

Current Signal-Based Fault Classification Using MFCC-DWT Feature Fusion and AI Techniques in IPMSM used in Electrical Vehicle

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Abstract:

Permanent magnet synchronous motor (PMSM) is known as one of the most promising machines for electric vehicle (EV) propulsion due to its high torque density, efficiency and excellent speed regulation. However, motor faults may seriously affect the performance, safety, and reliability of the system. Traditional methods of fault detection cannot provide satisfactory performance in the aspects of accuracy, adaptation to dynamic working condition and real-time performance. To address these issues, in this paper, we propose a hybrid fault classification framework by combining features from MFCC and wavelet transform. Comprehensive information from the time and frequency domains is combined together in the proposed method, which improves the discriminator for distinguishing the fault types better. The tests were conducted on dataset in two cases: with MFCC only and the combined version using two classifiers catboost and random forest. Finally, the obtained results are very encouraging with 97.10 % in the first case and 86.00 % in the second case.

1. Introduction

In the last few years, Permanent Magnet Synchronous Motors (PMSMs) have emerged as a major part of the propulsion system in electric vehicles (EVs) based on their excellent performance [1, 2]. They also have a higher torque density, high efficiency, small size and high speed fidelity in comparison to other motor types on the automotive landscape. Considering the worldwide urges for decreased carbon emissions and sustainable transportation, prevalence of PMSMs in modern electric vehicles will continue to increase in importance. While these benefits are compelling, PMSMs have their drawbacks [3]. Like all electrical machines, PMSMs are susceptible to a number of faults (i.e. demagnetization, stator winding faults, bearing faults, eccentricity, etc.) that may significantly affect the safety, reliability, and performance of electric vehicles. These faults may produce first-order consequences of severe system degradation, unexpected break down of hardware, or catastrophic failure given that they go undetected, and indicate the need for effective fault detection and classification methods to reinforce

the robustness and reliability of PMSM-based systems for electric vehicles [4, 5]. Traditional fault detection methodologies, including model-based and signal-processing models, have been extensively investigated. While traditional fault detection methodologies yield valuable information about fault dynamics, they are often inadequate in the assessment of fault detection methods under complicated or dynamic operating conditions. Factors such as low accuracy, limited ability to adapt to varying operating speeds and loads, and insufficient real-time performance capability impede the practical use of fault detection methods in actual EV systems. Moreover, as EV systems evolve to become more intelligent and data-driven, there is a rising demand for higher level fault diagnosis strategies that are both data-efficient and reliable under varying conditions [6, 7, 8]. To address some of these issues, this work proposes a new hybrid fault classification method with features derived from Mel-Frequency Cepstral Coefficients (MFCC) and wavelet transform. The MFCC method has been widely used in audio signal processing and has been shown to capture relevant characteristics of the signals in the frequency domain [9, 10, 11], while

wavelet transform offers advantages when dealing with the revealing transient and non-stationary behaviours in time-frequency domain [12, 13]. Combining the extracted features of both methods provided a more comprehensive representation of the operational state of the motor and was aimed at achieving improved fault classification accuracy. The performance of the proposed approach was assessed based on a labeled dataset and through two different feature extraction scenarios. The first case utilizes MFCC-based features only. The second case utilizes the MFCC features and additional features of the wavelet transform. Classification performance was assessed using two sophisticated machine learning classifiers, CatBoost and Random Forest. The results confirmed that classification performance was promising - with the MFCC only model providing 75% classification accuracy, while the hybrid model with MFCC and wavelet features provided classification accuracy of 91%. These results reinforce the value of combining various signal features in conjunction with machine learning models to improve fault detection in PMSMs. In conclusion, the proposed hybrid framework represented a notable advancement in the domain of motor fault diagnosis, with specific focus on EV applications. The proposed hybrid framework, besides providing improvement in fault classification accuracy, also exhibited robustness and adaptability which is promising for future intelligent condition monitoring systems for electric vehicle propulsion [14].

