LASSO-Based Feature Extraction with Adaptive Windowing via DTW for Fault Diagnosis in Rotating Machinery

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***Abstract*—In real-world engineering environments, faults in rotating machines typically occur for concise periods, which leads to poor stability and low accuracy in fault diagnosis. The traditional fault diagnosis of rotating machinery relies on analyzing time-series data to detect system degradation and faulty components. However, the complexity of rotating machinery and the presence of multiple fault types across different operating conditions challenges for conventional classification techniques. This paper proposes a LASSO regression-based feature extraction method with adaptive window based on Dynamic Time Warping (DTW) for fault diagnosis in rotating machinery. The approach effectively extract features by modeling the relationship between shaft rotational speeds (25, 50, and 75 rpm) and vibration signals from piezoelectric accelerometers. This research focus on single and combination faults analysis to include 11 faults, enhancing its applicability to real-world fault conditions. To assess its effectiveness, the proposed method is evaluated against Principal Component Analysis (PCA) and Independent Component Analysis (ICA) using the K-Nearest Neighbors (KNN) classifier. The experimental results demonstrate that the LASSO-based approach consistently achieves high classification accuracy across different speeds, outperforming PCA and ICA in both single and double fault scenarios. These findings highlight LASSO regression as a robust feature extraction technique for improving fault detection and predictive maintenance in rotating machinery.**

Keywords*—Rotating machinery; fault analysis; feature extraction, LASSO regression

I. Introduction

Rotating machinery, such as motors, pumps, gearboxes, and turbines, forms the backbone of modern industry, with its uninterrupted operation depending heavily on the integrity of key tribological components like ball bearings and shafts. These elements help reduce friction, support radial and axial loads, and ensure dynamic stability. However, they also endure fluctuating mechanical and thermal stresses that can lead to issues such as cracks, spall, imbalances, and lubrication degradation. Faults originating from a rolling element or a shaft shoulder can propagate in just a few revolutions, manifesting as subtle energy bursts in vibration signals [1], [2]. If undetected, these incipient defects can escalate into catastrophic failures, resulting in unplanned downtime, costly production losses, and heightened safety risks [3], [4]. In response, the growing emphasis on condition-based maintenance necessitates diagnostic algorithms capable of quickly and reliably detecting these short-lived, speed-dependent anomalies.

Fault diagnosis in industrial settings is fundamentally a pattern recognition task: sensor signals are pre-processed to extract key features, which are then mapped by a classifier to different fault conditions [5], [6], [7], [8]. The literature includes several feature extraction methods, ranging from statistical indicators of time and frequency domain techniques such as the Hilbert Transform, Fast Fourier Transform (FFT), and Wavelet Transform [9], [10], [11], [15]. Feature reduction techniques typically involve methods like Principal Component Analysis (PCA), Independent Component Analysis (ICA), and Linear Discriminant Analysis (LDA) [12], [13], [14].

However, real-world applications have critical constraints that must be addressed for successful implementation. First, the true mechanical period of a machine is unknown a priori. While operators may log the nominal speed, transient load changes, belt slippage, and controller drift introduce cycle-to-cycle variations, causing misalignment between the start points of consecutive revolutions. Second, vibration data is continuously collected without explicit tags marking the start of each shaft revolution. This lack of synchronization leads to the smearing of transient fault signatures, as even small phase offsets can disperse localized impacts over multiple windows, thereby reducing the signal-to-noise ratio of the extracted features.

According to those problems, a significant research gap exists in accurately capturing transient, speed-dependent fault signatures without the need for specialized hardware or precise synchronization signals. While methods such as tachometer-based synchronization or order tracking can mitigate some of these issues, they often demand additional sensors, clean speed signals, and extensive calibration, limiting their practicality, particularly in retrofitted or older equipment.

