Automatic fault detection in electric motors from real industries using vibration signals with Risk Area Support Vector Machine - RASVM

1st Amaury B Andre
Computation Institute
Unicamp
Campinas, Brazil
amaury.andre@gmail.com

2nd Jacques Wainer
Computation Institute
Unicamp
Campinas, Brazil
wainer@ic.unicamp.br

3rd Eduardo Beltrame
P&D
SEMEQ
Limeira, Brazil
eduardo@semeq.com.br

***Abstract*—Diagnosing electric motors from real industry applications using only vibration measurements is still a challenge nowadays. In this work, we propose a high sensitive data acquisition, powerful signal processing techniques, and feature extraction specific to electric motors vibration analysis. That makes it possible for a good pattern recognition algorithm to accomplish its goal of automatic segregation of defective motors to normal ones. In this work, the Risk Area SVM, an extension to Support Vector Machine algorithms is used, and compared to other cost-sensitive algorithms. The proposed approach can reliably classify normal electric motors, with zero false negative rates, having accurate results. Also, the performance of the new procedure is robust to the variation of load and speed values and shows good generalization capability for various rotating machinery assemblies.**

I. Introduction

Rotating machinery play an important role in industry, driving all kinds of processes in many industry segments such as: chemical, foundry, food, power generation, stamping, etc. The most common driving component present in rotating machines are electric motors, and being able to early detect faults in these components can not only improve their reliability, but also avoid catastrophic damage, big economic losses and even great environmental disasters. In this way, vibration analysis is undoubtedly the most effective technique to detect mechanical defects in rotating machinery [10], [13]. However, automatic diagnosis is still a challenging task in practical applications.

Automatic fault diagnosis on electric motors involves pattern recognition through a classification problem from features extracted out of vibration measurements [12]. In literature, many artificial intelligent methods have been applied to this goal, such as: experts systems [3], neural networks [5] and support vector machines [11]. But in practice, these conventional techniques suffer from the fact that only a very small number of real samples have fault patterns, resulting in very imbalanced datasets. Conventional classification methods are shown to have very satisfactory performance to controlled experiments only, where datasets can be more balanced in normal and defective samples, and where important parameters are well known, such as: rotation speed, system load, and intrinsic characteristics of all assembly components. When it comes to practical applications, in real industry monitoring, not all of these information are available for the automatic diagnostic tool.

In practical applications, vibration measurements in electric motors are often contaminated by noise, masked by other components vibration, and in different rotation speeds, depending on the moment where vibration signals are acquired. Developing an automatic diagnosis method, requires delicate data acquisition, enhanced signal processing, and good generic feature extraction. These are necessary prerequisites for a good pattern recognition algorithm perform well in real applications.

Another important characteristic on electric motor fault diagnosis, since it is a binary classification problem, is that false positives and false negatives doesn't have the same cost for real applications. False determining that an electric motor is defective, will incur in a scheduled stop in the industry process, to unnecessary maintenance, which is bad. But, the opposite scenario, diagnosing a faulty electric motor as normal, will lead to an unexpected failure, and possibly terrible consequences will occur. Cost sensitive techniques should be used in those cases. In this work, an extension to traditional SVM algorithm, the Risk Area SVM [1], [8] is employed. RASVM is able to keep false negative rates low, which is the main objective in practical applications, and also keep a satisfactory accuracy in classification.

The aim of this work is to propose an method for automatic fault detection in electric motors, comprehending: data acquisition (section II-A), signal processing (section II-B), feature extraction (section II-C) and pattern recognition (section II-D), applied to real vibration measurements, provided by a predictive maintenance company: SEMEQ. This enterprise is responsible for monitoring tens of thousands of components per month, including electric motors which are the main focus of this work. It uses many non intrusive techniques, such as: oil analysis, thermography, ultrasound and motor current analysis, but inthis paper, our focus of interest are their vibration datasets. The results of the proposed methodology is presented in section III, followed by a conclusion and future work in section IV.

II. Proposed Methodology

The proposed methodology performs automatic diagnosis on electric motor through a binary classification: segregates which electric motors are in normal condition, to which ones are defective. False negative rate (the number of defective motors classified as if they were normal divided by the total number of motors) must be kept as low as possible, in optimal condition it should be null, while classification accuracy must be maximized.

