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Efficient Gear Monitoring: Applying Deep Learning Models with Symmetrized Dot Pattern and Discrete Wavelet Transform to Detect Defects in Spur Gears

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Gears are frequently used in transmission components, and essential information regarding gear transmission can be effectively analyzed by performing vibration detection. Therefore, in this research, we proposed a method of using deep learning models to establish an effective defect detection system for spur gears. In this system, data are collected and transformed using the symmetrized dot pattern (SDP) and discrete wavelet transform (DWT) techniques to detect defects in spur gears. The results of this study revealed that convolutional neural network models and deep neural network models can perform SDP detection at accuracy levels of 99% and 96%, respectively. Therefore, SDP and DWT are suitable for detecting defects in spur gears.

1. Introduction

Gears are commonly used in transmission components, and their prolonged use inevitably causes wear and tear. Therefore, ensuring the effectiveness of gear inspections is crucial. Current gear inspection practices include visual inspection, ultrasonic testing, and vibration analysis. Vibration analysis involves techniques such as time-domain analysis, frequency-domain analysis, and symmetrized dot pattern (SDP) analysis.

Vibration analysis can be used to effectively extract crucial information during gear transmission. Wu *et al.*[1] employed the SDP technique for vehicle motors to enable the adjustment of delay coefficients and weighting coefficients, with the technique yielding high accuracy rates. Sun *et al.*[2] enhanced the SDP technique to improve Manhattan distance calculation and successfully diagnosed rolling bearing faults; their results demonstrated the considerable feasibility and effectiveness of their proposed method. Huang *et al.*[3] converted SDP data into 2D images to enable the inspection of permanent

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magnet synchronous motors and demonstrated the considerable advantages of their proposed method with a small sample size. Liu *et al.*(4) transformed signals into SDP data and employed a ResNet50 deep learning model for detection purposes; they reported that their proposed detection method shows excellent performance under both transient and steady-state conditions. Sun and Li(5) applied the SDP technique and convolutional neural networks (CNNs) to perform detection with remarkable stability across various bearing conditions. Tang *et al.*(6) analyzed faults in rotary machinery by applying the SDP technique and employing random forest classification; their proposed method yielded highly accurate and stable results. Sian *et al.*(7) diagnosed faults in power cables through the discrete wavelet transform (DWT) and SDP techniques and a deep learning model based on probability neural networks, and they achieved a high accuracy rate of 96%. Ye *et al.*(8) inspected infrared gas systems by employing the SDP technique, and they identified a 99% correlation among infrared absorption spectroscopy results, the peak maximum radius, and methane concentration. Lin *et al.*(9) employed deep learning methods to diagnose faults in ball bearings and achieved improved classification accuracy relative to that achievable through traditional methods.

In this study, we proposed an efficient detection method based on deep learning models and used it to create a detection system for spur gears. In the model, collected signals are transformed into SDP and DWT data. Subsequently, CNN and deep neural networks (DNNs) are used for deep learning to detect defects in spur gears. The primary contributions of this study are as follows.

1. A novel detection method to enhance the accuracy of defect detection for spur gears was proposed.
2. A spur gear fault detection system involving the application of the SDP and DWT techniques was developed.
3. The effectiveness of the proposed method was validated through deep learning models.
4. A fault detection accuracy of up to 99% was achieved during spur gear inspections.

2. System Architecture

2.1 SDP

The SDP technique is a method of transforming time-domain signals into 2D images. Each point in the signal is projected onto the diameter of a polar coordinate, and adjacent points are projected onto the angle of the polar coordinate. Finally, these points are transformed into a snowflake pattern in the polar coordinates. Zhu *et al.*(10) applied the SDP technique and CNNs to perform rotor fault detection and achieved a high level of accuracy. Xu *et al.*(11) combined the SDP technique and image matching to develop a straightforward and effective method for performing fan defect detection.

Figure 1 depicts the principle for performing the SDP technique. $r(i)$ represents the radius in polar coordinates, which is calculated using Eq. (1). $\varnothing(i)$ denotes the counterclockwise rotation

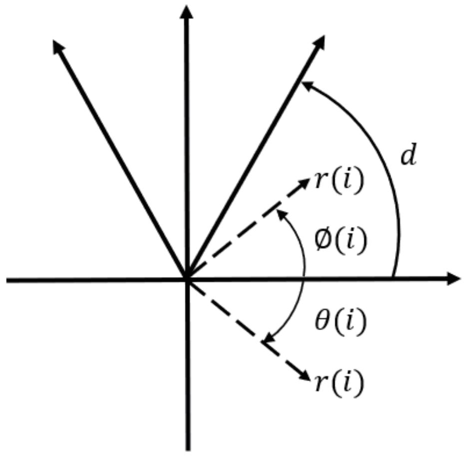


Fig. 1. Principle for performing SDP technique.