Traditional fixed-window sampling was utilized to solve problems by assuming a constant period [15], [16], [17]. If the window is shorter than the true mechanical cycle, fault signatures are truncated; conversely, if the window is too long, irrelevant data dilutes the fault energy. Adaptive approaches, such as those based on tachometer pulses or order tracking, can alleviate some of these issues but require additional hardware and clean speed signals, which may not be available in retrofitted plants. Dynamic Time Warping (DTW) provides an alternative that is sensor-agnostic. Specifically, originally developed for speech alignment, DTW computes the optimal nonlinear mapping between two time sequences [18], [19]. In this work, DTW is used to align consecutive revolutions of the vibration waveform. By using the first detected loop as a reference and minimizing the distance between it and subsequent candidate segments, DTW can dynamically select the window boundaries that correspond to the true mechanical period. In this work, the DTW-driven window selection ensures that transient impacts are confined to a single revolution while compensating for speed fluctuations at various rotational speeds (25, 50, and 75 rpm).

Once the correct windows are identified, the challenge shifts to selecting a compact discriminative set of features. While deep learning models excel at capturing high-order correlations, they require large, labeled datasets and substantial computational resources. The statistical methods, though more interpretable, tend to suffer from high dimensionality. To solve those problems a balance between simplicity and performance, we utilized the Least Absolute Shrinkage and Selection Operator (LASSO) regression [20]. By penalizing the l_1-norm of the regression coefficients, LASSO encourages sparsity in the model , driving irrelevant features to zero and preserving only the most fault-sensitive information [21], [22]. The resulting sparse feature vectors are then fed into a simple k-nearest neighbors (k-NN) classifier. This end-to-end pipeline is efficient, interpretable, and well-suited for real-time applications [23].

This paper proposes a novel LASSO-Based feature extraction with adaptive windowing via DTW for fault diagnosis in rotating machinery. The main contributions of this paper are summarized as follows:

- A speed-aware feature extraction paradigm that explicitly models the interaction between shaft rotational speed and vibration response under fault conditions, capturing subtle speed-dependent dynamics at 25, 50, and 75 rpm.
- A DTW-based adaptive windowing strategy that identifies the true mechanical period on the wheel by minimizing the DTW distance between consecutive revolutions, thus preventing dilution or truncation of transient fault signatures.
- A sparse LASSO feature selection framework that eliminates redundant descriptors, improving classifier accuracy while maintaining a computational footprint suitable for embedded systems.
- Comprehensive validation on public rotating machinery datasets covering eleven single-fault classes (and combinations of double-faults for robustness), where the proposed method consistently outperforms PCA- and ICA-based baselines in terms of accuracy, F1-score, and model compactness.

The organization of this paper is as follows: In Section II, we summarize the literature review in the field of fault diagnosis in rotating machinery. The data presentation is described in Section III. The methodology is outlined in Section IV, including the proposed LASSO regression with adaptive windowing, which is detailed in Section IV-A. The experimental evaluation and results are presented in Section V. The limitations and future work are mentioned in Section VI. Finally, the conclusion is discussed in Section VII.

II. Literature Review

Effective fault diagnosis in rotating machinery has long been a significant area of research due to the importance of predictive maintenance in industrial applications. Several researches have explored various feature extraction techniques to accurately identify faults using vibration signals [25], [26].

Traditional techniques, such as Fast Fourier Transform (FFT), Wavelet Transform (WT), and Hilbert Transform, focus on frequency-domain analysis to identify characteristic frequencies associated with specific faults [10], [11], [27], [28]. FFT, despite its widespread use, struggles with non-stationary signals, limiting its effectiveness in real-world scenarios involving transient faults [10], [11], [27]. Wavelet transform offers improved performance in analyzing transient events due to its time-frequency localization capability but still requires careful selection of basis functions to optimize results [11], [28].

