A Five-Class Recognizer for Sounds of Induction Motor Overload

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Abstract—**This paper presents research on the recognition of induction motor overload levels using sound analysis. Stable and durable operations of induction motors are very important in home appliances and industries. Overloading is one of faults that can shorten the operating life of these electromechanical machines. In our studies, five levels of overload status are classified using sounds collected by a single microphone. Three acoustic features and six classification models are evaluated. The accuracy rate of 94.85% shows that this is a promising way to classify and therefore to monitor induction motor overload.**

Index Terms—**induction motor overload, classification, sound analysis, machine learning**

I. Introduction

Induction motors are used in various sectors of life. They offer many advantages, such as high reliability and low pollution. They are usually employed continuously for long duration, so condition monitoring and fault diagnosis for induction motors is recently almost compulsory in complex systems, because any interruption can cause huge losses.

According to [1], faults of induction motors can be divided into four classes: bearing (e.g., wear out of bearings), stator (insulation damages, for instance), rotor (broken rotor bars or cracked rotor end-rings), and other faults (eccentricity, for example).

Because induction motor is an electromechanical conversion device, so in order to detect its faults, one can use electrical and mechanical signals. Besides, thermal and chemical signals are also clues leading to some certain faults.

Electrical signals consist of current, voltage, magnetic flux, etc. Motor Current Signature Analysis (MCSA) [2] is probably the most popular approach. This is to detect faults such as eccentricity, broken rotor bars or cracked rotor end-rings, opening or shorting of stator phase winding, bent shaft, bearing and gearbox failures. Voltage signals are employed to detect supply voltage unbalance [3] or stator winding inter-turn faults [4]. Magnetic flux can be used for fault detection in rotor cage [5] or eccentricity [6].

Vibration, noise, and torque are the most widely used mechanical signals for condition monitoring. Vibration analysis are employed in [7] for bearing fault diagnosis and in [8] for detection of eccentricity. Noise monitoring is another approach. It can be applied to detect eccentricity [9] and local defects of gearboxes [10], or even to predict resident lifetime [11]. For torque monitoring, one can employ it for gearbox fault detection [12].

Thermal monitoring is another good way for induction motors, for example, to identify turn-to-turn faults and bearing faults [13].

In chemical monitoring, insulation degradation can be detected chemically using coolant gas analysis [14]. Oil analysis is also a chemical tool to detect wear debris because faults such as misalignment or overload may lead to wearing [15].

In operating induction motors, overload is an abnormal condition. When a motor is overloaded, it can draw more current, causing excessive temperatures. A too high temperature may burn motors. Besides, overload can result in tooth breakage, or wear in roller bearings and gears. In order to detect these consequences, we can use approaches mentioned above.

We try to detect this phenomenon itself, not its consequences. In our research, sound analysis is used to classify the full load (100 percent of full load), 10 percent overload (110 percent of full load), 20 percent overload (120 percent of full load), 50 percent overload (150 percent of full load), and 100 percent overload (200 percent of full load) operations. It should be mentioned that an induction motor with 10 percent overload can still operate about 30 minutes, while a 100 percent overload can last 10 minutes only. Our approach has three advantages. Firstly, sounds of overload appear earlier than its consequences (excessive temperatures, tooth breakage, etc.), so detecting an abnormal sound can prevent these consequences. Secondly, a sound sensor and its installation and maintenance are inexpensive. And finally, it does not need to stop the motor during the detection.

The organization of the paper is as follows. Section II informs the studies recently presented in the literature that refer to motor fault detection using audio signal. The corpus used in this research is presented in Section III. Section IV describes in detail experiments for frame classification. The output of Section IV is applied to classify one-second segments in Section V. The selected feature set and classification model for our recognizer is in Section VI. Section VII concludes the paper and presents future developments.