angle in polar coordinates from the initial position and is computed using Eq. (2). $\theta(i)$ representing the clockwise rotation angle in polar coordinates from the initial position is calculated using Eq. (3). x_i denotes any point in the data, x_{min} the minimum value in the data, x_{max} the maximum value in the data, x_{i+l} the rotated angle of the symmetrical figure in the SDP diagram, ϑ the initial rotation angle, and d the weighting coefficient.

$$r(i) = \frac{x_i - x_{min}}{x_{max} - x_{min}} \tag{1}$$

$$\varnothing(i) = \vartheta + \frac{x_{i+l} - x_{min}}{x_{max} - x_{min}} d \tag{2}$$

$$\theta(i) = \vartheta - \frac{x_{i+l} - x_{min}}{x_{max} - x_{min}} d \tag{3}$$

2.2 DWT

The DWT technique is effective in extracting local features from signals. Unlike the continuous wavelet transform technique, the DWT technique involves a discrete approach, which enables rapid computation. In the DWT technique, signals are decomposed into high-frequency and low-frequency components, and the details obtained through decomposition are subsequently reconstructed. Generally, the inverse DWT technique is employed for reconstruction. Lai and Wu(12) employed the DWT technique and DNNs for gear defect detection, and they discovered that the DWT technique can effectively identify defects in spur gears. Bouzida *et al.*(13) employed the DWT technique to accurately perform fault diagnosis on electromechanical systems under various loads. *DWT*(i, k) represents the discrete wavelet coefficient at level i and position k. $x(t)$ denotes the original discrete signal, with t representing time. φ represents the wavelet function. The formula for performing DWT is

$$DWT(i,k) = \frac{1}{\sqrt{2^i}} \int_{-\infty}^{\infty} x(t) \varphi\left(\frac{t - 2^i k}{2^i}\right) dt. \tag{4}$$

2.3 CNN

A CNN is a type of deep learning model with an architecture comprising convolutional layers, pooling layers, and fully connected layers. The convolutional layers perform feature extraction, which is achieved through the operation of convolutions with kernels of varying sizes. The pooling layers, typically placed after convolutional layers, compress image data, which reduces the computational complexity. The fully connected layers comprise flattened, hidden, and output layers, which can predict the results of the convolutional and pooling layers, and adjust the weights of the fully connected layers, thereby enabling a CNN to perform complex learning tasks. The CNN architecture implemented in this research is depicted in Fig. 2. Jian *et al.*(14) applied a CNN model to detect defects on metal surfaces after cutting and reported that their proposed method enhanced detection efficiency and reduced inspection costs. Wang *et al.*(15) used the SDP technique and CNNs to detect power quality faults, and they reported that their proposed method was accurate in identifying fault conditions.

2.4 DNN

A DNN is a type of feedforward neural network that builds on the feedforward neural network structure by incorporating multiple hidden layers, with each containing multiple neurons. The first layer of the DNN is the input layer, which is responsible for receiving data. The second layer is the hidden layer, which assigns weights to received data and then activates

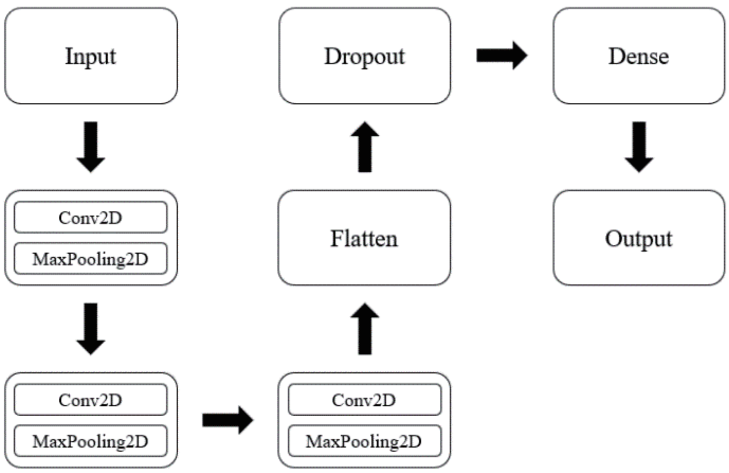


Fig. 2. CNN architecture.

the data. The third layer is the output layer, which classifies data and produces output. The CNN architecture used in this study is depicted in Fig. 3. Park *et al.*[16] used a multi-DNN model to detect defects in cover glass, achieving an accuracy rate of up to 99%. Malekzadeh *et al.*[17] employed a DNN model to swiftly and accurately detect defects in aircraft fuselage.

