest will be shown in Section III. The classification step is shown in Section IV. Finally, conclusions are given in Section V.

II. CCTV-Based Laser Profiler

CCTV images are often difficult to interpret. Spatial reference is needed if faults are located, and illumination is not always sufficient to allow fault identification. This is specially the case with small cracks and holes in the pipe surface (Fig. 1). In this work, a laser-based profiler can easily be incorporated into existing camera-based systems is employed with this problem. The transducer consists of an optical pattern generator. The optical ring generator is made of an assembly of a laser generator and diffractive diffuser optics. The experimental rig used a semiconductor laser diode wavelength and a diffractive diffuser generating a ring pattern. The circular patterns of light are fetch by a calibrated CCD camera, and stored in a computer via a frame grabber (see Fig. 2).

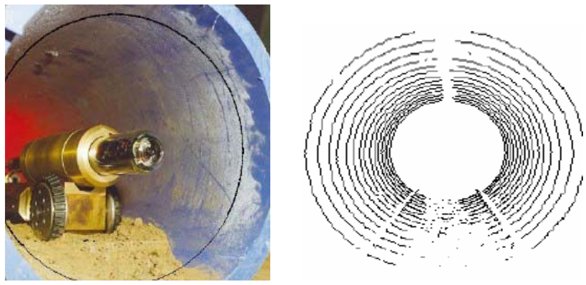
Tests were conducted on PVC pipe sections with inner diameters of 260 and 300 mm. Holes were pierced into the walls of the pipe segments in order to simulate defects. Local discontinuities, such as cracks or holes can be detected by analysing the light intensity of the projected rings. At points where discontinuities occur, the laser light is scattered resulting in changes of intensity levels in the acquired camera image (see Fig. 2). With analyzing these intensity levels defects can be detected. Therefore, as the geometric characteristics of the cone of light are fixed for a given diffuser optic, the location of the surface under investigation relative to the platform is known. Consequently discontinuities can be identified and located.



(a) (b) (c)

Fig. 1 Images of a pipe with a 2 mm hole

In Fig. 1, the images of a pipe with a 2 mm hole has been presented, the location of the hole is also highlighted with a small circle, see Fig. 1 (a). This is shown that the image acquired using the laser-based transducer, where the crack can be easily identified. At the Fig. 1 (b) shown the image acquired with a conventional CCD camera and lighting system. Note that the white spot next to the circle is created by a light reflection; it is not a defect (c) that presents the image acquired using the laser-based transducer, corresponding to the location of the non-defective point caused by light reflection as referred to in b). This image shows that the proposed method correctly presents this point as non-defective.



(a) the traversal algorithm (b) the curve from sensor

Fig. 2 The identification process

The identified technique has applied using the computer interfacing to receive the image signal during the traversal algorithm. The digital signal of signature curves has been applied to the identification process as monitoring method. This traversal algorithm and identification process have been presented in Figs. 2(a) and 2(b).

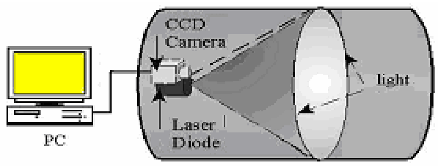


Fig. 3 The experimental test rig set-up

In Fig. 3, this shown the test rig as the experimental set-up, where a camera and a laser projector are placed next to each other. The camera images are loaded into a Personal computer by means of a frame-grabber process for using in the identified algorithm.

III. Image Segmentation

A sequence of image processing stages is used to identify the location and specific shape of the ring profile and to separate it from the image background. Once a ring profile is properly extracted, a feature extraction algorithm scans the profile. This process is repeated for each of the acquired profiles, instead of searching the entire and potentially very large pipe wall image for defects. This approach has been shown to considerably reduce the amount of data to be processed, and consequently the computation time. The projection of a circle into the camera image is an ellipse. Also, any misalignment of the projector device with respect to the pipe centre will cause the ring projection to degenerate into an ellipse. Fitting the acquired pixels to an ellipse equation becomes a need. Clustering methods such as Hough transform were tried, but besides some advantages like high robustness to occlusions and lack of pre-segmentation requirements.