Dimensionality reduction methods like Principal Component Analysis (PCA), Independent Component Analysis (ICA), and Linear Discriminant Analysis (LDA) have been widely applied to simplify complex vibration datasets, enhancing classification accuracy by reducing redundant or irrelevant features [12], [13], [14]. PCA, for example, captures dominant variance but often misses subtle fault signatures [12], [13]. ICA addresses this limitation by separating mixed signals into independent sources but still encounters difficulties with transient signals affected by varying operational conditions [14].

Recent advancements have introduced adaptive and dynamic approaches to overcome these limitations. Techniques involving Dynamic Time Warping (DTW) have demonstrated potential in accurately aligning and comparing vibration signals under fluctuating speeds without relying on external synchronization methods [18], [19]. Similarly, sparse representation methods have gained attention for their ability to effectively extract relevant sparse features, improving diagnostic accuracy while maintaining computational efficiency [29], [30].

Despite these advancements, few studies have combined adaptive windowing techniques with sparse regression models explicitly to handle speed-dependent transient faults comprehensively. This literature review highlights the critical need for methodologies that integrate these strategies to enhance the precision and robustness of fault diagnosis systems in rotating machinery.

III. Data Presentation

A. Mechanical Faults Dataset

In this paper, we employ vibration and rotational speed signals obtained from a multi-speed fault dataset [24]. This dataset is an open-access resource that provides vibration and rotational speed data from various fault scenarios involving ball bearings and shafts. The dataset consists of 39 distinct fault scenarios, collected using a Rotary Machine Fault Simulator from SpectraQuest Inc., which includes a DC motor, Bearing 1, Bearing 2, and a shaft supporting two weighted disks. The data is captured using a National Instruments Compact DAQ system.

To collect the data, a tachometer and eight piezoelectric accelerometers are used to record the rotational speed and vibration signals. These sensors are strategically mounted on the motor, gearbox, and both bearing housings, in the x, y, and z directions. The dataset includes one no-fault scenario and 38 fault scenarios, each recorded at three different rotational speeds: 25 rpm, 50 rpm, and 75 rpm. The data are sampled at a rate of 6.4 kHz over a 10-second period, resulting in 64,000 data points for each scenario in time-series format. Each fault scenario is recorded 25 times, providing a comprehensive representation of the machinery's behavior under various conditions.

Table I provides a summary of the rotating machinery fault dataset, listing the different fault scenarios, their corresponding conditions, and the parameters used during data collection. This dataset is critical for the subsequent feature extraction and fault diagnosis tasks, as it offers detailed insights into the relationship between vibration signals and fault conditions at different operational speeds.

TABLE I. DESCRIPTION OF MULTIPLE MECHANICAL FAULTS DATASETS

Description	Details
Scenarios	39 scenarios
Rotational Speed	25 rpm, 50 rpm, 75 rpm
Time record	10 Seconds/scenario
Number of Trial	25 trials/scenario
Sampling rate	6.4 KHz
Data points	64,000 points/scenario
Sensors	1 Tachometer (Shaft), 8 Piezoelectric Accelerometers (6 bearing housings, 2 gearbox housing)

B. Data Preparation

In this paper, the rotating machinery dataset [24] consists of time-series data for 39 fault scenarios involving ball bearings and shafts. Each trial is grouped into a single file corresponding to each fault scenario and rotational speed. However, the data from trial number 17, which corresponds to a ball bearing number 2 defect at 50 rpm, is shorter than the others. To ensure consistency across all data, we discard the data from trial number 17 across all fault scenarios and rotational speeds. As a result, the length of each grouped file is standardized to 1,536,000 data points per fault scenario at each rotational speed. In total, 117 files are generated, corresponding to the 39 fault scenarios recorded at three distinct rotational speeds. This standardized dataset is now ready for feature extraction and classification analysis.