3. Experimental Setup

In this study, we developed a deep-learning-based gear defect detection model by employing CNN and DNN models for training. Experiments were conducted using gears with a module of 3 and either 30 or 20 teeth. The gears were categorized as being in a healthy or worn state. During the experimentation, a small gear and a large gear were set as the driving gear and driven gear, respectively. An accelerometer was placed above the bearing to record the vibration during gear transmission. Recorded signals were then transformed into DWT and SDP data. A DNN and a CNN were trained using DWT and SDP data, respectively. The detection process performed in the present experiment is depicted schematically in Fig. 4.

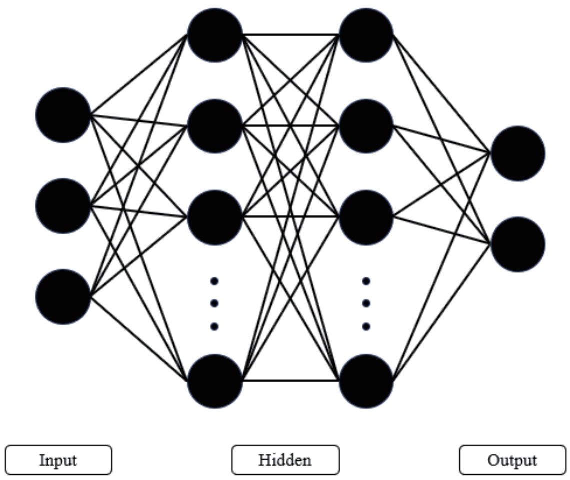


Fig. 3. Deep neural network architecture.

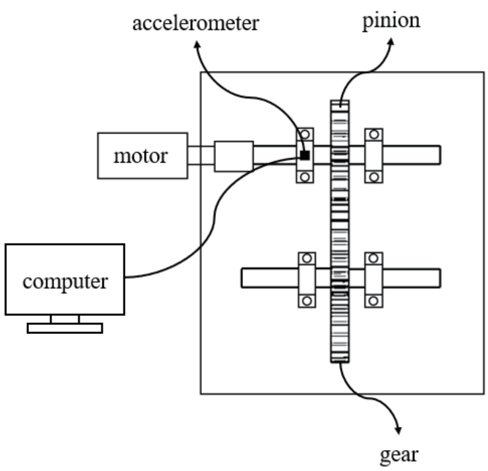


Fig. 4. Gear defect detection system.

In our experiment, the vibration signal was sampled at a frequency of 1024 Hz for a total acquisition duration of 800 s, resulting in 819200 data points. For each state of the gears during transmission, 800 data samples were collected. These 800 data samples were divided into a training set and a test set at an 8:2 ratio. Therefore, for the healthy state of the spur gears, 640 and 160 data samples were allocated to the training and test sets, respectively. Similarly, for the worn state of the spur gears, 640 and 160 data samples were allocated to the training and test sets, respectively.

4. Results and Discussion

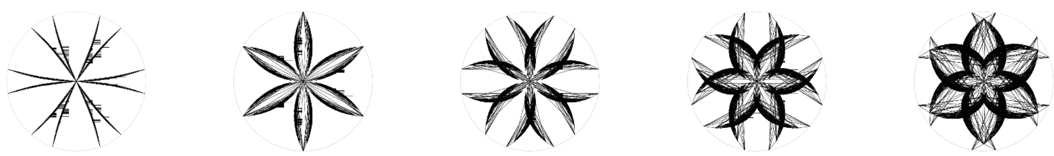
In this study, we focused on detecting faults in spur gears. The vibration signals that were generated during gear transmission were collected using accelerometers and transformed into DWT signals and SDP data. Subsequently, the DWT signals and SDP data were analyzed using a DNN model and a CNN model, respectively, as part of a deep learning process. This process was performed to establish a reliable gear inspection system.

In this study, we investigated the influences of delay coefficients and weighting coefficients on SDP images. During the plotting of SDPs, weighting coefficients (values = 10, 30, 50, 80, and 100) and delay coefficients (values = 0, 1, and 2) were used. The patterns were plotted with 60° intervals to create snowflake-like visualization. The symmetrized dots during gear transmission were mapped (Fig. 5). When the delay coefficient increased and the weighting coefficient changed, the overlapping points in the images spread out, and the lines became more pronounced.