Vibration measurement data were retrieved from predictive maintenance programs implemented in a set of different industry segments, such as: beverage, food, agribusiness, cement, foundry, chemical, power generation, pharmaceutical, and any other production industry. Even though our component of interest is the electric motor, they can be coupled to pumps, compressors, gearboxes, fans, blowers, drive trains, machine tools and many other types of rotating machinery. Also, electric motors can run at different loads, and in different rotation speeds, due to the presence of speed variators, or because of the line frequency inside the plant. All of these practical challenges demands the proposed methodology to be efficient in data acquisition, signal processing, feature extraction and pattern recognition, which are explained as follows.

A. Data acquisition

In electric motors, vibration measurements are normally recorded in two different places (from coupling and non-coupling sides), in radial directions (horizontal and vertical), and in axial direction from coupling side. They can be seen in figure 1.

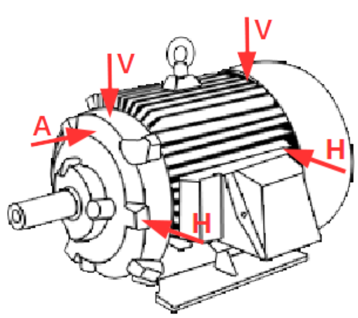

Fig. 1. Vibration measurements position and directions in electric motors. (V: vertical, H: horizontal, A: axial)

A piezoelectric type accelerometer is used, with $100mV/g$ sensitivity, in conjunction to an acquisition system, working in a sampling rate of $48kHz$. This relative high sampling rate is used together to a high sensitivity accelerometer to make it possible to implement sophisticated signal processing techniques, such as the kurtogram based envelope, explained in section II-B.

All measured data are acquired monthly in the predictive maintenance program, and conditions such as system load, sensor placement and rotation speed are stick the same for one electric motor. It is done so in order to produce repeatability in the measured data, so a coherent historical is generated for every machine. Although those parameters can vary from one machine to another, they are kept the same for repetitive measurements in one motor, so the historical of measurements can be compared. This comparison is useful as proposed in feature extraction, at section II-C.

B. Signal processing

There has been a great amount of research over the years using signal processing techniques for emphasizing defect signals from raw vibration measurements [4], [7], [9], [13]. In this work, for every point measured, three parameters are calculated: velocity, acceleration and envelope power spectra.

Velocity is the most common unit to identify various electric motors defects such as: unbalance, misalignment, looseness (machinery structural, foundations, or bearings), blade pass, belt frequencies, and other issues in the machinery frequency range and some multiples of actual speed.

Acceleration data is very important for detection of faults with gear mesh, electric and lubricant issues, in high frequency ranges, while velocity has much more sensitivity with low frequencies.

Envelope analysis is responsible for much more accurate bearing fault detection [9], since it is based on demodulation of high frequency resonance associated with bearing element impacts, inside a higher frequency window. The technique used to identify an appropriate envelope window is Spectral Kurtosis [2], [6].

Besides those parameters, global levels as root mean square rms and peak-to-peak $pkpk$ are also calculated from raw vibration signals. All these values, and the spectra generated in each parameter (velocity, acceleration and envelope) are use to extract features.

C. Feature extraction

From every electric motor, five points are measured. In each point, global levels such as rms and $pkpk$ are taken, together with three different spectra (velocity, acceleration and envelope). Every spectrum has at least one thousand spectral lines. So it is clear that the volume of information gathered for one single electric motor is very large. Considering too a reasonable historical of measurements for the electric motor, it becomes infeasible for any pattern recognition algorithm to deal with all this amount of data. The datasets gathered have thousands of electric motors measured. So it is crucial to use features that correctly resumes the information necessary to detect faults and that permits electric motors to be classified.

The features used in this work are:

1) maximum velocity root mean square level
2) maximum elevation from last measured to actual data in velocity spectra
3) maximum elevation from the reference measure to actual data in velocity spectra
4) maximum acceleration root mean square level

5) maximum elevation from last measured to actual data in acceleration spectra
6) maximum elevation from the reference measure to actual data in acceleration spectra
7) maximum peak to peak value from acceleration measures
8) maximum root mean square level from fundamental frequency in velocity spectra measured from horizontal or vertical directions
9) maximum root mean square level from fundamental frequency in envelope spectra
10) maximum root mean square level from the first harmonic frequency in envelope spectra
11) maximum root mean square level from fundamental frequency in velocity spectra measured from axial direction
12) maximum root mean square from two times the line frequency (100 or $120Hz$) from velocity spectra

The first seven features summarizes global levels values for the electric motor. They can be divided in two categories: maximum absolute values (features 1, 4 and 7), and maximum relative values, which are also divided in: the elevation from the actual measurement to the last measurement in the same component and point from the previous month (features 2 and 5); and the elevation from the actual measurement, to a reference measurement in the same component and point within the motor historical (features 3 and 6). The reference value, is the lowest vibration measure ever acquired on the same component.