IV. METHODOLOGY

This section outlines the methodology employed in this paper, providing detailed insights into the feature extraction process, with a particular emphasis on LASSO regression. Additionally, we present the evaluation of the proposed feature extraction techniques using the k-NN classifier. The overall workflow is organized into four main steps, as illustrated in Fig. 1. The first step describes the algorithm developed based on DTW for adaptive window sampling, while the second step explains the application of LASSO regression for feature extraction. The final step focuses on the k-NN classification technique used to evaluate the extracted features. This structured approach enables a comprehensive assessment of the proposed methodology's performance in fault diagnosis.

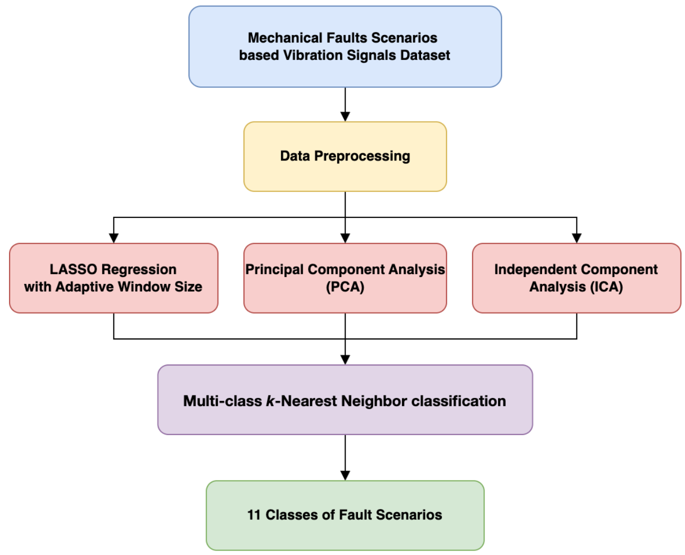

Fig. 1. Workflow of ball bearing and shaft fault classification.

A. Adaptive Window Based on DTW

In fault diagnosis of rotating machinery, selecting the appropriate observation window size is essential for extracting meaningful features from vibration and rotational speed signals. The window size must cover the entire rotational period, which can vary based on the specific characteristics of each signal. To address this, Dynamic Time Warping (DTW) is employed to evaluate the similarity between two time-series signals, allowing the alignment of successive machine rotations. The proposed adaptive windowing Algorithm 1 is designed to dynamically determine the optimal window size for each fault scenario by calculating the DTW distance between different segments of the vibration signals. The algorithm begins by initializing the vibration signal data, $\mathbf{D}$, and an array to store the optimal window size for each fault scenario. For each case, the algorithm iterates over a range of possible window sizes, from a minimum value, $n_{\min}$, to a maximum value, $n_{\max}$. At each step, two segments of the signal are extracted: $\mathbf{d}_1$ (the first segment) and $\mathbf{d}_2$ (the second segment), and the DTW distance between them is computed. DTW measures the dissimilarity between the two time-series, providing an optimal alignment even if the signals are shifted or stretched in time. The window size that minimizes the DTW distance is chosen as the optimal window for the current scenario.

Once all fault scenarios have been processed, the algorithm selects the largest optimal window size across all scenarios, taking into account the varying rotational speeds and the effect of disturbances. This ensures that the window size is adequately adjusted to cover the true mechanical period, even when the machine experiences fluctuations in speed. By utilizing DTW, the algorithm effectively addresses the problem of varying signal periods without requiring additional hardware or external speed sensors.

The adaptive windowing approach improves fault diagnosis by accurately localizing transient fault signatures, enhancing the feature extraction process. This method is not only sensor-agnostic but also provides the flexibility to adapt to different fault scenarios, thereby improving the classification accuracy and robustness of the system. The DTW-driven window selection process ensures that transient impacts are captured accurately, facilitating efficient and precise fault detection in real-time applications.

