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A reliable unsupervised sensor data fusion method for fault detection in brushless direct current motors

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ABSTRACT

This paper introduces an efficient and reliable unsupervised method for detecting faults in a brushless direct current (BLDC) motor based on abnormality identification in sensor-acquired vibration and sound signals through multi resolution decompostion and analysis. The research utilizes the double-density dual-tree complex wavelet transform (DD-DT-CWT) to extract important features from vibration signals, and incorporates audio feature extraction for the sound signals. The captured signals are divided into overlapping segments to improve fault localization, and the features of each segment are organized in a coefficient matrix. Subsequently, singular value decomposition (SVD) is applied to the resulting coefficient matrix from the vibration and audio signals. To effectively monitor the motor's condition, the singular values from both sets of sensor data are combined. Analysing the decay patterns of the singular values enables the identification of faults in the BLDC motor under test. By establishing a suitable threshold for the decay slope of the singular values, the proposed method can accurately and precisely identify and categorize various faults in BLDC motors. This early fault detection can prompt predictive maintenance to ensure the optimal performance, reduced downtime and longevity of BLDC motors.

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1. INTRODUCTION

Brushless direct current (BLDC) motors are extensively used in applications such as electric and hybrid vehicles, industrial automation systems and aerospace due to their efficiency, dependability, and minimal maintenance needs [1]. However, the occurrence of faults in these motors wreak havoc on system performance, jeopardizing efficiency, safety and reliability, leading to significant operational downtimes and financial losses [2]. Hence, continuous monitoring of the motor's health in real-time using sensors and data analysis, improves system uptime and production efficiency. By fusion of data obtained from different sensors, the subtle changes in motor behaviour can be identified and these early warning signs can activate predictive maintenance before they cause significant damage or downtime.

BLDC motors, though known for their reliability, experience various faults that affect the performance of the entire system. The major faults include electrical faults such as winding faults, sensor faults, inverter faults and mechanical faults like bearing fault, air gap irregularities, overheating and aging [3]-[5]. Eccentricity faults in BLDC motors occur when the rotor is not perfectly centered within the stator, creating an uneven air gap around it [6]. This can arise due to various factors and lead to several negative consequences for the motor's performance.

A glimpse into the review of the related works on predictive maintenance can be can be broadly categorized into machine learning-based and non-machine learning-based approaches. Traditionally, fault identification methods for BLDC motors primarily utilized model-based strategies and signal processing methods that require extensive domain knowledge and are often limited by their dependency on accurate modeling of the motor dynamics. Recent advances have seen the application of machine learning methods, particularly supervised learning, which have demonstrated promising results in fault classification. However, these methods often require large, labeled datasets, which may not always be available in real-world scenarios. Also ensuring that data from multiple sensors is time-synchronized is crucial for accurate fusion and fault detection.

A brief review of the related works using machine learning is given below. Suawa *et al.* [7] predictive maintenance by the effective use of sensor data fusion and with deep learning methods, including deep convolutional neural networks (DCNNs), long short-term memory (LSTM), and convolutional neural network and long short-term memory (CNN-LSTM) were described. The authors have innovatively used the sensor fusion method for improving detection efficiency. But it demands significant computational power and there is no effective discussion on efficiency of real time systems. Shifat and Hur [8] have introduced a sensor fusion based frame work for identifying stator related faults in BLDC motors based on fast kurtogram and autogram of the measured signals. There is an enhanced diagnosis accuracy, leading to more reliable motor operation and reduced downtime. But the signal processing methods are conventional and limited applicability to real time scenarios. Also this method is not very effective in varying operating conditions. Hossein and Abedi [9] have demonstrated the wavelet based approach for detecting the fault between the turns of the stator winding, by extracting the wavelet energy features. The method using wavelets is very effective in this case as wavelets are very strong in processing non-stationary signals like inter-turn faults. This work is done as a simulation study and its applicability to real time situations can not be assessed.