2. Related works

Recently, there has been considerable interest in the reliability and performance of Permanent Magnet Synchronous Motors (PMSMs), especially with its applications in electric vehicles (EVs). PMSMs are popular in EV propelling systems, owing to their high torque density, high efficiency, and good speed control capabilities. Performance degradation caused by faults, such as inter-turn short circuit, demagnetization, and bearing faults can degrade performance and reliability, thus suitable detection and classification of the faults is necessary. Traditionally, PMSM fault diagnosis was accomplished through model based techniques and signal processing techniques. Model based techniques often require knowledge of detailed parameters of the motor, which makes them susceptible to failure due to parameter deviations, thereby making model-based diagnosis defective in dynamic operating modes [1]. Signal processing techniques, including Fast Fourier Transform (FFT) and Park's Vector method, have been extensively used for feature extraction, but also do not capture

the non-stationary nonlinear signal; real-world signals [15]. Increasingly, academic literature has focused on time-frequency domain analysis for greater and more effective fault detection. For example, the Discrete Wavelet Transform (DWT) is useful for detecting localized attributes in transient signal making it very viable for the fault classification of rotating machinery [3]. Additionally, the original application of Mel-Frequency Cepstral Coefficients (MFCCs) comes from speech processing but has since gained popularity for motor fault diagnosis because of their ability to detect minor changes in signal envelope [16]. Ortega et al. (2025) present two adaptive observer structures—one simple linear and one parameter-estimation based—to detect inter-turn short-circuit faults (ITSCFs) in interior PMSMs. The linear observer offers exponential convergence, with a rate entirely determined by motor parameters; however, this convergence may be slow in practice. To address this, the parameter-estimation-based observer employs an adaptive mechanism that estimates resistance and inductance online, resulting in guaranteed finite-time convergence under minimal interval excitation assumptions. Unlike Kalman-based approaches, these observers yield an explicit estimate of the fault current amplitude and severity. Simulation results using realistic motor models show robust, fast detection performance. This work advances model-based diagnostics by offering both simplicity and speed in ITSC detection [17]. Lv et al. tackle the challenge of not only detecting but locating fault coils in direct-drive PMSMs with parallel branch winding. Existing FFT, voltage-sequence, and wavelet methods could detect the presence of inter-turn short circuits (ITSC) but lacked coil-level localization. The authors propose branch differential current (BDC) and branch residual current (BRC) indicators, which can be extracted using external current sensors on each branch—simplifying retrofit applications. To automate localization, they construct a knowledge graph (KG) that captures relationships among fault indicators, coil branches, and known fault patterns. This graph-based structure allows intelligent reasoning to pinpoint faulty coils without retraining or extensive offline models. Experimental validation confirms accurate coil-level fault localization and improved maintenance decision-making. This method uniquely enables early-stage fault localization in finished motors using minimal sensors and AI reasoning [18]. Pietrzak et al. (2024) present a diagnostic pipeline for PMSM stator-winding inter-turn short-circuit faults that utilizes Continuous Wavelet Transform (CWT) to extract features from three-phase stator currents. They compute wavelet coefficients that are sensitive to the

fault severity, and then feed these as the features into SVM, KNN, and MLP classifiers. The important part: systematic feature selection to identify the most discriminative wavelet-based coefficients reduced waste in the detection accuracy through computation, one important aspect in a real time implementation setting. Testing classification accuracy over various loads and fault severities produced significant classification accuracy (98–99%), and detection performance remains achievable for real-time implementation. By emphasizing human-engineered interpretable features from classic ML and avoid using "deep-learning" models, the work demonstrates an effective low-complexity solution to reliable fault detection in cognitively easy to explain and implement approaches—suitable for an embedded or industrial platform under repetitive constraints [19]. Zerdani et al. (2020) explore the idea of fault detection of inter-turn stator winding faults via Power Spectral Density (PSD) extracted from stator current signals as a supporting background for our work. Their study compared PSD estimators using Fourier analysis (Welch and Burg) which extracted frequency domain features that are sensitive to faults. Following a feature selection process, the authors noted that some PSD bands correlated more with severity of fault level than others, which increases interpretability of a model and reduces dimension of features to model. These specific features were ultimately used as an input to a linear SVM. They found the linear SVM had optimized performance using the Welch estimator. They validated the approach through simulation, and showed that the models were robust to classification of fault or healthy models across motor operating regimes. This paper demonstrates how spectral feature engineering together with a selective ML approach can provide minimalistic but effective PMSM fault detectors without the need of heavy deep models [20]. In addition, machine learning methods have shown promise for automating the classification of motor faults. Algorithms, like Support Vector Machine (SVM), Random Forest (RF), and most recently, gradient boosting methods such as CatBoost, have been used to develop higher classification accuracy under varying operating conditions. However, there are still many studies that look at either time-domain or frequency-domain features. Focusing only on one or the other may limit the classification ability of each classifier by increasing the specific classifier's dependence on individual fault types and operational states [21].

