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Multi-Kernel Neural Network-based Visualization of Pipe Vibration Frequencies from Video Data

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ABSTRACT

Pipe networks in industries operate similarly to human blood vessels. Vibration in a pipe is a natural occurrence generated by external motors and fluid movement inside the pipe. Unexpected sources such as wall contact by loose parts or abnormal fluid flow can have a significant impact on the pipe vibration, resulting in unusual vibration patterns compared to normal operation. That is why pipe vibration frequency is one of the most important structural condition monitoring factors to track. Thus, a monitoring system that detects the vibration frequency of each pipe aids in the early detection of these anomalies. In this research, a multi-kernel neural network is proposed to visualize pixel-by-pixel vibration frequencies from sixty frames of video data. The network estimated the vibration frequency of each pixel via learning its color-changing characteristics. The vibration region and its frequency were visualized by synthesizing the input and the output from which the vibration frequency was estimated. The result showed that the probability that the vibration frequency estimation error was within 1 Hz was 89.25% and within 5 Hz was 98.96%. This supports that the proposed model can effectively visualize the pipe vibration and be used to detect vibrational anomalies.

INTRODUCTION

In industrial settings, such as power plants, it is crucial to monitor the structural integrity of pipes that transport gases and liquids. These pipes vibrate naturally during operation, but factors such as blockages, impacts to the walls, abnormal flow rates, or defects can alter these vibrations. Changes may include different shell mode frequencies, shock waves from loose parts, vibrations from leaks, or unusually high vibrations leading to large displacements. Monitoring vibrations is crucial for ensuring the safety and integrity of piping systems, especially in nuclear power plants where self-induced vibrations from fluid flow are common. Studies by Park et al. (2019, 2021) and Jeon et al. (2008, 2009) have shown that unexpected vibration sources, such as loose parts contacting the wall or unusual vibration patterns, can significantly impact the mechanical integrity of these systems. Identifying the sources of abnormalities in vibration frequency during normal operation requires tracking changes.

Accelerometers and laser measuring devices are commonly used to monitor pipe vibration. However, their installation in the field environment and facility construction has limitations, and monitoring large-scale pipes is uneconomical. To address this issue, technologies that measure vibration using camera images have been proposed. To determine the frequency range and characteristics of interest that match the monitoring target for these technologies, one must select the appropriate frequency components. An image processing algorithm must then be developed to effectively extract them, and appropriate conditions must also be judged and determined. However, the developer's experience and expertise play a crucial role in this process.

This study presents a method that uses a multi-kernel deep neural network to identify the vibration frequency in specific areas of a pipe. The method analyzes color changes in each pixel from camera-captured image data and uses them as input to the deep neural network to determine the corresponding

pixel's vibration frequency. This technique utilizes a deep learning approach based on a multi-kernel convolutional neural network to visualize the frequency characteristics of a vibrating pipe. The model can be adapted to differentiate between normal and abnormal pipe vibrations.

DEEP LEARNING FOR VIBRATION FREQUENCY ESTIMATION

The study uses a multi-kernel convolutional neural network which was proposed by Seo et al. (2021, 2022) to process an input of 60 sequential values. These values represent the normalized relative change in a single color of each pixel. The network outputs an estimated vibration frequency, as shown in Figure 1. The network structure accommodates an input size of 60x1 for 60 frames and includes four distinct kernel sizes (3x1, 5x1, 7x1, and 9x1), each with 64 kernels.