Despite their success, supervised learning methods faced several challenges, such as the need for labeled data, which is often expensive and time-consuming to obtain. Moreover, these methods struggled to generalize across different fault types and operating conditions. Unsupervised learning approaches have been suggested to tackle these challenges by learning patterns from unlabeled data, however, they are often limited by their sensitivity to noise and their dependency on feature engineering, which can impact their fault detection accuracy. Hence the need for robust and scalable unsupervised methods that can effectively detect a wide range of faults in BLDC motors without requiring labeled datasets or extensive feature engineering is the need of the hour.

In the proposed method we have designed a precise, multi-sensor data fusion model to predict the faults and its diagnostics in BLDC motors using advanced signal processing techniques. This detection can achieve optimal machine maintenance scheduling, ensuring controlled downtime with minimal impact on overall production processes [10]. Vibration and sound signals are among the most commonly utilized sensor data types for anomaly detection and assessing the condition of motors [11], [12]. The defects in BLDC motors can be precisely diagnosed by analysing the fault characteristics of fast changing vibration and sound signals.

The proposed work addresses the main challenges of identification of the health conditions of a BLDC motor. The samples of vibration and sound signals of the motor working under healthy and faulty conditions were captured using the established experimental test bench as described in section 3.1. This sampled data were processed and a fault diagnostic framework was proposed for fault detection and classification. The major highlights of the above method are:

a. Real time monitoring of health condition of BLDC motors based on multi-senor data.
b. Gentle but coherent feature extractions from multi sensor data were adopted.
c. Accurate fault detection and classification using unsupervised learning methods which offers a powerful method for deriving insights from unlabeled data.
d. Incorporating sensor fusion reduces noise in individual sensor measurements by leveraging their strengths and compensating for weaknesses.

The structure of the rest of the paper is as follows, section 2 presents the proposed method with subsections 2.1 and 2.2 providing a detailed theoretical foundation and the algorithm employed in the method.

Section 3 presents the results and discussion of the study. Subsection 3.1 outlines the experimental setup and data acquisition process used in the introduced method, while subsection 3.2 discusses the results and compares the proposed method with existing approaches, and the conclusion is in section 4.

2. METHOD

This research paper introduces a robust approach for detecting and classifying faults in BLDC motors using double-density dual-tree complex wavelet transform (DD-DT-CWT) [13] and singular value decomposition (SVD) [14]. This method is evaluated using the vibration and sound data collected from an experimental set-up as described in section 3.1. Its performance was assessed using metrics such as accuracy, precision, F1 score, and recall. The combination of DD-DT-CWT and SVD for fault detection in BLDC motors proved to be a powerful and insightful approach. The proposed method focused on capturing and analysing the vibration and acoustic responses of BLDC motor so as to identify various types of faults. The captured signals were preprocessed and segmented into overlapping windows for computational efficiency and complexity reduction. Segmentation also provides better localization of faults. The audio feature extraction were conducted on each windowed segment to extract features including spectral contrast, chroma, tonnetz, zero-crossing rate, mel-frequency cepstral coefficients (MFCCs), pitch, and spectral centroid [15]. The DD-DT-CWT was instrumental in extracting the relevant features of non-stationary signals like vibration signals [13]. The extracted feature vector coefficients were organized into a coefficient matrix, and SDV [16] was performed on both audio and vibration coefficients. The singular values from both vibration and acoustic signals were merged to provide a more reliable representation of the motor's condition addressing the limitations of individual sensors. By analysing the decay characteristics of the merged singular values and applying appropriate thresholds, the faults in the BLDC motor under different operating conditions can be detected with higher accuracy and reliability. The steps involved in the introduced method are described in the Algorithm 1.

Algorithm 1. Fault detection in BLDC motor

1: **Input:** Vibration signal $v(t)$, Sound signal $n(t)$
2: **Output:** Classification of faulty and healthy conditions
3: Set up the experiment as described in Section 3.1 to acquire $v(t)$ and $n(t)$ under different loading conditions during healthy and unhealthy states.
4: Sample $v(t)$ and $n(t)$ at a frequency of 44100 Hz under various loading conditions.
5: Divide the acquired $v(t)$ and $n(t)$ into segments $v_i(t)$ and $n_i(t)$ using an overlapping segmentation scheme to localize the faults.
6: Perform a two-layer DD-DT-CWT on $v_i(t)$ to extract the most relevant features, resulting in feature set F_v.
7: Extract versatile audio features from $n_i(t)$, resulting in feature set F_n.
8: Evaluate SVD on the coefficient matrix of F_v and F_n, obtaining singular values S_v and S_n.
9: Fuse S_v and S_n using weighted combinations to get fused singular values S_f.
10: Fit an exponential model to S_f and determine faults by analyzing the decaying characteristics of S_f.
11: Classify faulty and healthy conditions by applying a suitable threshold τ based on the decaying constant.
12: Evaluate and compare the performance indices.