They are computationally complex and result in multiple solutions. In this work, a highly efficient specific ellipse-fitting algorithm is used. It is preceded by a signal-conditioning and filtering stage, which enhances the quality of the images and facilitates the identification of the ellipse [3].

A. Signal Conditioning

Prior to applying the conic-fitting algorithm, image quality needs to be enhanced. Low-pass filtering steps are applied, followed by an edge detector [3]. One essential operation to cope with lighting variations is histogram adaptation. In our case, the intensity levels of all the image pixels are adjusted to span the entire available intensity range (0,255). This is an adaptive image processing step where the pixels intensities are mapped in such a way that all input intensities that fall below the average intensity value (background) are mapped to zero intensity, and all intensities higher than the average are "expanded" to span the entire image intensity range. The effect is that the resulting image is considerably brightened, and the dynamic range of the dark portions of the original image is widened, making it much easier to identify the circle of light. A median filter is applied then, so that noise is attenuated and edges are preserved. Finally, a canny edge detector has been found most efficient to pre-segment the image by finding the edges of the ring of light [3].

B. Ellipse Extraction – Curve Fitting

The methodology has been used in this research to efficiently fit the image to a conic. It is based on the ellipse fitting method proposed by Fitzgibbon [2], improved by a method suggested by Halýr [4]. The approach is a non-iterative algorithm based on a least squares minimization of the algebraic distance between the data points and the ellipse. A quadratic constraint guarantees an ellipse-specific solution even for scattered or noisy data, or for a partial occlusion condition, which can occur when the sewer is partially flooded. Also to improve the behaviour of the algorithm in the presence of noise, a weighted function is applied to the points before feeding them to the above algorithm.

The method is based on the representation of a conic by an implicit second order polynomial:

$$F(\bar{a},\bar{x})=\bar{a}\cdot\bar{x}=a\cdot x^2+b\cdot x\cdot y+c\cdot y^2+d\cdot x+e\cdot y+f=0 \qquad (1)$$

Where $\bar{a}=[a\ \ b\ \ c\ \ d\ \ e\ \ f]^T$ and,

$$\bar{x}=[x^2\ \ xy\ \ y^2\ \ x\ \ y\ \ 1]^T$$

and $F(\bar{a},\bar{x})$ is the algebraic distance of a point (x, y) to the conic $F(\bar{a},\bar{x})=0$.

The curve fitting consists of minimizing the squares of the distances, $\sum_{i=1}^{N} F(\bar{a},\bar{x}_i)^2$, subject to the equality constraint, $4ac-b^2=1$, incoporating both scaling and ellipse-specific conditions. Then, the smooth curve can be fitted and applied to the experimental signal. Using the interpolating polynomial of n^{th} degree then we can obtain a piecewise use of polynomials, this technique is to fit the original data with the polynomial of degree through subsets of the data points. This result is quite suitable approach as a least square curve fit algorithm [10].

C. Feature Extraction

At that stage, the extraction of the intensity information along the segmented ellipse is completed. In order to achieve this, a partial histogram of the image is created using local averages of intensity along the ring profile. Subsequently, faults can be identified and located analyzing successive histograms. The feature extraction algorithm computes local averages of intensity along a defined number of segments of the ellipse. The local average intensity is computed using the formula:

$$\frac{\Sigma\mu - x}{\Sigma\mu} \qquad (2)$$

Where,

x is the grey level of a certain image point, and

μ the frequency of that grey level.

Since the image of the ring of light is wider than one pixel, the average is computed over a sliding window covering area along individual ellipse segments. Fig. 3 shows the results of the feature extraction process displayed as a partial image histogram. In the current experiment, a pipe of 260 mm of diameter is used. A 2mm hole has been pierced at 122 degrees from the horizontal axis. The partial histograms have been computed with steps of one degree along the ellipse segments. Successive histograms are computed from the pipe surface images that are taken while the platform travels along the pipe, to create an image of the pipe wall. Steps of 5 mm in the longitudinal direction were used in this experiment. A sliding window is applied along the ellipse. The peak indicates the location of a potential discontinuity, which shown in Fig. 4.

