Multi-kernel Neural Network-based Visualization of Pipe Leakage from Video Data

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1. Introduction

Pipes are the parts of the industrial construction that functions similarly to human blood vessels. It is one of the main monitoring priorities as the pipe leaks are dangerous to the structural integrity of the structure [1-5]. If the inspector ignores the leakage, access to the pipeline for the test can lead to serious physical injuries. For the safety of not only the facilities but also the inspectors, it is required to run a monitoring system that identifies the leaking area [6]. In this study, a multi-kernel neural network is proposed to visualize leaking zones using deep learning of the characteristics of pixel-wise color variation in normal and leakage zones from video data. We show that it the visualization quality can be adjusted based on controlling precision and recall.

2. Methods and Results

2.1 Pipe Leakage Simulation System

The piping for simulated leakage is shown in Fig. 1. The pipe was connected to a steam generator capable of generating steam so that high-temperature and high-pressure steam could flow into the pipe. Pipe leakage can be simulated by opening and closing the needle valves installed in seven locations. Using four cameras installed to record the pipe condition as a video with a size of 1280 pixels in width and 720 pixels in height.

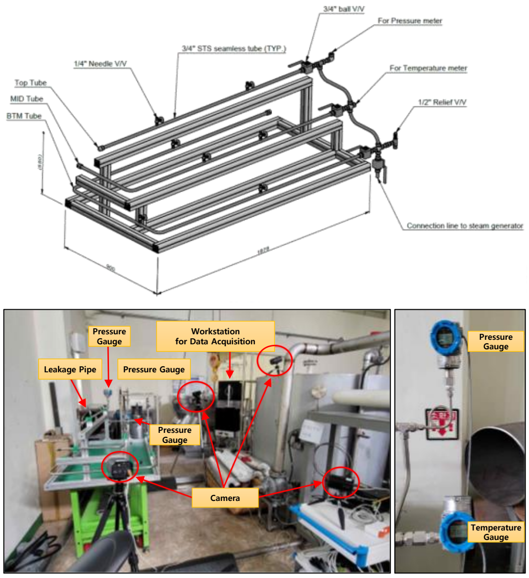

Fig. 1. Pipe leakage monitoring multiple camera system.

2.2 Deep Learning for Leakage Probability Estimation

A multi-kernel neural network [2, 6] takes as input a sequence, corresponding to a normalized relative color variation in each pixel, and outputs an estimate of the leakage probability, as shown in Fig. 2. Using the trained model, the leakage areas can be visualized in the frame where the leakage occurred, as shown in Fig. 3. After every sixty frames were extracted from the original video, they were fed into the model and output the leak probability for each pixel. If the leakage probability is greater than a preset threshold, a leak label is created with a red marker, and the pipe leakage pixels are visualized by synthesizing the label with the input frame.

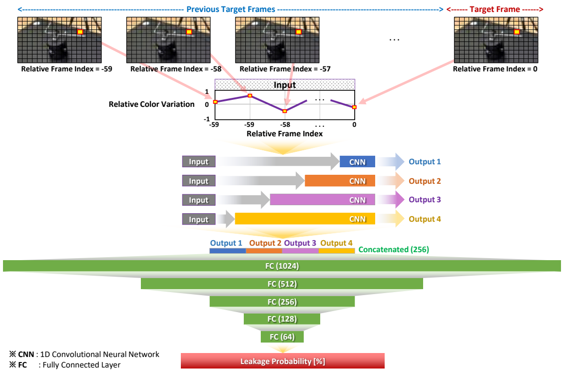

Fig. 2. Multi-kernel neural network for leakage probability estimation.

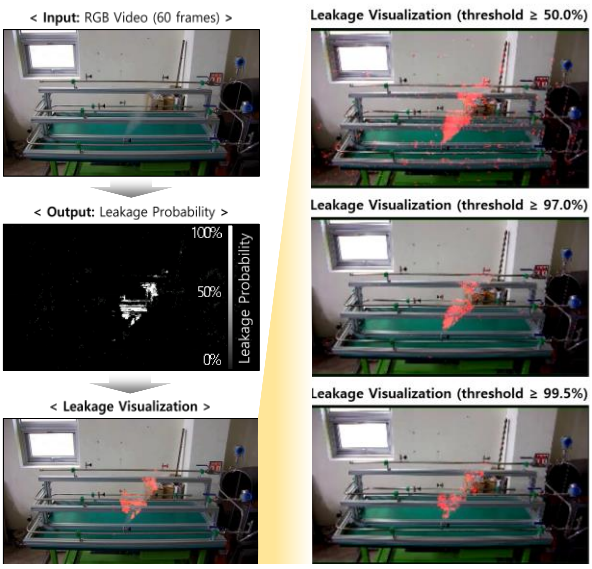

Fig. 3. Pipe leakage visualization and synthesis concept.

2.3 Leakage Visualization and Its Characteristics

Under the condition of setting the threshold to 50%, the accuracy was 92.58% and 92.09% for the training and validation datasets, respectively. The accuracy for the evaluation dataset was 97.47%. However, the precision was at 24.09%, which is relatively low. In visualizing leak areas in the leakage cases through the proposed model, the frequency of non-leakage pixels is overwhelmingly higher than that of cases where leaks are detected. For this reason, even when the leakage region is not properly detected, the accuracy of the leakage detection tends to be calculated high. To rationally evaluate the leak area visualization performance, it is necessary to review the precision and recall according to the critical value. Precision is the ratio of pixels that are leaky among pixels that the model judges to be leaky, and recall is the ratio of pixels found to be leaky by the model among pixels that are leaky. In an environment with many risk factors, such as toxic gas pipelines, where the urgency of responding to leaks is high, it is required to ensure a high reproducibility through a low threshold value, and in the opposite environment, false positives can be detected by raising the threshold value and visualizing only when it is certain. Doing so can reduce false alarms. In general, it is reasonable to choose a critical value that maximizes the harmonic average of precision and recall (F1-score). In this study, the harmonic average was maximum when the critical value was 97%.

3. Conclusions

A multi-kernel neural network is proposed for leakage probability estimation, and it is used to visualize the leakage area from video data. Pixels with an estimated leak probability greater than a preset threshold are marked in red, and the marked area is composited with the input frame to finally visualize the pipe leakage zone. The visual characteristics of the leakage area can be adjusted according to the threshold value. If the threshold value is high, the accuracy is increased and only the area where the leakage is sure to be leaked is determined. Depending on the risk of leakage, it is recommended to properly control the proportion of false positives that are determined to be leaks even though they are not leaks. Through leakage visualization performance using the proposed neural network and threshold analysis process, it is shown that a neural network is a practical monitoring tool for visualizing the leakage area by the environment and the purpose of monitoring pipe leakage.

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