Algorithm 1 Adaptive Window Size Estimation Using DTW

Require: $\mathbf{D}$: Vibration Signals in Time-series
Ensure: Optimal window size

Let $\mathbf{D}_{all} \leftarrow$ optimal window size of all cases
for case $= 1$ to last case **do**
  for $n = n_{\min}$ to $n_{\max}$ **do**
    Extract segment 1: $\mathbf{d}_1 = \mathbf{D}(1 : n, 1)$
    Extract segment 2: $\mathbf{d}_2 = \mathbf{D}(n + 1 : 2n, 1)$
    Compute DTW distance: $d(n) = \mathrm{DTW}(\mathbf{d}_1, \mathbf{d}_2)$
  end for
  Select optimal window size:

$$n^* = \min d(n)$$

  Output n^* for current state
  Store n^* to $\mathbf{D}_{all}$
end for
Select maximum window size from all cases:

$$\hat{n} = \max \mathbf{D}_{all}$$

return Optimal window size $\hat{n}$

B. LASSO Regression

LASSO regression is an extension of Ordinary Least Squares (OLS) regression [20] designed to perform both variable selection and regularization, which enhances the prediction accuracy of the model. This method aims to minimize the sum of squared residuals while imposing a constraint on the sum of the absolute values of the regression coefficients. This constraint encourages sparsity by forcing some of the coefficients to shrink to exactly zero, which effectively removes unimportant features and helps avoid overfitting. The LASSO objective function is expressed as:

$$\hat{\beta} = \operatorname{argmin} \left\{ \sum_{i=1}^{N} \left(y_i - \sum_{j=1} \beta_j x_{ij} \right)^2 \right\} \quad (1)$$
$$\text{s.t.} \sum_{j=1} |\beta_j| \leq \lambda,$$

where N represents the number of observations, y_i is the response variable at observation i, x_i is the vector of predictors associated with observation i, and λ is a non-negative regularization parameter. The parameter $\hat{\beta}$ represents the estimated regression coefficients, which include both the intercept and the coefficients for each predictor. The value of λ controls the strength of the penalty applied to the regression coefficients, with larger values leading to more coefficients being shrunk to zero, thus simplifying the model but potentially sacrificing accuracy. A smaller λ value results in less regularization, which may lead to overfitting. In this paper, we set λ to 1×10^{-8} to balance regularization and model performance. By using the L^1 norm of the coefficients, LASSO encourages sparsity in the model, helping to identify the most relevant features while reducing the dimensionality of the dataset. This sparsity is crucial for improving classification accuracy, as it focuses the model on the most important variables.

The LASSO regression process in this study is applied after using the adaptive window technique to determine the optimal window size for segmenting the time-series data. This ensures that each segment used for feature extraction corresponds to a meaningful portion of the signal. The extracted features are then processed using LASSO regression to estimate the coefficients, which are stored in a matrix for classification. This sparse feature set is then used to train a classifier, improving the accuracy of the fault diagnosis model while keeping computational demands manageable. The use of LASSO regression for feature extraction is particularly beneficial for real-time applications, where both high diagnostic accuracy and efficient use of computational resources are critical.

C. Classification

The k-Nearest Neighbors (k-NN) algorithm is employed as the classification model to evaluate the effectiveness of the proposed feature extraction method. k-NN is a non-parametric, instance-based learning algorithm widely used in statistical pattern recognition and classification tasks. It is particularly effective in handling multi-modal class distributions, where an instance may be similar to multiple class types. For implementation, the fitcknn function in MATLAB is utilized to construct and evaluate the k-NN model, specifically tailored for diagnosing faults in ball bearings and shafts.

The classifier is configured to distinguish among 11 different fault scenarios, as outlined in Table II, which include both single and compound faults such as outer and inner raceway defects in bearings and various shaft misalignment. Feature datasets generated from the proposed method, as well as benchmark methods including Principal Component Analysis (PCA) and Independent Component Analysis (ICA), are used to construct the training and testing sets. The datasets are partitioned using holdout cross-validation, with 70% of the data allocated for training and the remaining 30% for validation.