By analyzing the influences of the weighting coefficients and delay coefficients on deep learning accuracy, we discovered that when the delay coefficient remained constant, a high accuracy of 99% can be achieved, regardless of changes in the weighting coefficient (Fig. 6). However, when the weighting coefficient remained constant, varying the delay coefficient did not lead to the desired level of accuracy.

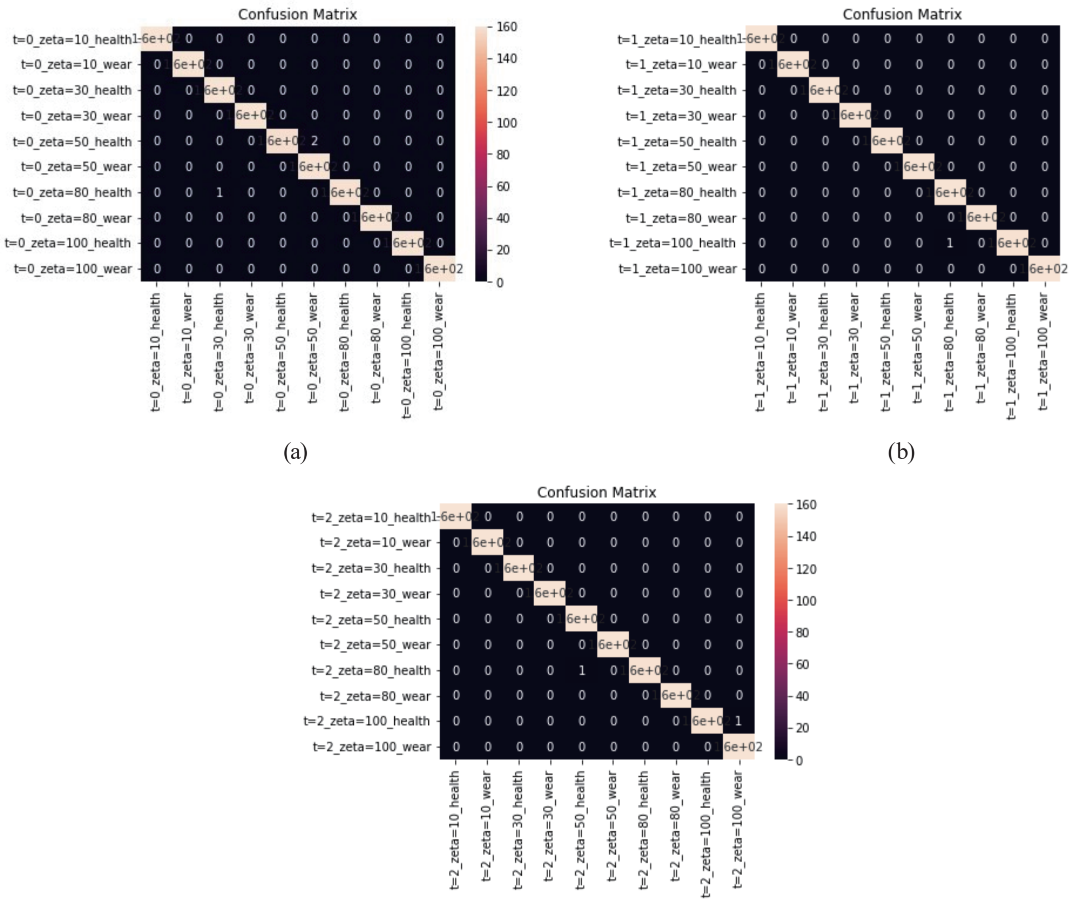
The average vibration amplitude for healthy teeth gears was ±0.004568572, whereas that for worn teeth gears was ±0.011178025 (Fig. 7). A vibration amplitude of approximately ±0.011 during gear transmission indicates the presence of wear on gears. When this occurs, the gears should be maintained or replaced.

In this study, a DNN deep learning model was built using DWT. The model was trained using different numbers of epochs (i.e., 10, 30, 50, 80, and 100). As indicated in Fig. 8, when the number of epochs was set to 10, a 93% accuracy was achieved. When the number was set to 30, the accuracy improved to 96%. The accuracy remained consistently at 95% when 50 epochs



(a) (b) (c) (d) (e)