2.1. Double density dual tree complex wavelet transform

DD-DT-CWT is an advanced version of the dual tree complex wavelet transform (DT-CWT) which improves the shift-invariance and directional selectivity [9]. It decomposes the multi sensor vibration and sound signals into sub-bands along both horizontal and vertical directions, offering better directional feature extraction compared to DWT. The Figure 1 describes the DD-DT CWT filter network [9]. The diagram consists of two parallel branches, labeled as "Real Branch" and "Imaginary Branch." Each branch contains a series of high-pass filters $(h_0^{(n)}, h_1^{(n)})$ and low-pass filters $(g_0^{(n)}, g_1^{(n)})$, followed by downsampling operations. The outputs from corresponding high-pass and low-pass filters in both branches are then combined to form the complex coefficients at different scales and orientations. This enhances frequency resolution and enables detection of closely spaced fault related frequencies. The accuracy of fault detection is highly enhanced due to the shift invariance and excellent directional sensitivity. DD-CWT provides better localization and directional information compared to standard DWT. This allows precise identification of fault signatures in the motor's vibration, or acoustic signals, even if masked by noise or other components. The dual-tree structure minimizes phase distortion, preserving crucial information about the temporal evolution of the signal. Also, the double density filter bank captures subtle changes in the signal making it possible to detect incipient faults before they progress to severe failures [17]. This allows for early intervention and predictive maintenance [18] reducing downtime and repair costs. In this study a windowing approach is applied to the vibration signals and the wavelet coefficients are extracted using DD-DT-CWT transform. The DT-CWT decomposes the windowed vibration signals into multiple level thereby extracting the features at different frequency levels.

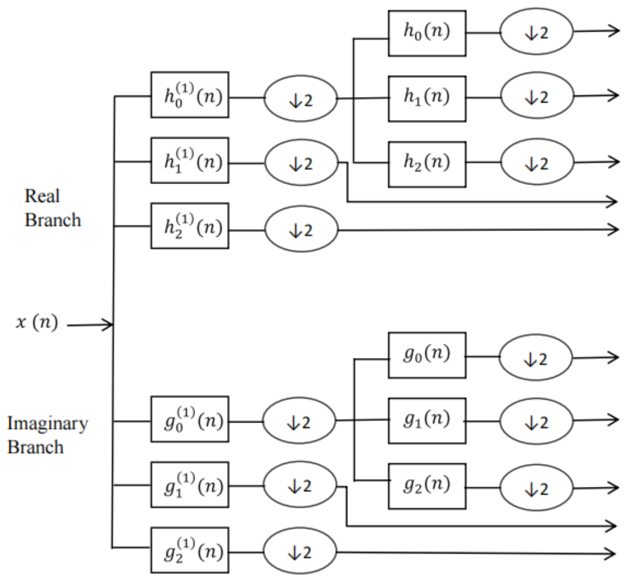

Figure 1. DD-DT CWT filter bank

2.2. Singular value decomposition

The SVD [19] is a 3-piece decomposition of a matrix, *A* of order *m x n*.