In the case of the proposed method, feature extraction is preceded by DTW-based adaptive window sampling, which identifies the optimal window size for each rotational speed condition using Dynamic Time Warping. These windows are then applied to both the training and validation datasets. Subsequently, LASSO regression is used to extract sparse features

TABLE II. DETAIL OF 11 SINGLE FAULT SCENARIOS

Number of Class	Detail of Fault Scenarios
Case 1	Outer Raceway defect (Bearing 2)
Case 2	Inner Raceway defect (Bearing 2)
Case 3	Ball and Raceway defect (Bearing 2)
Case 4	Ball defect (Bearing 2)
Case 5	Outer Raceway defect (Bearing 1)
Case 6	Inner Raceway defect (Bearing 1)
Case 7	Ball and Raceway defect (Bearing 1)
Case 8	Coupling end bent (Shaft)
Case 9	Centerally bent (Shaft)
Case 10	Ball defect (Bearing 1)
Case 11	No Fault

by establishing a relationship between the rotational speed and the corresponding vibration signals within each adaptively sampled window. This approach allows for the identification of the most discriminative and compact features.

In contrast, PCA and ICA are applied using a fixed window size of 640 data points, chosen based on the dataset's temporal resolution and recording parameters. For PCA, only the first principal component (PC1) is retained, which captured more than 95% of the total variance and is deemed sufficient for representing the feature space. Similarly, ICA decomposed the signals into statistically independent components, and the most informative component is selected as the feature representation.

By comparing the performance of these three methods under consistent classification settings, the paper aims to rigorously validate the superiority of the proposed DTW-adaptive LASSO-based feature extraction framework in terms of classification accuracy, computational efficiency, and robustness to varying operational conditions.

V. SIMULATION RESULTS

This research evaluates a novel feature extraction approach based on LASSO regression combined with an adaptive windowing strategy using Dynamic Time Warping (DTW). The proposed method is benchmarked against two widely-used dimensionality reduction techniques: Principal Component Analysis (PCA) and Independent Component Analysis (ICA). The objective is to assess whether the proposed LASSO-DTW method can achieve superior performance in fault classification using time-series data derived from vibration and rotational speed measurements of rotating machinery.

The experimental evaluation is conducted using a k-Nearest Neighbors (kNN) classifier, which was used to compare the effectiveness of each feature extraction technique. The classifier is configured to recognize 11 distinct fault scenarios across three rotational speeds: 25 rpm, 50 rpm, and 75 rpm. Four standard classification performance metrics are used: accuracy, precision, recall, and F1-score. These metrics provide a comprehensive evaluation of the models' ability to detect and classify faults reliably.

TABLE III. RESULTS FOR K-NN CLASSIFICATION PERFORMANCE BASED ON PROPOSED METHOD

Rotational Speed	Accuracy(%)	Precision(%)	Recall(%)	F1-Score(%)
25 rpm	96.97	97.73	96.95	96.88
50 rpm	93.94	95.45	93.94	92.86
75 rpm	84.85	87.88	84.85	84.85

TABLE IV. K-NN CLASSIFICATION PERFORMANCE FOR COMPARISON OF FEATURE EXTRACTION METHODS AT 25 RPM

Feature Extraction	Accuracy(%)	Precision(%)	Recall(%)	F1-Score(%)
Proposed method	96.97	97.73	96.95	96.88
PCA	36.46	35.89	36.56	35.96
ICA	90.85	94.75	90.89	88.97

The classification results using the proposed LASSO-DTW method are summarized in Table III, with corresponding confusion matrices shown in Fig. 2. At 25 rpm, the method achieved 96.97% accuracy, 97.73% precision, 96.95% recall, and a 96.88% F1-score. At 50 rpm, it maintained high performance with 93.94% accuracy, 95.45% precision, 93.94% recall, and a 92.86% F1-score. Even at 75 rpm, under more dynamic conditions, it achieved 84.85% accuracy, 87.88% precision, 84.88% recall, and an F1-score of 84.85%.

