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A Comparative Study of UNET Model for Bearing Fault Identification Based on Time-Series and Wavelet Transformed Vibration Images

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Abstract

In the era of industry 4.0, railways systems are becoming more advanced through employing modern methods like Deep Learning (DL) algorithms. DL algorithms have been able to accomplish excellent outcomes in condition monitoring of railway systems. Thus, railway industry has been adopting it for various processes for safe and uninterrupted operation. As the safe operation of traction motors rely on normal operation of bearing, thus they require timely detection and identification of various faults. In this paper, a comparative study on bearing fault identification using UNET method based on time domain vibration images and wavelet transformed vibration images is presented. The three-step method involves implementation of UNET model, extracting Wavelet Packet Transform (WPT) features from raw vibration data, and transforming the WPT data to gray-scale vibration images. The time-series vibration data is transformed into 32 × 32 × 1 WPT vibration images. The comparative analysis of UNET with time domain vibration images (TVI-UNET) and WPT based vibration images depicted best performance on later one. The UNET model with WPT based vibration images (WPT-UNET) achieved F1-score and MIoU of 99.3% and 50.26%, respectively. The proposed method demonstrated robust response and superior performance than the UNET with time domain vibration images.

Keywords: wavelet packet transform, deep learning, vibration images, condition monitoring

1 Introduction

Bearings are the crucial elements in transportation systems such as railways. Their failures not only causes halt in operation but also can harm human lives. Therefore, it is a matter of extreme importance to efficaciously monitor the condition of bearings in order avoid various losses caused by them [1-3]. Considering significance of timely bearing fault diagnosis, Deep Learning (DL) has been in the attention of researchers and can learn more efficiently with processed features compared to the models fed with the raw data [4, 5]. Thus, feature processing of data allows to improve generalization capability of DL models [6-9]. In recent years, development of various DL methods have witnessed their excellent performance in fault diagnosis and prognosis owing to their generalization capacity [10]. The investigations have shown promising results in terms of feature learning through linear/non-linear mapping functions [11, 12].

Convolutional Neural Network (CNN) has been in attention of researchers owing to easy training enabled by kernel sharing mechanism which highly reduces the network parameters [13, 14]. In this direction, researchers have been employing these upgraded models for bearing fault diagnosis. D. T. Hoang et al. [15] have used vibration image with CNN to identify various rolling bearing faults. The time-series data was transformed into the gray-scale images. Authors of [16] have employed S-transform with CNN (ST-CNN) for bearing fault classification. The ST-layer was added to the CNN model which automatically transformed the time-series vibration data to 2D time-frequency matrix. Y. Zhang et al. [17] have employed enhanced CNN with time-frequency vibration image for effective bearing fault diagnosis. STFT is applied of time-series vibration data to get time-frequency vibration images. In [18] authors have implemented WPT and CNN based bearing faults diagnosis system. They converted time-series vibration data to 2D gray images. In recent study [19], UNET model was employed to classify the bearing faults with gray scale vibration images. Different from existing studies, this research presents a novel method namely UNET and WPT based vibration images.

The aforementioned investigation have demonstrated high accuracy in bearing fault classification, however, these methods pose multiclass problem posed by the sliding window techniques and cannot perform dense predictions. These problems are overcome by UNET model which can accomplish dense predictions without losing label information that is caused by sliding window labelling [20-22]. Thus, considering these advantage, it has been used in this investigation for bearing fault identification.

2 Methods

The UNET model is an upgraded version of CNN which was fundamentally designed for biological images segmentation. It allows to avoid multiclass window issue posed by sliding window labelling method. It has capability to predict label for individual data example which is referred as dense prediction. It incorporates two paths including encoder and decoder. The encoder part performs down-sampling while the decoder part performs up-sampling. The UNET architecture used in this investigation is shown in Figure 1 which was presented by the Ronneberger et al. [23]. The Wavelet

Transform (WT) is employed to extract time-frequency information from obtained signals. It is applied on the signal by analysing mother wavelet function and then convolving the signal with the scaling and conjugate wavelet functions as expressed by Equation (1).

$$W_f(a,s) = \int_{-\infty}^{+\infty} x(t) \frac{1}{\sqrt{a}} \Psi \times \left(\frac{t-s}{a}\right) dt \tag{1}$$

Where, $\Psi(t)$ is the Morlet wavlet function, a denotes the dilation, s denotes the translation. The $\frac{1}{\sqrt{a}}$ is employed to preserve the energy. The value of the variables a and s can be varied to obtain different time-frequency segmentation.

