Centrifugal Pump Health Condition Identification Based on Novel Multi-filter Processed Scalograms and CNN

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Abstract. This paper proposes a fault diagnosis method for centrifugal pumps (CP) based on multi-filter processed scalograms (MFS) and convolutional neural networks (CNN). Deep learning (DL) based autonomous Health-sensitive features extraction from continuous wavelet transform (CWT) scalograms are popular adoption for the health diagnosis of centrifugal pumps. However, vibration signals (VS) acquired from the centrifugal pump consist of fault-related impulses and unwanted macrostructural noise which can affect the autonomous Health-sensitive features extraction capabilities of the deep learning models. To overcome this concern, novel multi-filter processed scalograms are introduced. The new multi-filter processed scalograms enhance the fault-related color intensity variations and remove the unwanted noise from the scalograms using Gaussian and Laplacian image filters. The proposed techniques identified the ongoing health condition of the centrifugal pump by extracting fault-related information from the multi-filter processed scalograms and classifying them into their respective classes using convolutional neural networks. The proposed method resulted in higher classification accuracy as compared to the existing method when it was applied to a real-world centrifugal pump vibration signals dataset.

Keywords: Multi-filter processed scalograms · Fault diagnosis · Centrifugal pump

1 Introduction

CPs play a crucial role in various aspects of business operations. Unexpected failures in CPs can result in extended periods of downtime, financial losses, costly repairs, and potential hazards to worker safety [1]. It is vital to promptly identify and diagnose faults to ensure the extended functionality of centrifugal pumps [2].

The amplitude of the VS serves as a valuable indicator for detecting mechanical faults in the CP arising from the mechanical seal and impeller. Time-domain features

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effectively identify emerging faults within the VS. However, their utility diminishes when dealing with severe faults due to the inherent variability in fault severity [3–6].

To address this issue, the frequency spectrum emerges as a more adept tool for pinpointing faults of varying degrees of severity, supported by the use of Frequency-Domain features for CP fault diagnosis. The VS obtained from the CP under a faulty health state is characterized by its complexity and nonstationary nature [7]. While spectrum analysis is optimal for stationary signals, non-stationary signals necessitate a different approach [8]. Time and multiresolution domain transformations, offering multi-resolution analysis suited for these dynamic signals. Empirical mode decomposition, an adaptive decomposition method, has found efficient application in diagnosing faults in rotating machinery. Nevertheless, EMD faces challenges like mode mixing and extreme interpolation, rendering it less attractive for VS analysis [9–12]. For analyzing CP's non-stationary transients, variational mode decomposition (VMD) and CWT emerge as favorable choices. In this context, The critical aspect is the selection of the fundamental wavelet, which profoundly influences the distinctiveness of the features extracted. This choice calls for a nuanced blend of domain expertise and exhaustive empirical exploration to ensure its suitability for the given diagnostic task [13]. To address the above-mentioned concerns, in this work, the paper introduces innovative MFSs that effectively enhance fault-related color intensity variations while eliminating undesirable noise in the CWT scalograms using Gaussian [14] and Laplacian [15] image filters.

The CP fault diagnosis system involves two key steps: extracting fault-related features from the VS and classifying the CP working conditions based on these extracted features. DL methods are preferred over traditional machine learning techniques because they can effectively analyze intricate data and autonomously derive meaningful discriminant information for pattern recognition tasks [16, 17]. Prominent DL methods used for fault diagnosis include neural auto-encoders, deep belief networks, CNN, and recurrent neural networks. CNN, in particular, mitigates overfitting risks, offers low computational complexity through weight sharing, and employs local representative fields, and special domain subsampling [18, 19]. Furthermore, CNNs have showcased their proficiency in effectively recognizing patterns in fault diagnosis situations related to bearings, CPs, and pipelines [12, 20–23]. For this reason in this paper, the proposed method uses CNN to identify the ongoing health condition of CPs by extracting crucial fault-related information from the MFS.

The arrangement of this study unfolds across the subsequent segments: In Sect. 2, the experimental testbed used in this study is described. Section 3 elucidates the details of the proposed framework. Sect. 4 describes the results and discussion. The conclusion and future direction are presented in Sect. 5.