3. Methods

3.1. PMSM Faults types

Permanent Magnet Synchronous Motors (PMSM) are becoming more attractive to a number of applications because of higher efficiency and the ability to precisely control motor operation. However, PMSMs are susceptible to numerous different types of faults, which may compromise the performance of the motor or lead to a failure. Faults can usually be characterized as one of five different types: electrical faults, mechanical faults, thermal faults, control system faults, and magnetic faults. Electrical faults can be devastating losses, such as shorting out of stator windings or magnet demagnetization. Mechanical faults usually involve errors such as bearing wear or misalignment of the rotor. Thermal faults can usually be attributed to some form of over-temperature. Control faults are typically associated with sensor faults or possible failures of the drive. Magnetic faults could interrupt torque activity or introduce some additional harmonic distortion.

Inter-turn stator winding faults are included in this list and those faults may lead to even worse situations if not remedied quickly and they may also be particularly serious depending on how many turns are shorted together. Some severity of inter-turn short circuit fault is based on how many turns are shorted together. In the work presented herein, we focus particularly on analyzing and diagnosing 1-turn and 5-turn inter-turn short circuit faults, as these represent early-stage and moderate stage fault situations, respectively, and also allow us to study and understand the evolution and effect of stator winding faults in permanent magnet synchronous motors (PMSMs), as shown in figure 1.

3.2. Dataset used

In this work we used the dataset used by S. kang and N. Kim in [22]. Table 1 show the main parameters of permanent magnet synchronous. Data information and categories are shown in Table 2. Also, we organized data for a binary classification as shown in the next tree figure

4. Proposed system

The proposed system is designed to perform efficient and accurate classification of audio signals (or any other applicable signals such as speech, biomedical, etc.) using a modular pipeline consisting of four main stages: Preprocessing, Feature Extraction, Feature Selection, and Classification. Each stage plays a critical role in enhancing the performance and reliability of the final model. The overall system architecture is depicted in Figure 3.

4.1. Data acquisition

Every analysis process has a preprocessing stage that accepts a raw input signal and prepares it for feature extraction and classification. Preprocessing is important because it circumvents complications such as inconsistencies, noise, and undesirable artifacts to ensure that the signal is segmented properly, and can be cleanly processed. The following preprocesses are dealt with on the input:

Noise-reduction: Environmental and system noise must be removed from the signal. A variety of basic noise removing filters can be used (see spectral subtraction), and more advanced techniques using adaptivity, stability, and step response. Bandpass filtering: Now that noisy segments of the signal have been removed, we now can bandpass filter the signal to keep the frequency components of interest. This has the effect of removing low-frequency drifting from the signal, while also removing high-frequency noise. The bandpass filter will pass through a Low cut-off frequency of 40 Hz and high cut-off frequency = 500 Hz. As the spectral properties of the signal vary (e.g., voice or physiological signals), these cut-off frequencies are determined to be the informative frequency components of interest while controlling for extremes that are not informative or desired.

4.2. Feature Extraction

The core of the processing pipeline involves segmentation of the input current signal into overlapping windows to enable efficient feature extraction and fault diagnosis. Specifically, the signal is divided using a sliding window approach, where each segment contains 1000 consecutive samples, and the window slides backward with a step size of 500 samples. This results in a 50% overlap between consecutive segments, ensuring temporal continuity and improving the system's sensitivity to transient features. The system constructs an initial feature vector of 1,060 dimensions for each audio instance, combining two sets of descriptors: 1,034 features derived from Mel-Frequency Cepstral Coefficients (MFCC), which encode the spectral characteristics of the signal, Delta 1 and Delta 2 of MFCC in 22 features, and 26 features obtained from wavelet transformation, offering additional time-frequency resolution. To ensure uniformity across all samples, vectors with fewer than 1,082 elements—typically due to variation in signal length—are padded with zeros. The figure 4 illustrates the difference between Healthy and Not Healthy in the three cases of test.

4.3. Feature Selection

Once a consistent feature representation is established, a feature selection process is applied to reduce dimensionality and enhance model performance. Specifically, the Recursive Feature Elimination (RFE) algorithm is employed to identify and retain the 150 most informative features. RFE iteratively trains a base estimator and removes the least important features based on model weights, resulting in a reduced feature set that preserves the most discriminative information for the classification task.

4.4. Faults Classification

For the classification phase, the system uses two supervised learning algorithms; Random Forest and CatBoost. Random Forest is an ensemble method that creates many decision trees and averages their output to improve prediction accuracy and mitigate overfitting. CatBoost is also used, as it is an ensemble gradient boosting algorithm adapted to mutable features; it was chosen due to its high performance and resiliency to different feature types. Both classifiers (Random Forest and CatBoost) are trained on the 150 features chosen from our feature selection, using standard measure to use measure the performance of each model.