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II. Related Works

Among mechanical signals, sounds of electric motors are reported to be capable of detecting some mechanical and electrical problems. Compared to other signals, sounds can be acquired inexpensively and easily using microphone(s). Authors in [16] employ a microphone and a high-resolution spectral analysis based on the MUSIC algorithm for detection of three faults: unbalance, bearing, and broken rotor bars. [17] measures acoustic signals by the acoustic camera (microphone arrays), the acoustic spectrum is then used to detect static eccentricity and soft foot. A method for detecting abnormal sounds of the motor for condition monitoring and fault diagnosis is proposed in [18]. Ref. [19] presents an approach to detect bearing and broken rotor bars faults. The acoustic signals are collected by five microphones positioned around the motor. Then the presence of faults is determined by calculating the power spectral density. In [20], acoustic signals (recorded with a digital voice recorder) are combined with the Bayes classifier and k-Nearest Neighbor (kNN) classifier to detect faulty rotor bars and shorted rotor coils. The approach in [19] is improved in [21] by using the Self-Organizing Maps method for the separation of healthy and faulty motors. The diagnosis of electric motor in [22] is done with acoustic noise and convolutional neural network. This approach is to detect tooth damage in the gearbox.

To our best knowledge, no study of using sounds to recognize induction motor overload levels has been published so far.

III. The Corpus

The object of our study is a 4 kW three-phase induction motor. Sounds of full load and overload operations are recorded by a microphone. This microphone is connected directly to the audio input of a laptop (see Fig. 1), so the recorder is actually the laptop's sound card. The distance between the motor and the microphone is about 20 cm. Soundtracks are acquired with the following parameters: sampling frequency is 44.1 kHz, bit resolution is 16, and mono channel. Levels of overload and durations of acquired sounds are listed in Table I. This database is used in the next step of our research. Spectrograms of those sounds are in Fig. 2. Frequency of these signals ranges approximately from 10 Hz to about 8 kHz. It can be seen that there are differences of spectrograms, especially between 200% and the four other types. When we listen to them, we notice that 150% and 200% sounds are a little more jarring than the three others. On the other hand, it is rather difficult to distinguish between 100% and 110% sounds just by listening.

Figure 1. The sound recording/recognition system.

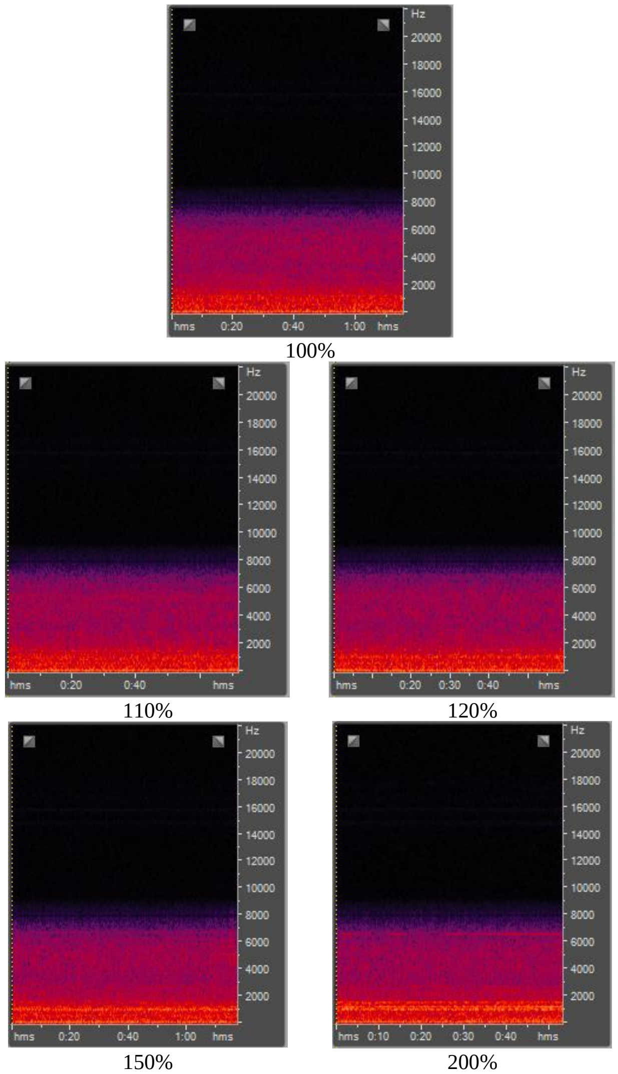

Figure 2. Spectrograms of full load and overload sounds.