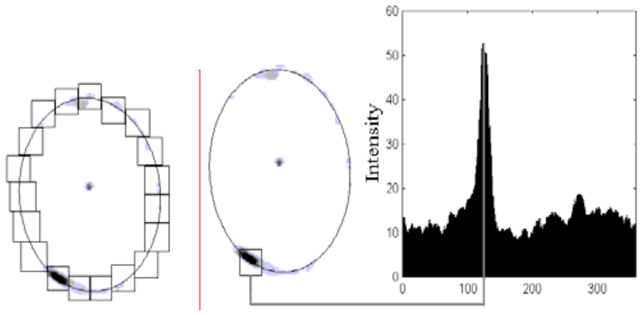


Fig. 4 Extraction feature (with the sliding window)

IV. Classification Using RBF Neural Network

The aim of the neural network is to identify defective and non-defective pipe sections and to classify different defects in the surface of the pipe. This work focuses on the identification and classification of holes. In further work, the neural network is intended to classify between other discontinuities such as longitudinal cracks, radial cracks, holes and obstacles. Sets of pre-processed data representing 360-degree profiles are fed into the network. The main aim of the pre-processing stage is to remove measurement noise from the training data that could otherwise enter the RBF NN algorithm and interfere in the learning process and probably complicate the classification task. Open-up representation of the inner surface of the pipe and the peak intensity shows the location of a potential hole/defect shown in Fig. 5.

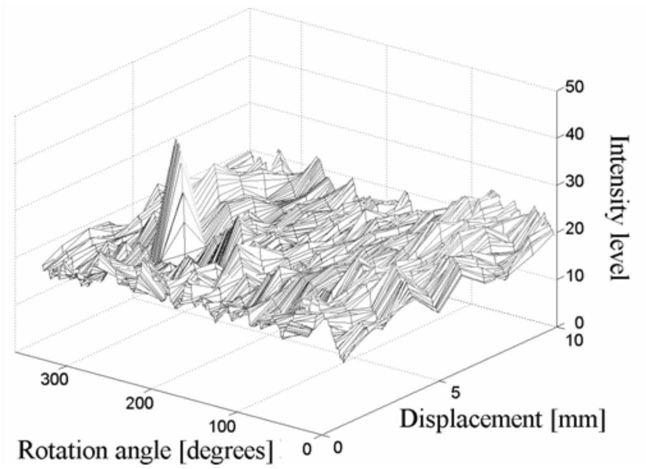


Fig. 5 Open-up of the inner surface of the pipe

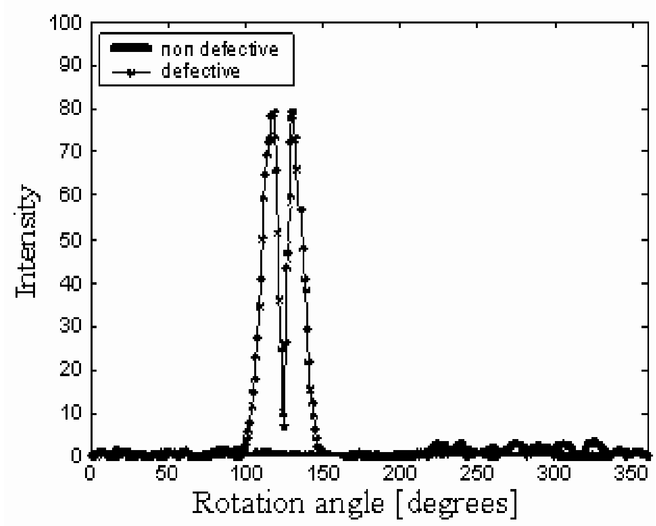
A. Pre-processing

Before feeding the neural network, the raw data is pre-processed to filter out non-relevant data. In our case the goal is the identification of holes in the surface of the pipe. The main interest here is to locate the points where the variation in intensity levels is high, both in the radial and in the displacement direction, regardless of the lighting conditions (Fig. 4). The first step consists of emphasising sharp intensity variations (associated to possible holes).