2 Experimental Setup

For experimental purposes, a test rig has been created, comprising various components: a CP (PMT-4008) powered by a 5.5 kW motor, a control panel featuring an ON/OFF switch, speed control, flowrate control, temperature control, water supply control, and display screens. Additionally, it includes pressure gauges, transparent pipes, and two tanks, namely the main tank and buffer tank. To ensure an efficient CP suction head, a water tank has been placed at an elevated position. The test rig setup, along with a schematic representation, is displayed in Fig. 1. Once the primary setup was established, the test rig was set in motion to circulate water within a closed loop. Vibration data from the CP were gathered while maintaining a constant speed of 1733 rpm. This data was collected using four accelerometers, with two affixed to the pump casing using adhesive, while the other two were positioned close to the mechanical seal and near the impeller. Each sensor recorded the pump's vibrations through its own dedicated channel. The recorded VS was subsequently directed to a signal monitoring unit. Within this unit, the signal underwent digitization via a National Instruments 9234 device. Data was collected over a duration of 300 s, with a sampling frequency of 25.6 kHz. In total, 1200 sets of samples were gathered, and each set had a sample length of 25,600 data points. These measurements were obtained from the CP under various operational conditions such as normal and defective operating conditions. The faults considered in this study are mechanical seal scratch defect (MSS-D), mechanical seal hole defect (MSH-D), and impeller defect (IF) The description of the whole dataset is shown in Table 1.

Table 1. CP dataset.

CP condition	Defect specification			VS samples
	Defect length (mm)	Defect diameter (mm)	Defect depth (mm)	
Normal	–	–	–	300
MSH	–	2.8	2.8	300
MSS	10	2.5	2.8	300
IF	18	2.5	2.8	300

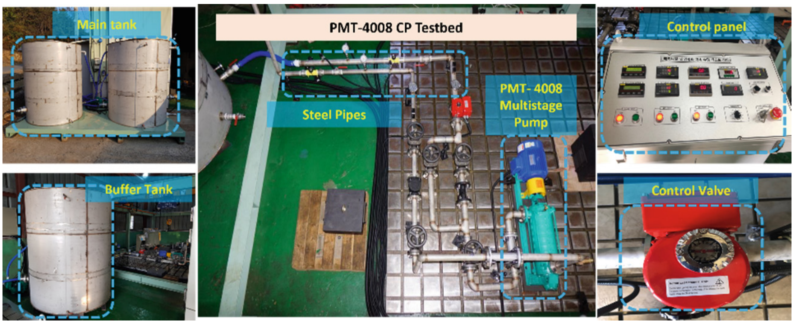


Fig. 1. Experimental testbed for data acquisition

3 Proposed Framework

The proposed approach is depicted graphically in Fig. 2. The method comprises the following steps:

Step 1: VSs are collected from the CP.

Step 2: The acquired VSs are represented in their respective time-frequency scalograms using CWT. The scalogram images illustrate variations in energy levels across various time-frequency scales through the application of distinct color intensities.

Step 3: VSs Vibration signals acquired from the centrifugal pump encompass fault-related impulses as well as unwanted macrostructural vibration noise. This noise can potentially impact the autonomous health-sensitive feature extraction capabilities of the CNN. To extract discernible health-sensitive features, the current step involves the processing of CWT scalograms to derive new MFSs.

The process of generating MFSs comprises several crucial stages. Initially, the proposed method employs a Gaussian filter on the CWT scalogram to achieve smoother results and effectively mitigate any noise interference. Subsequently, a Laplacian filter is applied as an edge detector to the CWT scalogram. This enhances the accuracy of edge detection within the CWT scalogram, ultimately leading to the extraction of MFSs.

Step.4: To identify the ongoing health conditions of the CP, fault-related information from the MFS is extracted and classified into their respective classes using CNN in this step. The CNN model used in this study is presented in Table 2 which consists of three convolutional layers followed by max-pooling layers, designed to extract intricate features from input data. These layers utilize the ReLU activation function for introducing non-linearity. After feature extraction, the flattened data is processed through three densely connected layers, each with ReLU activation, gradually reducing dimensionality and capturing higher-level patterns. The final output layer employs the softmax activation function, enabling the model to make multi-class predictions, making it well-suited for tasks like image classification. Overall, this architecture excels at feature extraction and pattern recognition, facilitating the accurate classification of diverse objects or categories.