The Wavelet Packet Transform (WPT) is employed to approximate wavelet coefficients of various frequency bands. The node value for each frequency band can be expressed by Equations (2) & (3):

$$W_{j+1}^{2k} = W_j^k(n) \times h(-2n) \tag{2}$$

$$W_{j+1}^{2k+1} = W_j^k(n) \times g(-2n) \tag{3}$$

Where, W_{j+1}^{2k} denotes the jth decomposed level of 2k frequency band. The h(-2n) and g(-2n) represent low-pass and high-pass filters, respectively. Their values rely upon the scaling function $\phi(t)$ and the mother wavelet function $\Psi(t)$. The relationship between these two function can be given by Equations (4) & (5):

$$\phi_j(t) = \sum_k h(k) 2^{\frac{j+1}{2}} \phi\left(2^{j+1} \times t - k\right) \tag{4}$$

$$\phi_j(t) = \sum_k g(k) 2^{\frac{j+1}{2}} \phi\left(2^{j+1} \times t - k\right) \tag{5}$$

The one-dimensional (1D) vibration data can be mapped into two-dimensional (2D) vibration images using the relation given by Equation (6):

$$P[i,j] = A[(i-j) \times M + j] \tag{6}$$

Where, P[i, j] denotes the intensity of pixels in M × N gray-scale vibration image, A[·] denotes normalized amplitude of each example in the data, i ranges from 1 to N, and j ranges from 1 to M. In Figure 2 the vibration images obtained after applying WPT method are shown.

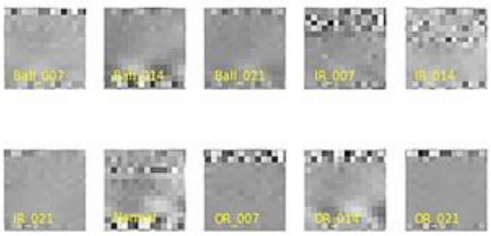

Figure 1: A white dog in the snow.

In Figure 2 the method used in this investigation is depicted.

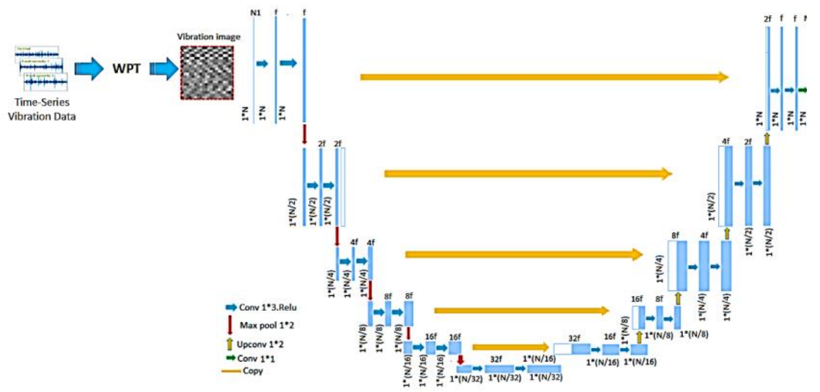

Figure 2: UNET Structure for WPT images based bearing fault classification

To analyse the performance of the proposed method the Case Western Reserve University (CWRU) bearing dataset is used [24].

3 Results

The results of the two approaches including the TVI-UNET and WPT-UNET with WPT are summarized in Table. The results provided in table clearly indicate the WPT-UNET method achieves highest performance scores including accuracy, F1-score, and MIoU. Although, TVI-UNET has demonstrated satisfactory performance but WPT features allowed it to improve dense predictions by improving the semantic segmentation and representation learning performance of the WPT-UNET. Overall, WPT-UNET is able to demonstrate robustness and superiority in terms of dense predictions compared to the TVI-UNET. In Figure 3 the confusion matrices are shown in terms of individual bearing condition predictions, the WPT-UNET is able performance better than the TVI-UNET model.