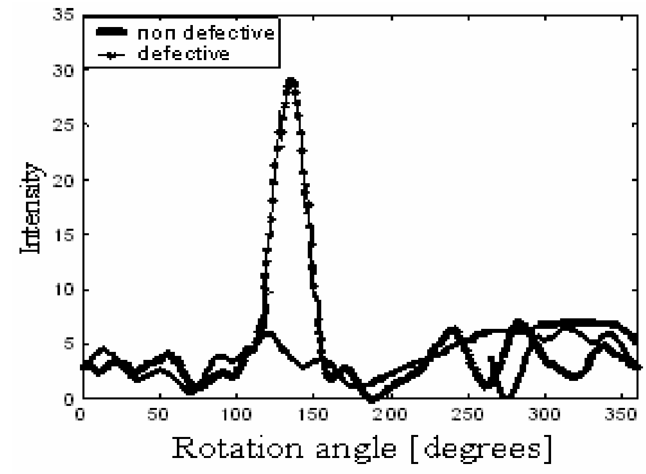
The computation in this stage is based on obtaining the partial derivatives $\partial f / \partial d$ and $\partial f / \partial \alpha$, with d being the displacement along the pipe in the longitudinal direction, and α being the rotation angle along a pipe profile. Both partial derivatives at the point where the hole is located present sharp peaks of amplitude (Fig. 5).

This operation effectively attenuates slow changes in intensity that is primarily due to simple differences in illumination across the section under study. As a lateral effect, low-amplitude noisy data transitions will be emphasised as well. A low-pass moving average filter is applied to remove this high-frequency noise. Fig. 5 shows sample pipe profiles after filtering. It can be noticed that defective sections present sharp peaks of intensity in both partial derivatives.

Therefore, the curve fitting method has been employed using an algorithm of the polynomial technique to fit on this captured curves [11] into this signal after noise filter.



(a)



(b)

Fig. 6 Pipe profiles after filtering

Pipe profiles representations after filtering can be noticed that defective sections present a sharp peak of intensity in both partial derivatives in Fig. 6(a) are Partial derivative respect to the rotation angle of non-defective and defective sections;

Partial derivative respect to the displacement of non-defective and defective sections shown in Fig. 6(b)

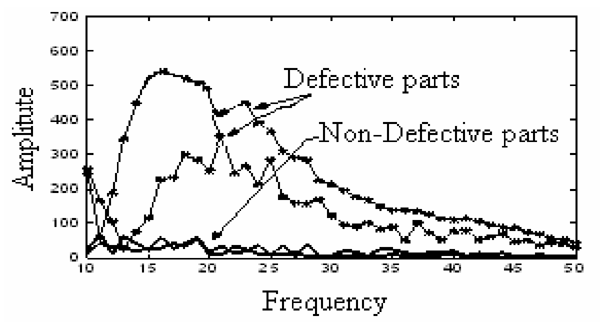


Fig. 7 FFT of defective and non-defective sections

In Fig. 7, FFT of defective and non-defective sections have presented. Although the resulting data could probably be used to feed the NN (Fig. 6), a further step is taken in order to reduce the amount of data supplied to the network. Fig. 7 shows defective and non-defective pipe profiles together with their Fourier transforms. The peaks that can be observed in the mid-frequency range of the Fourier domain correspond to intensity variations due to physical defects.

The interesting feature is the fact that a neural network can use this FFT data in order to consider defects, regardless of their position in the spatial domain along a certain profile. In other words, by using Fourier data, the NN does not need to be trained with a stream of sections that contain defects at all possible points in the pipe section (see Fig. 7).

B. Network Structure

The network used in this work that consists of three layers composed of neurons. These neurons are arranged in such a way that each of them has a weighted connection coming from every neuron in the previous layer. Each neuron performs a summation of all its inputs and passes the value through a non-linear function before sending it to the output. Choosing the parameters for these operations is done through a training process. The training algorithm used in this work is based on RBF, which is widely used for classification problems. The training method is gradient descent with momentum and variable learning rate. The training rule is: $\Delta w_{ij}(n+1) = \eta(\delta_{pj} O_{pi}) + \alpha \Delta w_{ji}(n)$, where n is the index for the presentation number, α is the learning rate , and Δ is a constant that determines the effect of the past weight changes [1,6].