TABLE I. The Corpus of Overload Sounds

Overload level	100%	110%	120%	150%	200%
Duration (s)	137	131	142	146	112

IV. Frame Classification

In order to classify signals into five categories, a five-class classifier should be used. It includes a set of discriminant features and a classification model. Our discriminant features consist of F0, Mel-Frequency Cepstral Coefficients (MFCC, 12 coefficients, [23]), and Band Energy Ratio (BER, 4 bands, [24]). These very popular features in audio signal processing form a starting feature set of 17 elements. Then the Principal Component Analysis (PCA, [25]) is applied to reduce the dimension of our feature vector without losing too much information. Essentially, the PCA extracts the important information from the original feature set to rebuild them as a set of new orthogonal features (principal components), and hence to gain a better representation of classes by reducing the number of features (n-o-f). In order to find the appropriate number of new features, we test six classification models for frame classification:

Artificial Neural Network (ANN [26]), decision tree (DT [27]), Fuzzy Inference System (FIS [28]), Gaussian Mixture Model (GMM [29]), kNN [30], and Support Vector Machine (SVM [31]). The selected model is then applied to classify one-second segments.

In the first step of our experiments, we try to categorize a frame of 1024 samples. For each classification model, the n-o-f varies from 1 to 17, and a 10-fold cross validation is applied to find the best n-o-f for that model. The accuracy rate is employed in model evaluation. Plots of average accuracy rates depending on n-o-f are in Fig. 3. It is noticeable that these plots are of the same trend: start at a very low rate (corresponding to one feature), then rise up rapidly when the n-o-f increases from 3 to 4 (except DT), and finally go nearly horizontally. DT begins at a very high rate, but its finishing one is not very impressive. For SVM, it starts at the lowest rate, but finally it is not left far behind compared to others. One can see that besides kNN, the best numbers of features of the other five models are not 17. The best n-o-f of SVM is only 11, resulting in the fourth best performance among the six. DT and FIS are very close to each other when n-o-f varies from 12 to 17. GMM has a drop when n-o-f reaches its maximum value, but this model is still the best so far.

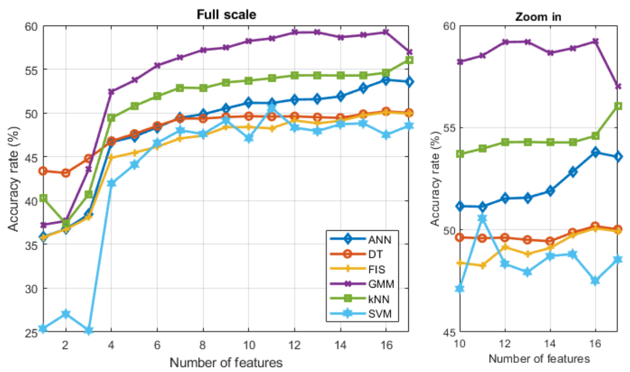

Figure 3. Average accuracy of six models for frame classification.

TABLE II. ANN (16 FEATURES, 25 HIDDEN NEURONS, FEEDFORWARD NETWORK)

Confusion matrix (%)	True class	100%	13.09	80.56	8.26	0.55	0
		110%	3.57	76.46	16.46	1.95	0.092
		120%	2.12	61.95	31.73	7.89	0.35
		150%	0.059	7.70	27.31	61.87	6.21
		200%	0	0.044	0.70	10.18	85.79
Standard deviation (%)	True class	100%	0.82	3.93	0.99	0.24	0
		110%	0.47	1.03	0.77	0.37	0.10
		120%	0.33	3.06	1.67	0.92	0.24
		150%	0.081	1.11	2.77	1.80	1.10
		200%	0	0.063	0.33	1.29	1.25
			100%	110%	120%	150%	200%
			Predicted class				