Table 2. CNN for feature extraction and classification:

Type of layers	Output	Param#	Activation function
Conv2D	[None, 62, 62, 32]	320	ReLU
MaxPool2D	(None, 31, 31, 32)	0	–
convo2D_1 (Convo2D)	(None, 29, 29, 64)	18496	ReLU
max_pooling2D_1 (MaxPooling2D)	(None, 14, 14, 64)	0	–
convo2D_2 (Convo2D)	(None, 12, 12, 128)	73856	ReLU
max_pooling2D_2 (MaxPooling2D)	(None, 6, 6, 128)	0	–
flatten (Flatten)	(None, 4608)	0	ReLU
dense (Dense)	(None, 512)	2359808	–
dense_1 (Dense)	(None, 256)	131328	ReLU
dense_2 (Dense)	(None, 128)	32896	–
dense_3 (Dense)	(None, 4)	516	softmax

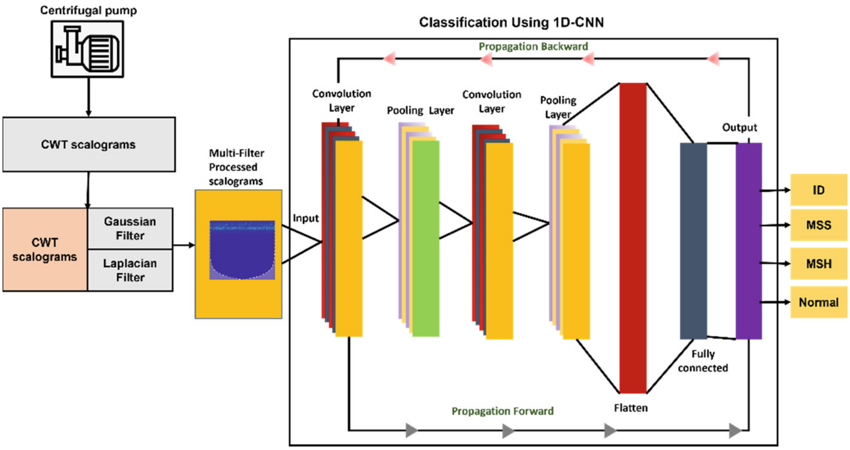


Fig. 2. Graphical flow of the proposed method

4 Results and Performance Evaluation

This study utilized a k-fold cross-validation (k = 3) approach, to gauge the effectiveness of the proposed methodology. To enhance result reliability, these experiments underwent 15 iterations. In each iteration, 200 samples were selected at random for model training per class, while the remaining samples were designated for model testing. Readers can find a comprehensive dataset description in Table 1.

A comparison is made between the proposed method and the reference technique proposed by Gu et al. [17]. For evaluation, matrices such as average accuracy (AA), precision (Pm), Recall (Rm), and F-1 score are calculated from the confusion matrices presented in Fig. 3. These matrices are computed using Eqs. 1,2,3, and 4.

$$AA = \frac{\sum_k^K TP_k}{N} \times 100, \tag{1}$$

$$P_m = \frac{1}{K}\left(\sum_{k=1}^{K} \frac{TP_k}{TP_k + FP_k}\right) \times 100, \tag{2}$$

$$R_m = \frac{1}{K}\left(\sum_{k=1}^{K} \frac{TP_k}{TP_k + FN_k}\right) \times 100, \tag{3}$$

$$F1 - score = 2 \times (\Pr ec_m \times \text{Rec}_m)/(\Pr ec_m + \text{Rec}_m), \tag{4}$$

The true positive and negatives are represented by *TP* and *TN*, False negatives of the classifier is represented by *FN*, while *N* denotes the total count of samples within each class.

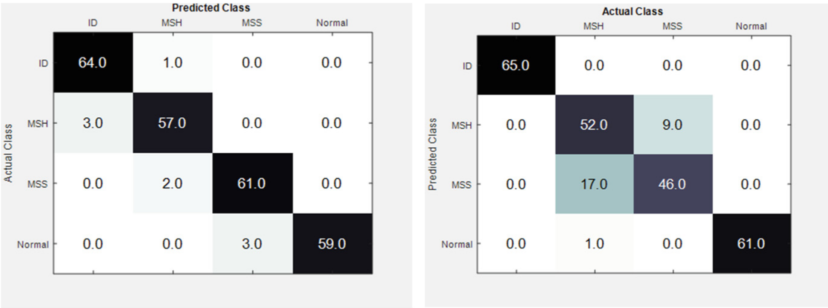
The CP health conditions classification results obtained from the proposed and reference comparison method are presented in Table 3. The proposed approach achieved a higher AA of 96.4% compared to the reference method with Pm of 96.50%, Rm of 96.25, and F-1 score of 96.50. The higher AA of the proposed method can be elaborated as follows. The VSs acquired from the CP consist of fault-related impulses and unwanted macrostructural vibration noise which can affect the autonomous Health-sensitive features extraction capabilities of the CNN. To overcome this concern, novel MFSs are used for CP health state classification. The new MFS enhances the fault-related color intensity variations and removes the unwanted noise from the scalograms using Gaussian and Laplacian image filters. For a classification model, the accuracy of classification is directly proportional to the quality of input features. As can be seen from Fig. 4 the features extracted by CNN from the MFS are highly discriminant which is the key reason for the higher AA of the proposed method. A slight feature space overlap between the MSH and MSS can be noticed in Fig. 4. To increase the classification accuracy, in the future, signal filtering can be used to increase the discriminancy of MFS for different classes.