In contrast, PCA and ICA yield significantly lower performance. At 25 rpm, PCA achieved just 36.46% accuracy, while ICA reached 90.85%. At 50 rpm, PCA dropped further to 18.44% accuracy, with ICA achieving 81.41%. At 75 rpm, PCA recorded 20.64% accuracy, while ICA reached 77.41% (Tables IV to VI).

Beyond classification accuracy, the proposed method significantly reduces feature dimensionality compared to PCA and ICA. The feature matrix generated using the LASSO-DTW method is sized at 6,564 × 55 for the training set. In contrast, both PCA and ICA produced much larger feature matrices of 18,700 × 640. Despite this reduction, the proposed method maintained superior diagnostic performance, illustrating its capability to extract compact and highly relevant features without sacrificing accuracy.

This dimensionality reduction is especially beneficial in real-time and resource-constrained environments, where computational efficiency is crucial. The sparsity-promoting nature of LASSO enables the model to retain only the most informative features, improving interpretability and scalability. The combination of high classification performance and reduced feature complexity underscores the practical value of the proposed method for real-world applications in industrial fault diagnosis systems.

VI. DISCUSSION

The simulation results demonstrated the substantial advantages of integrating LASSO regression with DTW-based

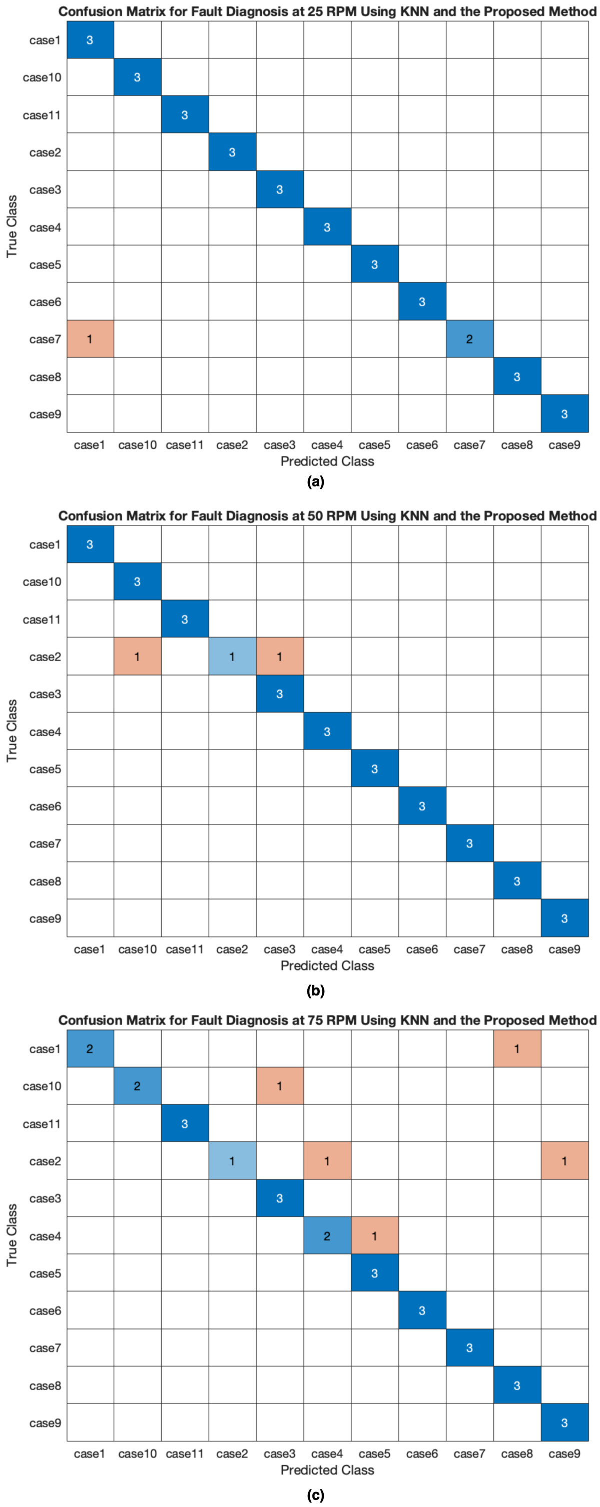

Fig. 2. Confusion chart of three rotational speeds (a) 25 rpm using KNN and the proposed method; (b) 50 rpm using KNN and the proposed method (c) 75 rpm using KNN and the proposed method.

adaptive windowing in fault diagnosis for rotating machinery. The proposed method consistently outperformed PCA and ICA across various operational speeds, illustrating its robust ability to manage transient and speed-dependent fault signatures

TABLE V. K-NN CLASSIFICATION PERFORMANCE FOR COMPARISON OF FEATURE EXTRACTION METHODS AT 50 RPM

Feature Extraction	Accuracy(%)	Precision(%)	Recall(%)	F1-Score(%)
Proposed method	93.94	95.45	93.94	92.86
PCA	18.44	18.84	18.39	16.77
ICA	81.41	82.77	81.82	82.77

TABLE VI. K-NN CLASSIFICATION PERFORMANCE FOR COMPARISON OF FEATURE EXTRACTION METHODS AT 75 RPM

Feature Extraction	Accuracy(%)	Precision(%)	Recall(%)	F1-Score(%)
Proposed method	84.85	87.98	84.85	84.85
PCA	20.64	20.77	20.51	20.00
ICA	77.41	77.41	76.29	77.41