To have a better view of the performances of these models, their confusion matrices (and the corresponding standard deviation matrices and parameters) are provided in Table II to Table VII. The first thing we can find is that 100-100 elements of ANN and FIS are small, meaning that they can hardly recognize this class. This may lead to their two largest off-diagonal elements (100-110 ones). All the six models have large 200-200 elements, hence they can recognize this class very well. It is worth noting that the largest standard deviation (the center element, 25.29%) of SVM is nearly ten times larger than those of other models. This can be explained that SVM is not stable in this task.

TABLE III. DT (16 FEATURES)

Confusion matrix (%)	True class	100%	40.97	28.86	25.01	4.82	0.20
		110%	28.57	35.63	24.21	7.66	0.50
		120%	26.40	26.54	32.42	15.42	1.86
		150%	7.03	10.37	17.03	58.04	12.51
		200%	0.16	0.64	1.72	10.00	83.83
Standard deviation (%)	True class	100%	1.38	1.86	2.09	0.56	0.15
		110%	1.20	0.99	0.95	1.08	0.14
		120%	2.05	1.47	1.53	1.79	0.53
		150%	0.91	1.19	1.79	1.69	1.07
		200%	0.12	0.25	0.43	1.43	1.48
			100%	110%	120%	150%	200%
			Predicted class				

TABLE IV. FIS (16 FEATURES)

Confusion matrix (%)	True class	100%	16.91	71.35	13.30	0.40	0
		110%	6.68	65.02	24.80	1.36	0.020
		120%	5.03	51.46	40.68	6.23	0.063
		150%	0.034	6.17	39.38	50.98	7.02
		200%	0	0.035	1.67	16.20	76.77
Standard deviation (%)	True class	100%	0.84	3.71	1.21	0.13	0
		110%	1.38	2.61	1.92	0.36	0.064
		120%	1.20	2.71	1.43	0.88	0.10
		150%	0.044	0.99	2.93	2.49	1.49
		200%	0	0.045	0.50	3.44	3.56
			100%	110%	120%	150%	200%
			Predicted class				

TABLE V. GMM (13 FEATURES, 2 MIXTURES)

Confusion matrix (%)	True class	100%	56.43	29.83	10.14	3.96	0.062
		110%	25.41	53.23	10.44	8.23	0.29
		120%	29.43	30.86	21.78	19.50	1.20
		150%	3.11	7.10	8.39	76.30	8.23
		200%	0.0085	0.14	0.79	8.09	88.26
Standard deviation (%)	True class	100%	1.40	2.14	0.82	0.64	0.086
		110%	2.23	1.60	0.94	1.20	0.21
		120%	2.42	2.29	1.17	1.77	0.30
		150%	0.74	1.23	0.88	1.30	1.33
		200%	0.027	0.087	0.22	0.79	0.74
			100%	110%	120%	150%	200%
			Predicted class				

TABLE VI. KNN (17 FEATURES, 65 NEIGHBORS)

			Predicted class				
			100%	110%	120%	150%	200%
Confusion matrix (%)	True class	100%	56.74	27.33	13.47	2.70	0.01
		110%	29.06	46.06	16.08	5.96	0.13
		120%	32.88	27.63	27.79	13.96	0.47
		150%	6.11	7.82	13.90	70.23	4.68
		200%	0.29	0.21	1.32	13.95	79.53
Standard deviation (%)	True class	100%	1.25	2.19	1.13	0.38	0.095
		110%	1.79	1.63	1.16	1.04	0.14
		120%	2.32	2.58	1.24	1.34	0.24
		150%	0.85	1.06	0.91	1.04	0.82
		200%	0.17	0.13	0.33	1.03	0.62

TABLE VII. SVM (11 FEATURES)