4.5. Results and Discussion

The classification performance of three models (SVM, Random Forest, and Cat-Boost) was evaluated using three different feature sets: MFCC only, MFCC + first and second order deltas (D1D2), and MFCC + D1D2 + Wavelet features (WL). This process was done in the two cases: 1) Healthy versus Not Healthy, then, 2) 1Turn versus 5Turn. The accuracy results are summarized in the tables and histograms.

The SVM classifier maintained a consistent 90.33% accuracy across all sets of features, showing that it could not capitalize on additional temporal or wavelet features. Random Forest started with relatively low accuracy using MFCCs alone (84.44%), but improved significantly with the addition of wavelet features to 95.59%. CatBoost consistently performed the best, with 90.78% using MFCCs, decreasing slightly with the addition of delta features, before leaping to 97.10% with wavelet features (see table 3).

Overall, these results highlight that MFCC features are already good descriptors, and delta features have limited extra value. In contrast, wavelet features provide significant gain in classification performance, particularly for ensemble classifiers. Among the classifiers, CatBoost was the most robust

and powerful, with Random Forest giving the highest relative improvement, and SVM being unconcerned by feature enhancement (see figure 5). Performance of classifiers was very varied for various feature sets. SVM was experiencing low and almost constant accuracy (around 57%), indicating that it could not make any use of the introduced temporal or wavelet features. Random Forest was doing better, starting at 71.19% when MFCCs were used, slightly higher when delta features were included, and then a huge jump to 91.73% when wavelet features were used. Moreover, CatBoost started at 64.02% using

MFCCs, slightly gained using delta features, and reached 86.00% using wavelets (see table 4). These results confirm that MFCCs alone provide a limiting baseline, with delta features adding little performance. Wavelet features improve significantly by utilizing more richer time-frequency information. Ensemble classifiers (CatBoost and Random Forest) benefitted the most from these features, although Random Forest achieved the best overall accuracy. SVM remained ineffective with all feature combinations, again highlighting its poor ability to generalize compared to ensemble-based classifiers (see figure 6).

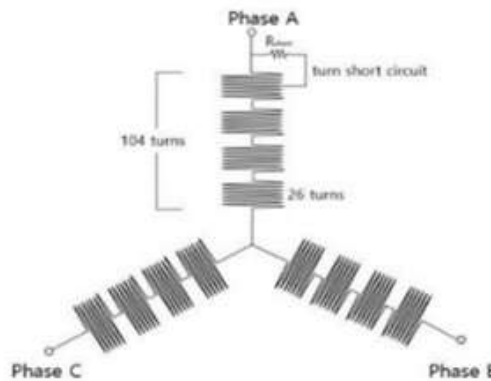


Figure 1: Phase A,B,C

Table 1: Main parameters of permanent magnet synchronous motor.

Parameter	Value
Stator outer diameter / mm	120
Stator inner diameter / mm	75
Number of stator slots / one	24
Number of turns per slot Winding layer / layer	26 2 4
Polar logarithm / pair	220
Rated voltage / V Rated power / kW	5

Table 2: Fault conditions for each Electromagnetic transient simulation

R P M	Fault	Rshort(Rfault)
3600	X	X
	1 turn	1, 0.01
	5 turns	1, 0.01
4800	X	X
	1 turn	1, 0.01
	5 turns	1, 0.01
6000	X	X
	1 turn	1, 0.01
	5 turns	1, 0.01
7200	X	X
	1 turn	1, 0.01
	5 turns	1, 0.01

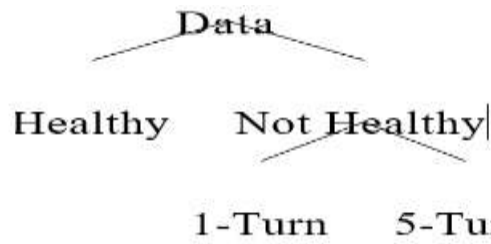


Figure 2: Classes hierarchy for binary classification.