effectively. The performance at lower rotational speeds (25 rpm and 50 rpm) was particularly noteworthy, achieving very high accuracy, precision, and recall. Even at higher speeds (75 rpm), where signal complexity significantly increases, the method maintained strong performance, highlighting its adaptability to real-world industrial environments. Moreover, the reduced dimensionality provided by LASSO regression significantly improved computational efficiency without compromising accuracy. This makes the proposed methodology highly suitable for real-time diagnostic systems, particularly in resource-constrained and applications.

However, the proposed method still has some limitations. Its effectiveness may depend on the quality and duration of the collected signals, and transient anomalies in extremely short-duration faults have still challenges. Moreover, it requires determining an optimal initial period for the adaptive windowing based on DTW, which directly affects the accuracy of identifying the rotational period. Future research could explore integrating advanced deep learning approaches or hybrid feature extraction methodologies based on sparse representation to further enhance performance. Additionally, validating the method across a wider range of operational conditions and fault types would help ensure broader applicability and reliability in diverse industrial scenarios.

VII. CONCLUSION

In this paper, we have proposed a feature extraction method based on LASSO regression for fault diagnosis in rotating machinery, enhanced by an adaptive windowing technique based on Dynamic Time Warping (DTW). We compared the classification accuracy of our proposed technique with PCA and ICA, and the results clearly demonstrate the effectiveness of combining LASSO with the adaptive DTW windowing approach. Specifically, our proposed method outperformed PCA and ICA in classifying ball bearings and shafts across multiple fault scenarios. For instance, our LASSO-based method achieved a classification accuracy of 96.97%

at 25 rpm, while achieving 93.94% and 84.85% at 50 rpm and 75 rpm, respectively. Furthermore, the integration of the DTW-based adaptive windowing technique enables dynamic adjustment of the observation window, ensuring that transient fault signatures are accurately localized within each revolution, even when rotational speeds vary. This improvement enhances the model's accuracy by addressing the challenge of unknown and fluctuating vibration periods. Additionally, the reduction in feature size achieved through LASSO regression, without compromising diagnostic performance, highlights the method's efficiency and potential for real-time applications.

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