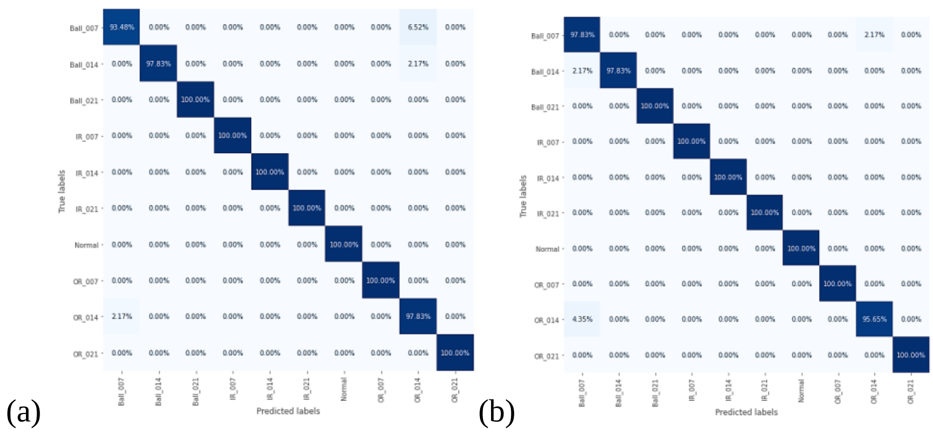

Figure 3: Confusion metrics of (a) TVI-UNET and (b) WPT-UNET

The results given in Table 1 confirm the WPT-UNET as better model than the TVI-UNET model. In terms prediction accuracy, the WPT-UNET achieved 99.13% while TVI-UNET was able to achieve 98.91% accuracy. F1-score of WPT-UNET is also higher than that of TVI-UNET. Moreover, sematic segmentation performance of the WPT-UNET is superior to that of TVI-UNET. It can be observed form the table that the MIoU score of WPT-UNET is 50.16% while MIoU score of TVI-UNET is 49.62% which is lower than that of WPT-UNET.

Metrics	**TVI-UNET**	**WPT-UNET**
Accuracy	98.91%	99.13%
F1-Score	99.00%	99.20%
MIoU	49.62%	50.16%

Table 1: Performance scores of the models

4 Conclusions and Contributions

This paper presents bearing fault identification using UNET model with WPT features. A comparative analysis of UNET with time domain and WPT-UNET is conducted in this investigation. The achieved results confirmed WPT-UNET as best method compared to UNET with the time domain image data. The WPT-UNET method is realized by converting vibration data to WPT coefficients and then transforming the WPT coefficients into the vibration images of $32 \times 32 \times 1$. The model with pre-processed data allowed to effectively learn representations and classify bearing conditions. It was able to perform dense predictions on the WPT vibration images by overcoming the multiclass window problem. Moreover, it achieved robust and excellent bearing fault recognition performance even on low resolution WPT vibration images. The motivation behind using low resolution vibration images was faster training of the model. The model outperformed the TVI-UNET owing to the WPT based input vibration images.
The main contributions of this investigation can be summarized as follows:

- A WPT (WPT-UNET) based approach is used for bearing fault identification which yield dense predictions through addressing the problems posed by sliding window method. As per authors' best knowledge, the method has not been used previously which can perform pixel level classification.
- Time-series vibration data is transformed into dense labelled and WPT based gray-scale images of size $32 \times 32 \times 1$ are fed to UNET model as input features. The motivation behind using WPT based vibration images with UNET is to improve learning capability of UNET for effective bearing fault identification.
- A comparative analysis between UNET with time domain vibration images (TVI-UNET) and WPT-UNET is conducted in order to determine the performance improvement in terms of effect of data pre-processing on performance of the UNET model for performing dense predictions.

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