To calculate features number 8 through 11, some post-processing are required. Since the electric motors measured can run in different rotation speed, it becomes necessary to identify it from the vibration signal acquired. To detect the fundamental frequency from each motor, that corresponds to the rotation speed, a search is performed by calculating the average and standard deviation on the spectrum, so only frequencies with higher amplitude than the average plus three times the standard deviation are considered. The first peak that satisfy the previous condition, inside a plausible range is considered to be the motor fundamental frequency, and by consequence, its rotation speed (when calculated from velocity spectra). See figure below:

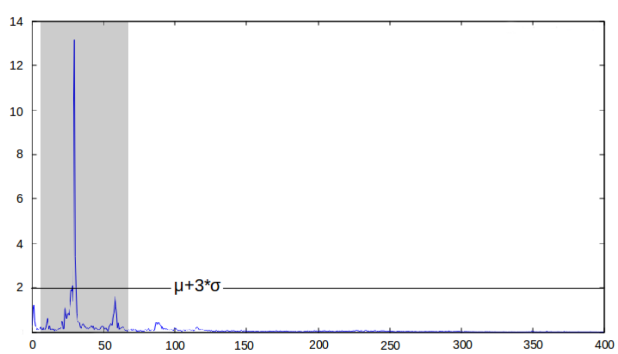

Fig. 2. Fundamental frequency detection.

In figure 2, detected fundamental frequency (f_{1x}) is calculated from: $\mu + 3 * \sigma = 0.12470 + 3 * 0.62687 = 2.0053$. So the first representative peak in spectrum, higher than this value is: $f_{1x} = 30Hz$.

Once the fundamental frequency is estimated, its harmonics can be calculated and found in the spectrum. Maximum fundamental frequencies levels are used as features 8, 9 and 11, while the maximum harmonics level are used in feature 10.

To finish feature extraction, feature 12 is the root mean square of a window of 2 Hz around two times the line frequency of the plant that the electric motor is installed. Since normally line frequencies are 50 or 60 Hz, windows of 100 and 120Hz are calculated and compared. The maximum value between them is used in feature 12. Two times the line frequency present in the spectrum, indicates possibly the presence of an electric defect in the induction motor.

These features cover the defects that can be detected in vibration signatures from electric motors [10], [13]. They are: motor base, unbalance, misalignment, electric, bearings and lubricant failures.

D. Pattern recognition

The problem of detecting incipient defects in electric motors is very imbalanced, since the number of training defective motors are very limited in comparison to normal condition ones. Besides that, a careful accuracy analysis should be made, since false negatives are much worse than false positives. False negatives is a misclassification of a defective motor as a normal condition one. When a false negative occurs, all the benefits of predictive maintenance are lost, but not only that, it can lead to catastrophic failures and result in huge economic losses. The opposite, classify a normal condition induction motor as a defective one, will lead to an unnecessary intervention, what is way less critical than an unexpected failure. Because of that, it is clear that cost sensitive algorithms should be used in this application.

Support Vector Machine (SVM) is a powerful algorithm for binary classification, due to its ability to perform well with imbalanced and high dimensional data. However, in order to reduce false negative rates to null, an extension of the traditional SVM classifier is used: the Risk Area SVM (RASVM) [8]. This algorithm is able to control false negatives through the presupposition that most misclassifications in an SVM classifier are close to the decision boundary [8]. A region close to the SVM's decision boundary is selected, and inside that region, the decision to classify a sample as negative (normal) is based on inspecting if its k nearest neighbors (k-NN) are also negative. This can be seen in figure 3.