$$A = U \sum V^T \tag{1}$$

where U is an *m x m* orthogonal matrix singular contains orthogonal basis vectors representing the signal's 'directions', $\sum$ is an *m x n* diagonal matrix with non-negative real numbers as its diagonal elements known as the singular value of matrix *A*, representing the importance of each direction, and V is another orthogonal matrix of order *n x n*, representing the transpose of the right singular vectors of *A* and gives 'components'in each direction. Columns of *U* corresponding to large singular values represent the 'characteristic signatures'of different fault conditions. Analyzing these signatures can help differentiate between motor's normal and defective condition. In the proposed method the vibration and sound signals which contain a lot of information regarding motors health and load conditions are analysed. SVD decomposes the complex vibration and sound signals into simpler components called singular values. Faults in the experimental set up can be interpreted from the decay rate of singular values. A fast decay indicates sudden change in system dynamics indicating a fault. In the proposed method exponential curve fitting is used to analyse the decay rate of singular values of the features derived from vibration and sound signal features. The general form of the exponential function is,

$$y = ae^{bx} \tag{2}$$

where *a* and *b* are coefficients which provide an insight into the behaviour of the system [18]. The coefficient *a* represent the initial value of the data and *b* is the base of exponential coefficient representing the rate of decay of the function. Curve fitting algorithm finds the value of initial value *a* and exponential coefficient *b* that best fit the measured data. A fault in BLDC motor could introduce a slower decay rate indicating sustained vibration and sound signals at specific frequencies. A fault could introduce additional independent vibration components, potentially increasing the rank of the SVD matrix. By effectively utilizing decay rate analysis, SVD rank, the condition of BLDC motors can be monitored continously. Thereby early identification of faults and preventive maintenance measures to ensure smooth operation and extend the motor's lifespan is possible [20], [21].

3. RESULT AND DISCUSSION

3.1. Experimental setup

An 8 pole 24V DC 3000 RPM BLDC motor is utilized in this study. BLDC motor is connected to a drive with working voltage of 12 V-60 V, rated current of 16 A, power of 300 W with pulse width modulated (PWM) speed regulation. The entire arrangement was fixed on a board. The BLDC motor's speed can be controlled with PWM [22]. The drive has inbuilt over current protection and PLC support with brush less hall less DC motor driver. In this method, we have focused on the vibration and sound signalsof the motor. The vibrations are captured by fixing a three axis digital accelerometer MPU7630 on the board. A hi-fi USB microphone is fixed close to the rotating shaft to pick up sound signals. The microphone is connected to the USB port and the accelerometer to the I2C pin of Rasperry Pi-4B for data acquisition and storage of data. It balances the processing power and has GPIO availability. Rasperry Pi OS Lite is used as the Rasperry-Pi operating system. The motor shaft is loaded with 3-D printed loads of precise weights. We have used centered and off-centered types of loads. The board contains a motor driver system to regulate the speed of motor. Python is used for coding. Figures 2 and 3 show the images of hardware set up used for the proposed work and different types of loads mounted on the BLDC motor's shaft.

Figure 2. Experimental setup for BLDC motor fault detection

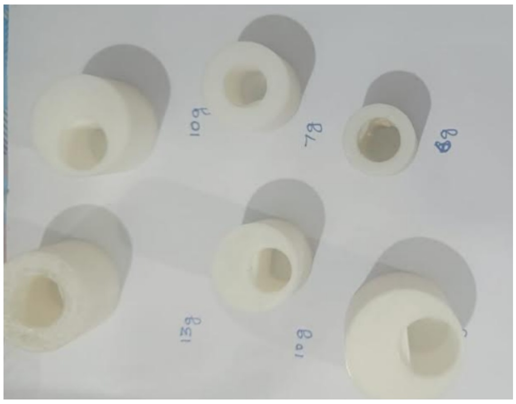

Figure 3. Different types of centered and off centered loads

This section presents the experimental results of analysis of sensor data using fusion technique. In the proposed method the sound and vibration signals were captured real time from the experimental set up using accelerometer and microphone. Both these signals were sampled at a sampling frequency of 44100 Hz. A total of 441,000 sound samples and 44100 vibration signal samples were captured from BLDC motor running under different loading conditions. The samples of the normal data and faulty data for both vibration and sound features are represented in Figures 4 and 5.

In order to localize the faults the acquired signals are divided into overlapping windows. The window size of 4096 samples were used for vibration signals and total data samples were divided into 11 segments. For each windowed signal the coefficients are computed using double layer DD-DT-CWT and the vibration features were stored in a coefficient matrix.