			Predicted class				
			100%	110%	120%	150%	200%
Confusion matrix (%)	True class	100%	41.62	3.69	19.43	3.38	0.062
		110%	20.23	51.42	19.26	6.10	0.27
		120%	26.31	34.53	27.50	13.31	1.24
		150%	8.87	12.80	23.41	47.68	12.58
		200%	0.42	0.22	2.24	8.94	84.66
Standard deviation (%)	True class	100%	22.65	21.74	22.42	4.00	0.11
		110%	20.66	23.99	22.63	5.81	0.29
		120%	15.95	19.72	25.29	9.49	1.25
		150%	8.09	8.46	13.40	16.47	9.05
		200%	0.78	0.26	2.55	4.000	6.14

In this experimental phase, GMM seems to be the best one with the highest accuracy rate and a pretty stable performance (low standard deviation), becoming the candidate for the next phase.

V. ONE-SECOND SEGMENT CLASSIFICATION

The number of 1-s segments is fewer than that of frames of 1024 samples, so in this stage, the "leave-one-out" cross validation is applied to GMM to classify 1-s segments.

A. *"The Winner Takes It All"*

Because the sampling frequency is 44100 Hz and the overlap is 512 samples, each 1-s segment includes 86 frames of 1024 samples. To categorize an 1-s segment, "the winner takes it all" tactic is employed. For example, if an 1-s segment contains 30 frames of 100%, 15 of 110%, 20 of 120%, 11 of 150%, and 10 of 200%, it will be recognized as an 100% one. Basing on Fig. 3, we test three values of n-o-f: 12, 13, and 16. Confusion matrices of classification are presented in Fig. 4.

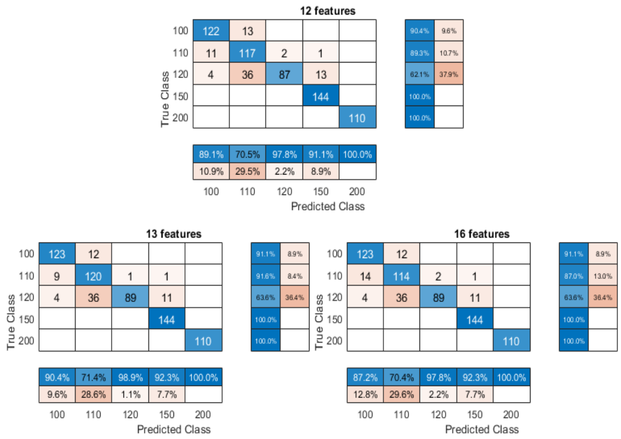

Figure 4. Confusion matrices of GMM for 1-s segment classification.

The three matrices show that the 200% class is recognized with a probability of 1. But the story is totally different for the 120% class. The highest rates belong to this class. They vary from 28.6% to even 37.9%. This is understandable if we once again see the center element of the confusion matrix in Table V. It is only 21.78%. According to Fig. 4, an n-o-f of 13 is the most suitable for GMM in this task.

In order to improve the 120% recognition, we try to find another way to treat this class. The solution and obtained results will be discussed in the next section.

B. *Usage of Threshold*

A threshold is used to recognize the 120% class. If the number of frames classified as a 120% one is greater than the threshold, the whole 1-s segment will be recognized as 120% (see Algorithm 1). Missed detection (MD) and false alarm (FA) are employed to find an appropriate threshold. The dependences of these ratios on threshold are plotted in Fig. 5.

Theoretically, the chosen threshold is the one at which MD and FA are both small. Fig. 5 shows that it should be 26. But when we test some other values, it is found that 26 is not the best. Confusion matrices of some other thresholds in Fig. 6 demonstrate that firstly these matrices are better than the one on the left of Fig. 4, and secondly, the competition is among 20, 21 and 22. The sum of the diagonal elements (trace) of the 21 matrix is 626, while that of the 20 and 22 matrices is 624. Finally, 21 is selected as the threshold for the 120% class. This value corresponds to two peaks of two curves in Fig. 6. It is also noted from the left curve in Fig. 6 that if the threshold is greater than 31, the trace becomes a constant. The 21 matrix in Fig. 6 results in an accuracy rate of 94.85%.