In figure 3 the hyperplane which is the decision boundary for a binary classification is represented by the continuous line. Support vectors and the margin of separation are represented in the dotted lines. Training sets are represented as plus and minus signals, while testing samples as numbered empty squares. In figure 3, both testing samples are inside the risk area. Following RASVM principle, for $k = 2$, both testing samples will be classified as positive, independently of their

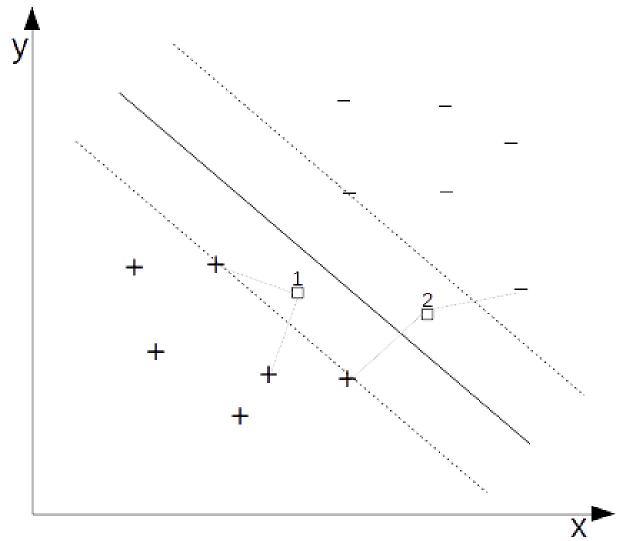

Fig. 3. caption

position relative to the decision boundary. Testing sample number one has all of its two nearest neighbors classified as positives, while testing sample number two did not achieved consensus of their neighbors, so it should be classified as positive too.

In RASVM, some parameters must be tuned in order to maximize the algorithm accuracy, keeping false negative rate null. Since a RBF kernel is used, necessary parameters are: C, misclassification of training examples against simplicity of the decision surface; γ, influence of a single training example. Specific to RASVM, there are these parameters: cp (cost proportion), difference of costs between false positives and false negatives; β, width of the risk area above and below the shifted hyperplane (see figure 4); δ, offset of the risk area with respect to the original SVMs hyperplane (see figure 5).

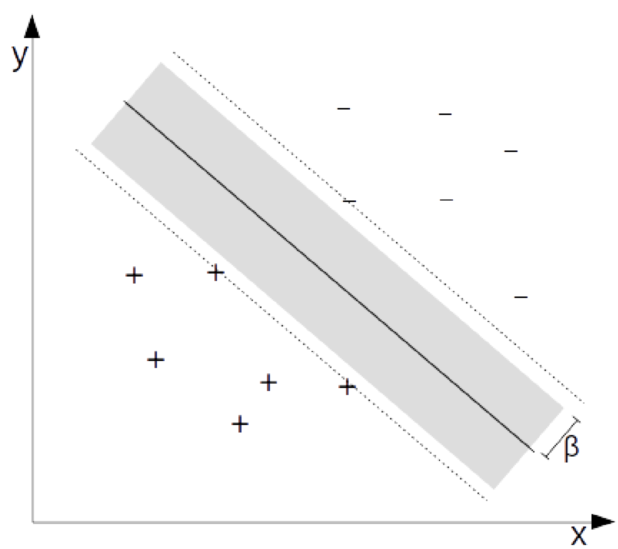

Fig. 4. RASVM parameters

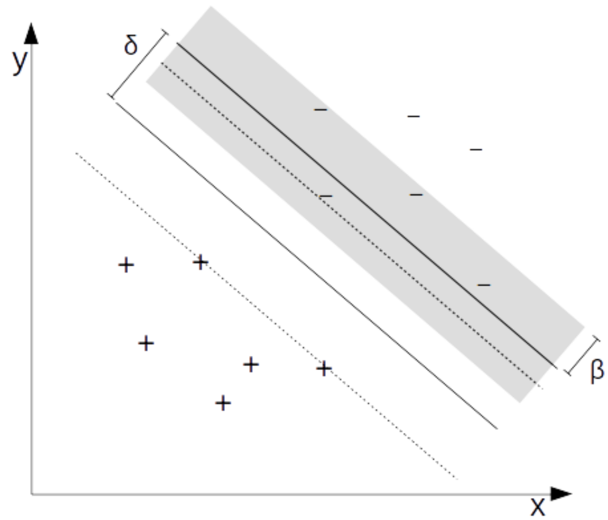

Fig. 5. RASVM parameters

III. Results and Discussion

A total of six datasets were obtained from both healthy and defective motors. Since all measured data were retrieved from predictive maintenance programs, each dataset consist of measurements from one month of monitoring, from many different industries and many different components assemblies. Each dataset consists on the following data:

- dataset 1 - 10833 instances: 10162 healthy and 671 defective motors.
- dataset 2 - 12916 instances: 12074 healthy and 842 defective motors.
- dataset 3 - 12383 instances: 11693 healthy and 690 defective motors.
- dataset 4 - 17449 instances: 16695 healthy and 754 defective motors.
- dataset 5 - 18293 instances: 17442 healthy and 841 defective motors.
- dataset 6 - 18127 instances: 17312 healthy and 815 defective motors.

