NOISE ELIMINATED ENSEMBLE EMPIRICAL MODE DECOMPOSITION SCALOGRAM ANALYSIS FOR ROTATING MACHINERY FAULT DIAGNOSIS

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SUPERVISOR'S DECLARATION

I hereby declare that I have checked this thesis and in my opinion, this thesis is adequate in terms of scope and quality for the award of the degree of Master of Science.

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STUDENT'S DECLARATION

I hereby declare that the work in this thesis is based on my original work except for quotations and citations which have been duly acknowledged. I also declare that it has not been previously or concurrently submitted for any other degree at Universiti Malaysia Pahang or any other institutions.

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ATIK FAYSAL

Thesis submitted in fulfillment of the requirements
for the award of the degree of
Master of Science

College of Engineering

UNIVERSITI MALAYSIA PAHANG

MARCH 2022

ACKNOWLEDGEMENTS

First of all, I would like to express my gratitude towards my erudite supervisor Ts. Dr. Ngui Wai Keng for bestowing me the opportunity of conducting research and achieving master of science degree in Universiti Malaysia Pahang. I am deeply grateful to him for his continuous support and guidance.

I am also thankful to UMP and my faculty for providing me excellent lab support and work environment. I thank all the faculty members, students and my labmates who have been very amiable and cordial to me during my journey to obtain this degree.

Lastly, I must express my gratitude to my family who endured my absence while I was away the whole time pursuing this degree. Their relentless support and encouragement helped me finish my work smoothly.

This work was possible due to the financial support provided by the Ministry of Higher Education Malaysia under the FRGS/1/2018/TK03/UMP/02/24 grant (RDU190157).

ABSTRAK

Jentera putar ialah sejenis komponen utama dalam industri yang mengalami pelbagai kerosakan disebabkan oleh beban kerja yang berterusan. Oleh itu, satu kaedah yang pantas dan boleh dipercayai untuk mendiagnosis kerosakan adalah penting untuk pemantauan keadaan mesin. Kecerdasan buatan boleh digunakan bagi penyarian dan pengelasan sifat kerosakan. Penggunaan kaedah penyarian sifat yang berkesan adalah penting untuk mendapatkan maklumat kerosakan dan alat yang teguh untuk mengelas sifat-sifat tersebut. Dalam kajian ini, satu kaedah yang lebih baik iaitu penguraian mod empirikal ensembel dihilangkan hingar (NEEEMD) dicadangkan untuk mengurangkan hingar putih dalam fungsi intrinsik dan mengekalkan ensembel yang optimum. Pengelas rangkaian neural konvolusi (CNN) digunakan untuk mengelas kerana keupayaannya dalam pembelajaran sifat. Reka bentuk CNN menyeluruh dicadangkan untuk mengurangkan masa latihan model tersebut. Input yang digunakan untuk pengelas tersebut ialah sampel skalogram RGB 64 × 64 piksel. Walau bagaimanapun, CNN memerlukan data latihan yang banyak untuk mencapai ketepatan dan keteguhan yang tinggi. Oleh itu, rangkaian pertentangan generatif konvolusi dalam (DCGAN) digunakan untuk pengimbuhan data semasa fasa latihan. Skalogram daripada kaedah penyarian sifat yang lain, seperti penguraian mod empirikal ensembel (EEMD), EEMD pelengkap (CEEMD), dan penjelmaan gelombang kecil berterusan (CWT) dikelaskan untuk menilai keberkesanan kaedah yang dicadangkan. Keberkesanan skalogram juga disahkan dengan membandingkan prestasi pengelas menggunakan sampel skala kelabu daripada isyarat getaran mentah. Keupayaan CNN dibandingkan dengan dua kaedah algoritma pembelajaran mesin tradisional, iaitu kaedah jiran terdekat k (kNN) dan mesin sokongan vektor (SVM) menggunakan ciri-ciri statistik daripada EEMD, CEEMD dan NEEMD. Kaedah yang dicadangkan disahkan menggunakan set data bearing dan bilah. Keputusan menunjukkan bahawa algoritma pembelajaran mesin mencapai ketepatan yang lebih rendah berbanding model CNN yang dicadangkan. Kesemua output daripada pengelas kerosakan bearing dan bilah menunjukkan sampel skalogram daripada kaedah NEEEMD yang dicadangkan mencapai ketepatan, kepekaan dan keteguhan tertinggi menggunakan CNN. DCGAN digunakan dengan skalogram NEEEMD untuk menambah baik prestasi pengelas CNN dan mengenal pasti jumlah data latihan yang optimum. Selepas pengelas dilatih menggunakan sampel terimbuh, keputusan menunjukkan pengelas tersebut memperoleh kesahihan dan ketepatan yang lebih tinggi dengan keteguhan yang lebih baik. Ketepatan bertambah baik daripada 98%, 96.31% dan 92.25% kepada masing-masing 99.6%, 98.29% dan 93.59% bagi model pengelas yang berbeza menggunakan NEEEMD. Kaedah yang dicadangkan boleh digunakan sebagai satu kaedah yang lebih umum dan teguh bagi mendiagnosis kerosakan jentera putar.

ABSTRACT

Rotating machinery is one type of major industrial component that suffers from various faults and damage due to the constant workload to which it is subjected. Therefore, a fast and reliable fault diagnosis method is essential for machine condition monitoring. Artificial intelligence can be applied in fault feature extraction and classification. It is crucial to use an effective feature extraction method to obtain most of the fault information and a robust classifier to classify those features. In this study, an improved method, noise-eliminated ensemble empirical mode decomposition (NEEEMD), was proposed to reduce the white noise in the intrinsic functions and retain the optimum ensembles. A convolution neural network (CNN) classifier was applied for classification because of its feature-learning ability. A generalised CNN architecture was proposed to reduce the model training time. The classifier input used was 64×64 pixel RGB scalogram samples. However, CNN requires a large amount of training data to achieve high accuracy and robustness. Deep convolution generative adversarial network (DCGAN) was applied for data augmentation during the training phase. To evaluate the effectiveness of the proposed feature extraction method, scalograms from the related feature extraction methods such as ensemble empirical mode decomposition (EEMD), complementary EEMD (CEEMD) and continuous wavelet transform (CWT) were also classified. The effectiveness of the scalograms was also validated by comparing the classifier performance using greyscale samples from the raw vibration signals. The ability of CNN was compared with two traditional machine learning algorithms, k nearest neighbour (kNN) and the support vector machine (SVM), using statistical features from EEMD, CEEMD and NEEEMD. The proposed method was validated using bearing and blade datasets. The results show that the machine learning algorithms achieved comparatively lower accuracy than the proposed CNN model. All the outputs from the bearing and blade fault classifiers demonstrated that the scalogram samples from the proposed NEEEMD method obtained the highest accuracy, sensitivity and robustness using CNN. DCGAN was applied with the proposed NEEEMD scalograms to enhance the CNN classifier's performance further and identify the optimal amount of training data. After training the classifier using the augmented samples, the results showed that the classifier obtained even higher validation and test accuracy with greater robustness. The test accuracies improved from 98%, 96.31% and 92.25% to 99.6%, 98.29% and 93.59%, respectively, for the different classifier models using NEEEMD. The proposed method can be used as a more generalised and robust method for rotating machinery fault diagnosis.

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