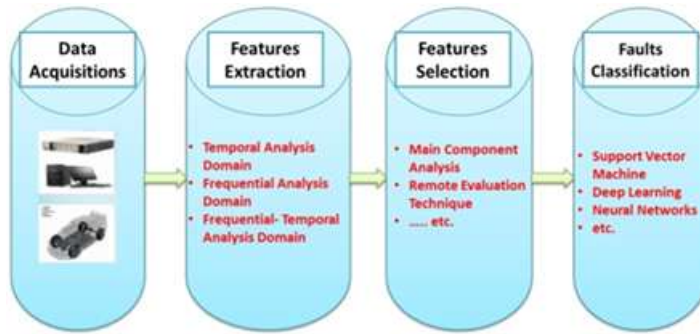


Figure 3: Smart Fault Diagnosis Flowchart

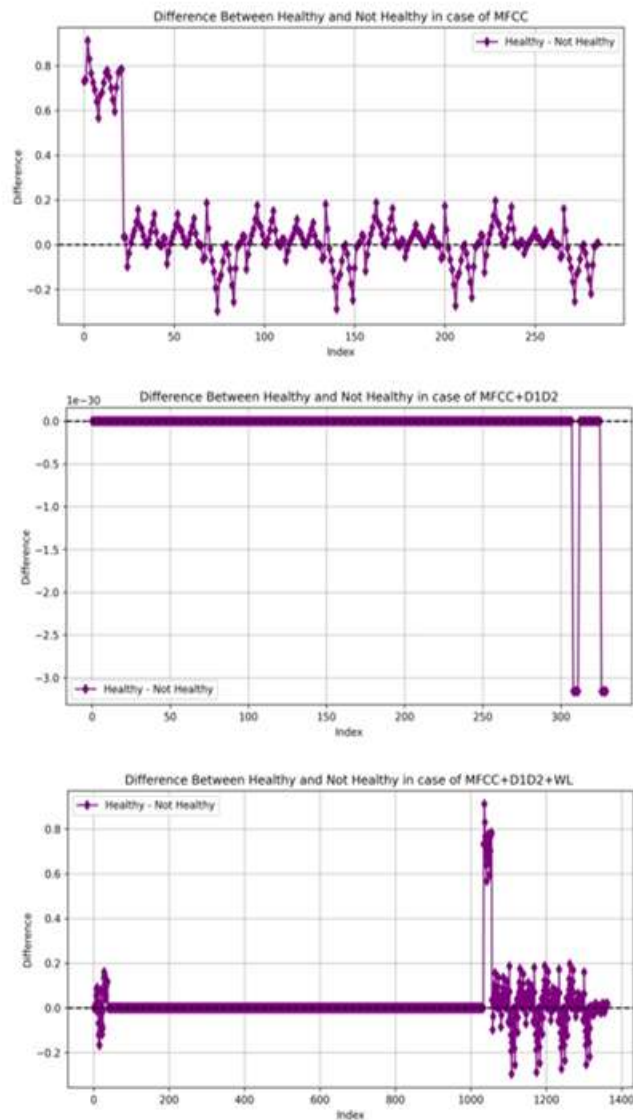


Figure 4: Difference between Healthy and Not Healthy in the three cases of test.

Table 3: Classifier performance with different feature sets in the case of Healthy / Not Healthy.

Classifier	MFCC	MFCC + D1D2	MFCC + D1D2 + WL
SVM	90.33	90.33	90.33
Random Forest	84.44	85.07	95.59
Catboost	90.78	90.08	97.10

Table 4: Classifier performance with different feature sets in the case of 1Turn / 5Turn.

Classifier	MFCC	MFCC + D1D2	MFCC + D1D2 + WL
SVM	57.54	55.73	57.61
Random Forest	71.19	72.66	91.73
Catboost	70.02	72.22	86.00

4. Conclusions and Future works

This work provides a hybrid fault classification framework for Permanent Magnet Synchronous Motors, (PMSMs), in attempts to provide more accurate and reliable high level fault detection in electric vehicle applications. This research evaluated the performance of different sets of features (MFCC, MFCC with delta features, and MFCC with wavelet features) in classification with SVM, Random Forest, and Cat- Boost. The results of accuracy showed that SVM performed low and nearly uniform accuracy with all sets of features, demonstrating poor adaptability. Random Forest and CatBoost, however, showed good improvement as wavelet features were incorporated, with 97.10% and 86.00% accuracy, respectively. These findings present that, while MFCCs in isolation provide a weak baseline and delta features slightly enhance it, wavelet features play a crucial part in enhancing classification performance. Ensemble methods, namely Random Forest, were shown to perform best at utilizing such richer representations and therefore are good candidates for noise-insensitive signal classification tasks. These results suggest the proposed framework under development will have an immense benefit and directly correlate towards real-time and accurate fault finding possible in real-time PM motors that are employed in the electromagnetic propulsion industry. Future work could include real-time deployment in these fields and variations on a larger selections of faults.

Author Statements:

- **Ethical approval:** The conducted research is not related to either human or animal use.
- **Conflict of interest:** The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper

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