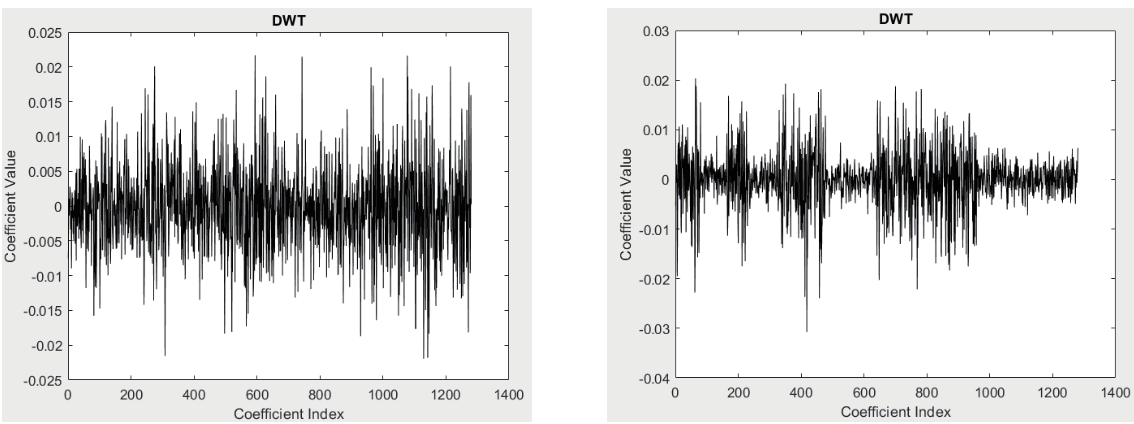
Fig. 5. SDP zeta = (a) 10, (b) 30, (c) 50, (d) 80, and (e) 100.



(a) (b)

(c)

Fig. 6. (Color online) Confusion matrices for detection with time delays of (a) 0, (b) 1, and (c) 2.



(a) (b)

Fig. 7. Coefficient charts for (a) healthy and (b) worn spur gears.

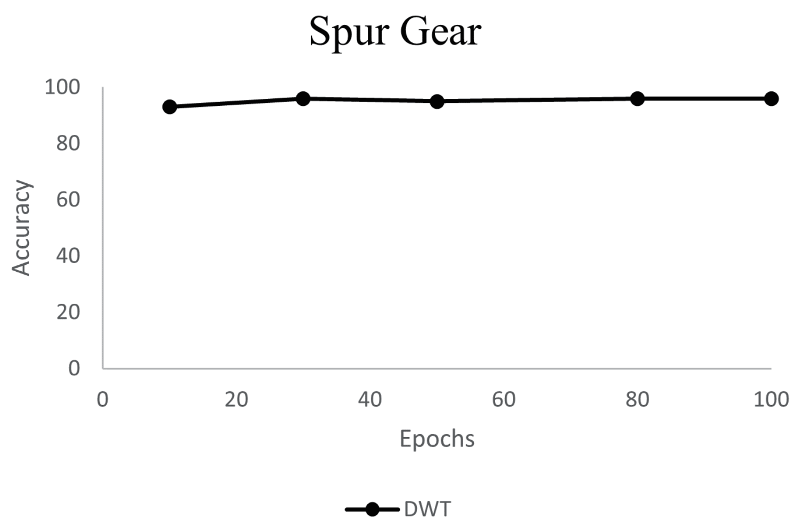


Fig. 8. Epochs and accuracy of DWT deep learning model.

were used but reached 96% when 80 and 100 epochs were used. The high accuracy attainable with 30 epochs indicates that the number of epochs does not directly influence accuracy.

5. Conclusions

In this study, we proposed a deep-learning-based system for detecting gear defects. CNN and DNN models were separately trained using SDP and DWT data. The accuracy levels of the CNN and DNN models for gear monitoring and detection were analyzed. On the basis of the results of the comprehensive analysis, the following conclusions were drawn.

1. We used accelerometers to collect gear transmission data. The collected data were transformed into SDP and DWT data. Subsequently, separate CNN and DNN deep learning models were built using the SDP and DWT data, respectively. Through analysis of the prediction results of both methods, the patterns indicative of gear wear during transmission were identified. The results indicate that a highly accurate and multicriteria detection system has been established.
2. The CNN model results revealed that the SDP technique achieved a detection accuracy of up to 99% for detecting wear in spur gears, indicating that the SDP technique is suitable for identifying defects in spur gears.
3. The DNN model results revealed that the DWT technique achieved a detection accuracy of up to 96% for detecting wear in spur gears, indicating that the DWT technique is suitable for identifying defects in such gears. Furthermore, the number of training epochs did not exhibit a positive correlation with accuracy.
4. In future research, we can continue to investigate the application of the SDP and DWT techniques, and additional cases involving helical and bevel gears can be incorporated to enhance the gear monitoring system proposed in this study.

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