SVD is applied on the coefficient matrix to extract the singular values from the vibration signals. Similarly the audio signals were divided into overlapping windows of size 40168 samples and the total sound data samples were divided into 11 segments. The relevant features were extracted from each segment using the function 'extractAudiofeatures' and stored in coefficient matrix, further SVD was carried out to derive the singular values of the audio signals. The audio and vibration singular values are combined using weighted sum w_1 and w_2. Here we have selected w_1 as 0.45 and w_2 =1- w_1. For each data in column of the fused data matrix, an exponential function is fitted. The fit function used in the proposed method is a single term exponential model. The slope of the fitted function is calculated and a threshold value set as - 0.75 is selected. In the proposed method if the slope exceeds the threshold value, data is classified as 'normal' else 'faulty'.

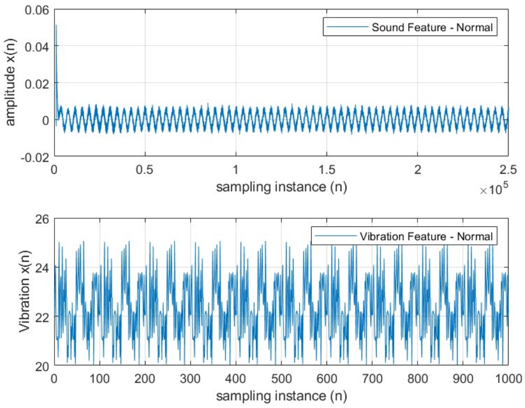

Figure 4. Sample of normal data signals

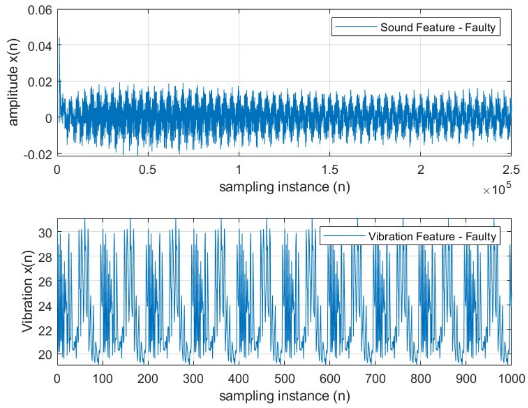

Figure 5. Sample of faulty data signals

Figures 6 and 7 represent the SVD's of normal and faulty motor conditions. It is observed that normal signals have higher singular values and the characteristics decay at a lower rate thereby depicting low rank. The SVD values are larger for the normal signals and comparatively smaller for the faulty signals.

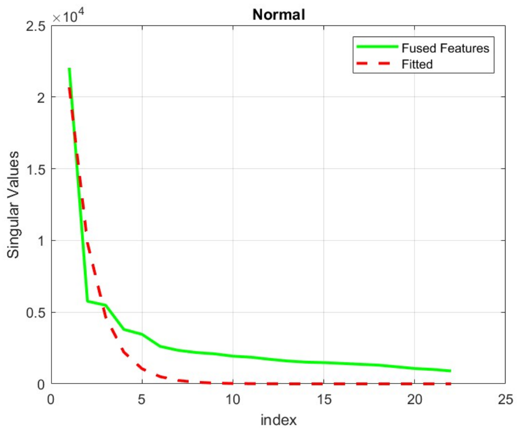

Figure 6. SVD of normal fused signals

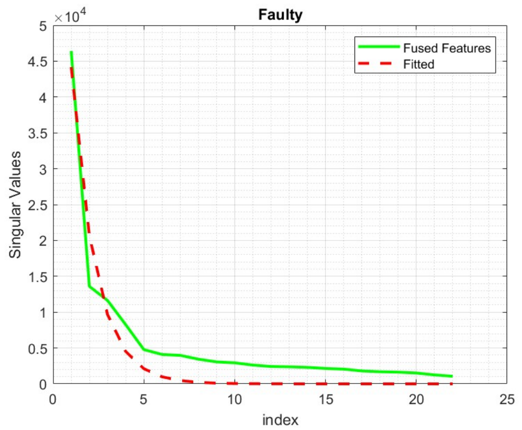

Figure 7. SVD of faulty fused signals

3.2. Results and comparison

In our study on unsupervised fault detection in BLDC motors using sensor data fusion, we found that integrating data from multiple sensors significantly enhances the accuracy of fault detection [23]. Specifically, the data fusion approach enabled us to identify correlations between vibration signals, sound signals, and electrical parameters, which are indicative of potential faults. Our method demonstrated a higher detection rate for anomalies compared to single-sensor methods, suggesting that sensor data fusion provides a more comprehensive understanding of the motor's condition.