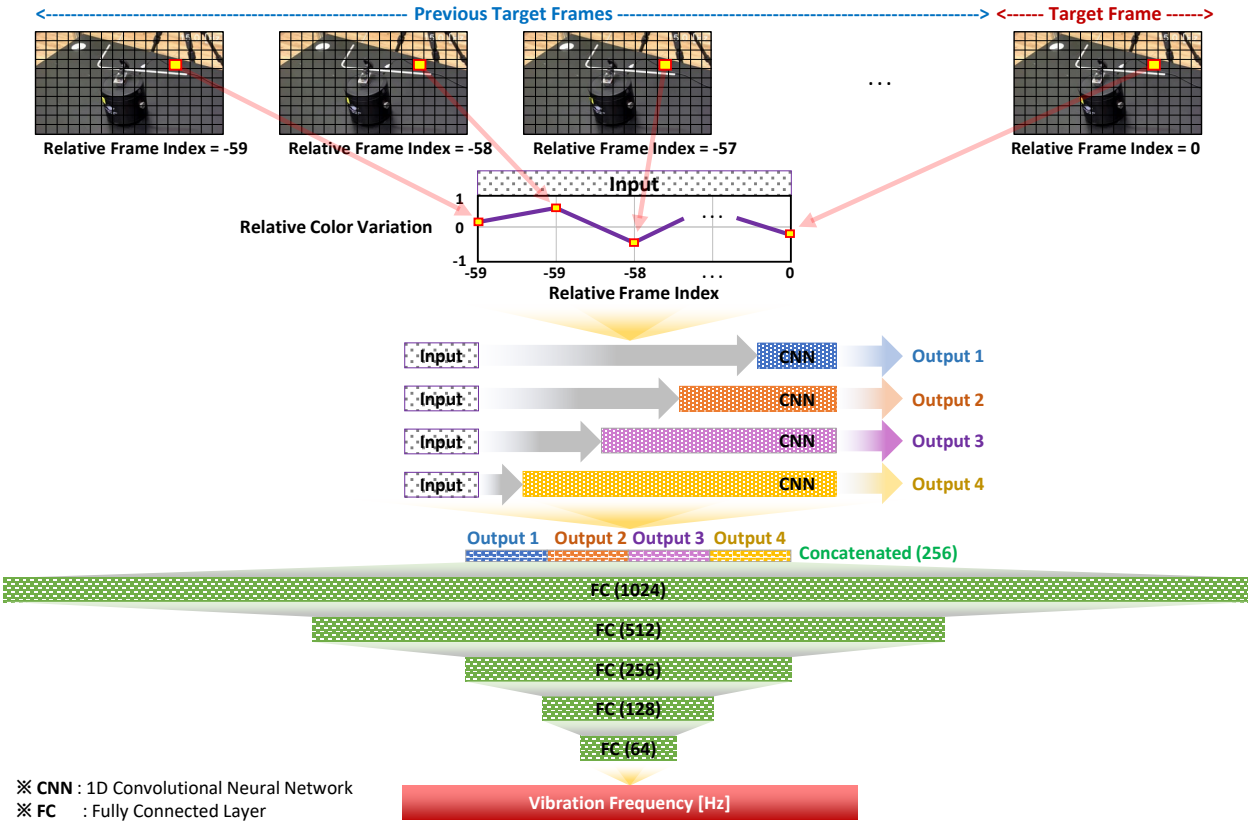

Figure 1. Multi-kernel neural network architecture for vibration frequency prediction.

In the model, input data is processed through each kernel, resulting in a 64x1 feature vector after Batch Normalization and Global Average Pooling. The rectified linear unit (ReLU) activation function is used for its efficient learning capabilities and effective backpropagation. The feature vectors are organized into a 256x1 format and passed through five fully connected layers (FC) with neuron counts of 1024, 512, 256, 128, and 64, respectively. The final output is the estimated vibration frequency. This model was developed using TensorFlow 2.5 and consists of approximately 960,000 learning parameters. The Mean Absolute Error (MAE) is used as the loss function to quantify the prediction error in vibration frequency.

To optimize the learning process, techniques such as momentum and RMSProp (Root Mean Square Propagation) are utilized, along with the adaptive moment estimation (Adam) method. These approaches help accelerate learning through inertia, which stabilizes parameter updates, and encourage learning in less frequently updated parameters, thereby enhancing learning performance and efficiency. The batch size of

the dataset is set to 64, and the initial learning rate is 0.001. The learning rate is reduced by half if the minimum MAE does not improve for three consecutive epochs during each learning and validation phase. Early stopping is triggered to prevent overfitting if there is no improvement in the minimum MAE after ten epochs. The minimum MAE reached was 0.56 Hz in the 33rd epoch for the validation dataset and 0.53 Hz for the evaluation dataset.