ALGORITHM 1: 1-s Recognition using Threshold

```
if number of 120%-frames is greater than threshold
        the 1-s segment is of 120% class
else
        apply "the winner takes it all" tactic
end
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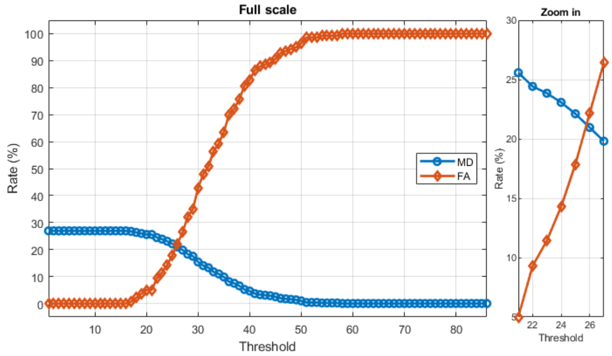

Figure 5. MD and FA plots for 120% class.

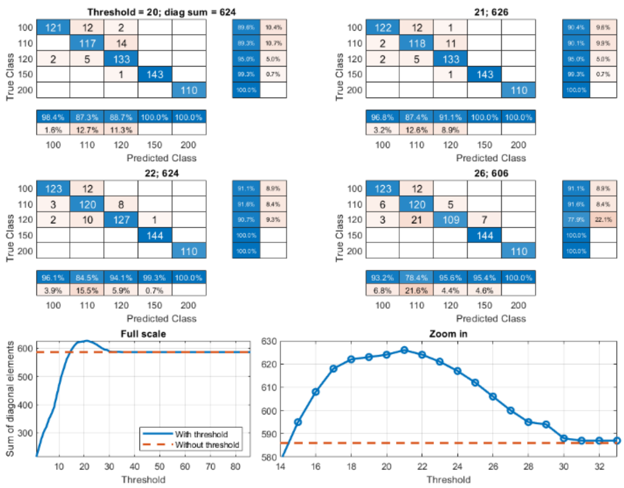

Figure 6. Performance with different thresholds for 120% class.

VI. The Selected Recognizer

Finally, we choose F0, MFCC, BER, and the usage of PCA for our application. It is difficult to compare the accuracy of our approach to the other ones, because we cannot find any published reports of accuracy of induction motor overload sound classification so far. In order to classify overloads, the system in Fig. 1 is set up. Sounds of the induction motor are collected by a microphone. For each sound signal, a Hanning window is applied to frames of 1024 samples, the overlap is 512 samples, then F0, MFCC, and BER are computed from each frame and fed to PCA to obtain a set of 13 new features. They are then fed to a GMM. One second of sound takes our algorithm (installed in a laptop with Intel Core i5 and 8GB of RAM) about 0.15 seconds to process. The output of this system will tell that the recorded signal came from one of five levels of overload. Because the 100% overload is the most dangerous level, the 100% recognition accuracy rate for this level is very considerable. By detecting and classifying overload condition, this system can come to the root of some problems, such as tooth breakage, wear in roller bearings and gears, excessive temperatures, or even burning of motors.

VII. Conclusion

This paper presents a method for classifying sounds of induction motor overload using audio signals and Gaussian mixture model. Audio signals are recorded by a microphone placed near an induction motor to monitor its overload. A feature set (including F0, MFCC, and BER) and six classification models are evaluated. Experiments prove that GMM fits our approach. Our proposed system can be an online monitoring method because it does not need to stop the motor. This system requires a microphone, so it is inexpensive. It is also flexible, meaning that if we can collect sounds of other faults, we can upgrade it by retraining it. Filtering techniques should be applied if this method is moved to industrial environment to reduce noises. Future developments can be related to other faults, such as eccentricity, bearing, rotor bars, etc.

Conflict of Interest

The author declares no conflict of interest.

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