The classification labels for the signal results are presented in Table 1. Key evaluation metrics for classification namely precision, recall and F1score were computed using the formulas provided in (3)–(6) [24].

The standard notations TP, FP, TN, and FN stand for true positive, false positive, true negative, and false negative counts [25]. The performance indices like accuracy, precision, recall, F1score were evaluated for the proposed work. These metrics were also compared against an existing fault detection approach utilizing machine learning model like DCNN, CNN-LSTM, and LSTM methods [7]. Table 2 summarizes the results. The proposed method proves to be more accurate and precise than the existing methods of fault detection using machine learning algorithms. The computational time, resources and requirement of huge amount of labeled data is drastically reduced in this method [26].

$$accuracy = \frac{TP + TN}{TP + TN + FP + FN} \tag{3}$$

$$precision = \frac{TP}{TP + FP} \tag{4}$$

$$recall = \frac{TP}{TP + FN} \tag{5}$$

$$f1score = 2 \cdot \frac{precision \cdot recall}{precision + recall} \tag{6}$$

Table 1. Signal result classification table

Signal classification	Description
TP	Fault exists and is detected
TN	Fault does not exists and is undetected
FP	Fault does not exists but detected
FN	Fault exists but undetected

Table 2. Comparitive analysis of the proposed method with existing methods

	DCNN [2]	CNN-LSTM [7]	LSTM [7]	Proposed method
Accuracy	0.988	0.935	0.736	0.999
Precision	0.997	0.930	0.734	0.999
Recall	0.994	0.925	0.734	0.999
F1 score	0.990	0.928	0.729	0.999

4. CONCLUSION

This research contributes by proposing a reliable unsupervised fault detection technique for BLDC motors based on multi-sensor fusion. The proposed method provides better accuracy and performance indices contributing to more reliable and efficient predictive maintenance strategies for BLDC motors. Our fault detection method does not rely on machine learning algorithms or the need for extensive labeled datasets. This approach offers the advantages of simplicity, requires less processing power and resources, and can be developed and deployed quickly. We conducted tests using both centered and off-centered loads with different weights to simulate different types of faults, namely bearing fault, shaft bending and rotor-stator scraping. However additional and in depth research may be required to generalize this method for analysing different types of faults. This requires more data from different sensors to be fused which increases the complexity in real-time fault detection systems where speed and efficiency are crucial.

In future, we aim to expand our work to include additional sensors to interface with a compact controller designed to transmit data to a central hub, where the real time analysis of the information will be performed for predictive maintenance. This study can be further expanded to include the diagnosis of various motor defects related to stator, demagnetization and rotor related faults. Analysis of the degradation patterns of BLDC motors as they transit from normal state to a faulty one, utilizing machine learning models to estimate the motor's remaining useful life is also a promising extension. Future research may also look into refining the fusion algorithms to improve their adaptability across different motor types and operational environments.

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AUTHOR CONTRIBUTIONS STATEMENT

This journal uses the Contributor Roles Taxonomy (CRediT) to recognize individual author contributions, reduce authorship disputes, and facilitate collaboration.

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Baburaj Madathil		✓	✓	✓	✓	✓		✓	✓	✓		✓	✓	

C : **C**onceptualization
M : **M**ethodology
So : **So**ftware
Va : **Va**lidation
Fo : **Fo**rmal Analysis
I : **I**nvestigation
R : **R**esources
D : **D**ata Curation
O : Writing - **O**riginal Draft
E : Writing - Review & **E**diting
Vi : **Vi**sualization
Su : **Su**pervision
P : **P**roject Administration
Fu : **Fu**nding Acquisition

CONFLICT OF INTEREST STATEMENT

Authors state no conflict of interest in this research work.

DATA AVAILABILITY

The data that support the findings of this study are available from the corresponding author, [initials: BBN], upon reasonable request.

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