C. Experimental Results

Experiments with different configurations of NN architectures and different number of hidden layer nodes were carried out. The best performance was achieved with three layers: One first layer of 50 inputs, the second of 100 hidden nodes and finally one output node as the third layer. The input to the training algorithm was a stream of pre-processed measurement data, as shown in section IV(A), containing both faulty and non-faulty pipe sections.

The training behaviour shown the algorithm is able to classify the training data bringing the error down to 0.0001 after 39 epochs (Fig. 8). The ability of the data to cope with unseen data is also tested. Table I is to conclude the output results of the network for four pipe profiles not seen during the training. The target column specifies the value ‘1’ or ‘0’ corresponding to non-defective and defective sections respectively. The output column represents the output node. The error is the absolute difference between the target and the output values.

These results show that the network is able to identify irregularities in the data, related to defective sections with holes, even if the data was not seen by the network beforehand.

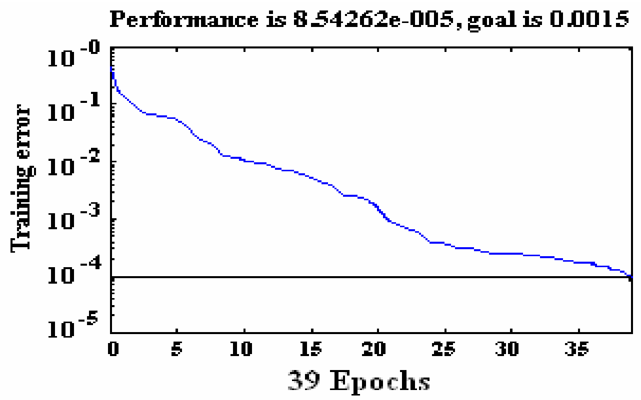


Fig. 8 Training error

TABLE I
NETWORK RESPONSE TO UNSEEN DATA

Section	Target	Output	Error
Defective sections	0	0.2169	0.0021
	0	0.0650	0.0050
Non-defective sections	1	1.2021	0. 032
	1	1.2324	0. 0161

V. CONCLUSION

A new laser-based inspection system for the automatic assessment of sewer conditions has been presented. The method is based on the projection of a laser-generated pattern onto the pipe walls, allowing the location of cracks in the inner surface of pipes by analyzing the light intensity of the projected rings. Classification is achieved by means of an RBF NN. The trained network is capable of distinguish between defective and non-defective pipe sections. Tests have been conducted in plastic pipes with different inner diameters and Holes as small as 2 mm. have been detected. Future work will focus on the classification of other discontinuities such as longitudinal and radial cracks.

This laser profiler as well as the suggested defect detection method can be easily incorporated into existing CCTV inspection systems, greatly improving their behaviour, especially under harsh lighting conditions. After these encouraging results, the next step will be to test the system in real pipes, in order to confirm its robustness and to improve the experimental set-up and the algorithms to cope with real conditions. Algorithms to retrieve the position of the platform with respect to the pipe are under research, since the platform is not expected to be always in the centre of the pipe. Besides that, the profile images could change, due to possible particles in the gaseous part of the pipe and roots penetrating through the walls of the pipe. To cope with such problems the algorithms and the experimental set-up could need further development to guarantee a clear representation of discontinuities.

The long-term objective of this research is to assess partially flooded pipes using a multi-sensor system. The transducer described in this paper inspects the non-flooded surface, while an ultrasonic sensor will inspect the flooded parts [1]. In order to get a complete image representing the condition of the entire surface of the pipe, sensor fusion can be carried out at the pixel, signal or feature levels. Moreover, the information acquired by the ultrasonic sensor will be used in order to improve the performance of the camera-based method described here, especially in the presence of noise or under conditions where the camera images are partially occluded.

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