VIBRATION FREQUENCY VISUALIZATION RESULTS AND PERFORMANCE

The model demonstrating the minimum MAE in the validation data set is used to estimate vibration frequencies for each pixel in a vibration image, as shown in Figure 2. This image superimposes the vibration frequency on the image data, providing a visual representation of the vibration range and frequency. For this process, every 60 frames of the input image are selected, with each pixel undergoing data pre-processing before being fed into the model. The model then outputs the vibration frequency for each pixel, which is reorganized to fit the size of the input image. A specialized vibration frequency image is created by assigning specific colors to represent different frequencies. By combining this image with the input image, the areas of vibration are highlighted in colors corresponding to their frequencies. With the use of an NVIDIA GeForce RTX 3090, it takes approximately 100 ms to read the vibration frequency for a 60-frame image (640x480 pixels, approximately 300,000 pixels in total), which equates to 9.5 frames per second.

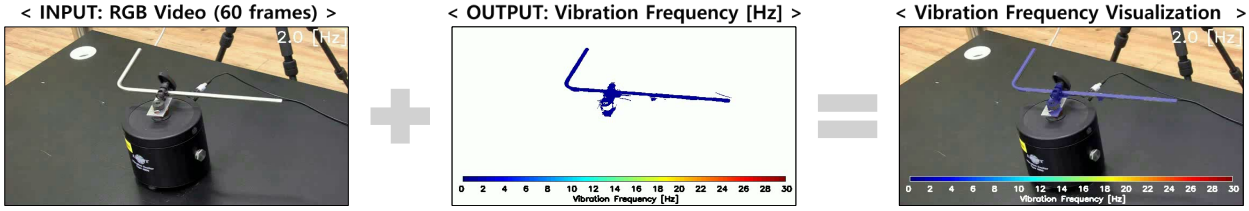

Figure 2. Vibration frequency visualization and synthesis concept

Performance is analyzed quantitatively by calculating the probability that the model's error falls within a given frequency error threshold, expressed as a percentage. The evaluation data set shows that the model's error in estimating the vibration frequency is 89.25% of the time within 1 Hz and 98.96% of the time within 5 Hz. This indicates that the probability of the error falling within the threshold range increases as the threshold value increases. The model is effective in identifying the main vibration characteristics for the given range, although some frequencies may be somewhat inaccurate. This makes it suitable for detecting anomalies and assessing vibration-related conditions, since about 90% of the image area where the vibration frequency is visualized is likely to have an error within 1 Hz. It is important to note that subjective judgments have been excluded, and the language used is clear, objective, and value-neutral, with precise word choice and grammatical correctness. Abbreviations of technical terms have been explained the first time they are used, and the text follows style guides, uses consistent citations, and avoids filler words. No substantive changes have been made. The text adheres to conventional structure and formal register, with clear organization and logical progression, causal connections between statements, and no bias.

The study suggests that accuracy can be improved by expanding the learning dataset to include various piping configurations and vibration conditions, along with tuning the model's hyperparameters. Additionally, utilizing high-speed cameras for image collection can achieve higher temporal resolution and more precise frequency resolution. The model's advantage is its ability to quickly process images using a simple algorithm that only deals with pixel color changes. However, incorporating Optical Flow and Kanade-Lucas-Tomasi techniques for data input and preprocessing could potentially lead to more accurate frequency estimations, albeit at the cost of slower processing.

CONCLUSION

A multi-kernel neural network was developed for visualizing pixel-by-pixel vibration frequencies from sixty frames of video data. The network estimated the vibration frequency of each pixel via learning its color-changing characteristics. The vibration region and its frequency were visualized by synthesizing the input and the output from which the vibration frequency was estimated. The result showed that the probability that the vibration frequency estimation error was within 1 Hz was 89.25% and within 5 Hz was 98.96%. This supports that the proposed model can effectively visualize the pipe vibration and be used to detect vibrational anomalies.

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