In each dataset, the defective electric motor have, in average, the failures presented in table I (shown in percentage of total defective motors).

Defect	%
Motor Base	54.0
Unbalanced	19.9
Lubrication	10.3
Groove wear	7.3
Rotating Looseness	4.8
Misalignment	1.4
Inner race (Bearings)	0.6
Outer race (Bearings)	0.6
Structural Looseness	0.5
Bearing Looseness	0.4
Belt tension	0.1
Overload	0.1

TABLE I
PERCENTAGE OF FAILURES TYPES PRESENTED IN VIBRATIONS DATASETS.

The goal of the proposed approach is to perform a binary classification, with the best accuracy subjected to the constraint of no false negatives. To compare results, classification accuracy is judged with three classifiers: cost sensitive SVM, cost sensitive Random Forest and RASVM. Results are presented in table II.

	CS-SVM		CS-RF		RASVM	
	FN	Acc	FN	Acc	FN	Acc
dataset-1	0	52%	0	60%	0	56%
dataset-2	0	51%	0	56%	0	55%
dataset-3	0	60%	0	54%	0	64%
dataset-4	0	60%	1	50%	0	65%
dataset-5	0	59%	0	51%	0	63%
dataset-6	0	56%	0	55%	0	61%
average	0	56.3%	0.2	54.3%	0	60.7%

TABLE II
FALSE NEGATIVES NUMBER AND ACCURACY FOR EACH PATTERN RECOGNITION ALGORITHM USED.

For each one of these algorithms, necessary parameters were selected using a grid search. This search was performed to achieve the maximum accuracy rate, under the constraint of zero false negative rate. The search was also limited to discard parameters tuning that could lead to classifying all samples as defective, which is the trivial solution to the problem of keeping zero false negative rate. In this way, values for selected parameters in each algorithm, for the presented results are:

- **CS-SVM**: $C = 0.014$, $\gamma = 0.007$, cost proportion $= 1 : 500$
- **CS-RF**: trees number $= 10$
- **RASVM**: $\delta = 0.9$, $\beta = 0.7$, cost proportion $= 1 : 500$, $k = 300$

Note that, for all datasets, both CS-SVM and RASVM were able to achieve zero false negative rates, while CS-Random Forest had one false negative for dataset-4, after the exclusion of the trivial solution. And, in average, RASVM outperformed the other algorithms, with an accuracy higher than 60%.

Since false negatives does not occur, all negative results in classification are guaranteed to be normal electric motors. So, in practical terms, normal electric motors are in fact segregated from defective ones, and segregation rate (SR) can be calculated as follows:

$$SR = \frac{true\_negatives}{total\_samples} \tag{1}$$

The results of segregation rate for RASVM in all six datasets are presented in table III.

	RASVM - SR
dataset-1	50%
dataset-2	49%
dataset-3	59%
dataset-4	61%
dataset-5	58%
dataset-6	57%

TABLE III
SEGREGATION RATES FOR RASVM.

Since all negative results are true negatives they can be automatically classified as normal. From the results in table III, the average segregation rate can be calculated, and it is 55.7%. It represents an automatic classification of 50100 electric motors from all the 90000 electric motor in the datasets tested. In average, it represents more than 8350 electric motor automatically classified per dataset.

IV. CONCLUSIONS

In this work, the proposed methodology for automatic classification of defective electric motor showed to be very effective for practical and real data situations. Using data acquisition, signal processing and the feature extraction proposed, together with the RASVM algorithm, it was able to achieve the goal of zero false negative rate. Accuracy and segregation rates were reasonable for real world practical applications. It represents automatically classification of more than a half of all electric motor measured in predictive maintenance programs, which reduces the amount of data needed to be further analysed by vibration expert analysts.

Since datasets tested contained all kind of rotating machinery driven by electric motor, the proposed methodology showed to have good generalization capacity. Specially because no extra information is passed to the methodology, other than vibration measurements. Also, it shows that extracted features are sufficient to detect failures described in table I.

In comparison to other cost sensitive algorithms, RASVM presented the best accuracy and consequently the best segregation rate for this application.

V. ACKNOWLEDGMENTS

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