The reference method Gu et al. [17] decomposed VSs obtained from the rotating machinery using VMD and selected the informative IMF of VMD. Scalograms of the selected IMF are created using CWT from which features are extracted using CNN. Instead of a softmax layer for classification, the reference method used SVM for this task. This method is selected for comparison due to its correlation with the steps involved in the proposed technique. Furthermore, both techniques utilized VSs for the diagnosis of mechanical faults in machines. To make the comparison fair, instead of SVM, the softmax layer is used for the classification task. After applying the steps presented in [17] to our dataset, an AA of 89.25% was obtained which is lower than the proposed method, as presented in Table 3. This underperformance can be elaborated as follows. The CWT scalograms illustrate variations in energy levels across various time-frequency scales through the application of distinct color intensities. These color intensities help the CNN to extract discriminant features for the health state identification of the CP. However, VSs acquired from the CP are heavily affected by macrostructural vibration noise. Thus it is important to further preprocess the CWT scalograms prior to feature extraction.

Table 3. Performance comparison of the proposed method with Gu et al. [12].

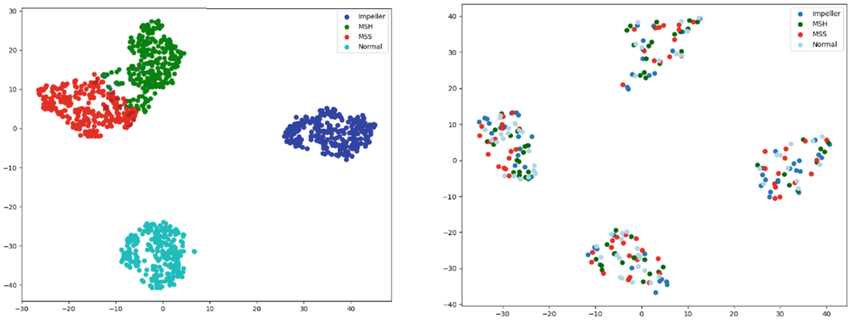
Approaches	Performance metrics			Accuracy (Average)%
	Precision	Recall	F-1 Score	
Proposed	96.50	96.25	96.50	96.40%
Gu et al. [17]	89.25	89.60	89.25	89.00%

Based on the fault diagnosis capability of the proposed method for CPs, it can be concluded that the framework is suitable for diagnosing CP faults. The main advantage of the proposed framework lies in its fundamental concept, which involves preprocessing VS and selecting health-sensitive features based on their ability to improve classification accuracy. As can be seen from Fig. 4 the features extracted by CNN from the traditional CWT scalograms are not discriminant enough to represent the health state of the CP which is the key reason for the higher AA of the proposed method.



(a) (b)

Fig. 3. Confusion matrices (a) Proposed (b) Gu et al. [17]



(a) (b)

Fig. 4. Feature space (a) Proposed (b) Gu et al. [17]

5 Conclusion

This paper proposed a fault diagnosis method for centrifugal pumps using multi-filter processed scalograms and convolutional neural networks. Traditional approaches using continuous wavelet transform scalograms struggle with unwanted noise in vibration signals from pumps, affecting diagnostic accuracy. The proposed method overcomes this challenge by using the new multi-filter processed scalograms that effectively enhance fault-related color intensity variations while eliminating undesirable noise using Gaussian and Laplacian image filters. It effectively identifies pump health conditions and outperforms existing methods when tested on real-world data with an average accuracy of 98.4%, offering significant potential for improving maintenance and operational reliability in industries relying on centrifugal pumps. In the future, the proposed method will be applied to diagnose cavitation-related faults in the centrifugal pumps.

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