ELLIPTICAL NOVELTY GROUPING FOR ON-LINE SHORT-TURN DETECTION OF EXCITED RUNNING ROTORS

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Abstract - A technique for the detection of shorted turns in the field-windings of operating synchronous turbine-generators is described. The measuring method used is the twin-signal sensing method, where pulses are injected into each terminal of the rotor. The reflected signals are subtracted to produce a signature signals that contains information about the rotor's state. The signature signals are sampled and accepted or rejected as valid based on an outlier detection criteria. Novelty detection is applied to the accepted signals. The current signature signal is compared to a range of signature signals taken when the rotor was known to be free of shorts. If the current signature signal strays too far from the known healthy signal, the signature signal is 'novel' and the possibility of a short is declared. The method was tested on a running test rotor with voltage excitation. A comparison of methods shows that an elliptical novelty grouping algorithm gives highly accurate results.

Keywords: novelty-detection, shorted-turn-detection, on-line-fault-detection, twin-signal-sensing, outlier-detection, synchronous-machines, condition-based-maintenance.

Introduction

Early detection of shorted turns in the DC-field windings of large synchronous turbine-generators is a very difficult problem. No general solution has been thus far proposed. Shorted turns can cause vibrations in the machine and eventually can lead to hazardous mechanical breakdowns. With periodic maintenance to avoid such catastrophes, significant down time cost is incurred even when no faults are present in the rotor. Condition based maintenance as a result of on-line short-detection will thus be extremely valuable in terms of operating cost reduction.

Several techniques for detecting shorted windings have been suggested in the literature. Some are not applicable for on-line use. Most require placement of probes inside the rotor. A good survey of past methods is presented by Streifel *et al.*[1] who also describes the *twin-signal sensing* technique - a method not suffering from this disadvantage. In twin-signal sensing, two sharp voltage-steps are simultaneously injected into both ends of the device windings. The difference between the reflected waveforms is measured, giving a *signature signal* for the rotor.

A specific test rotor was built to simulate the combined effect of applied voltage and rotation, with quick accessibility to the windings for shorting between adjacent turns. The test rotor is a three foot long iron core, with four wound poles connected in series. The rotor is wound with polymer insulated stranded wires lying in 12 slots, evenly distributed around the circumference of the core, with inner and outer windings alternating in these slots. Rotation is provided by an external motor, and slip-rings connect the rotor windings to the voltage supply and the measuring circuit at one end. At the other end, the windings are accessible for connecting two and two of the wires together to produce shorts.

Twin-Signal Sensing Method

To implement the twin-signal sensing method, a dedicated signaling circuit was built to provide a sharp leading edge signal of alterable voltage levels, synchronous to the AC power source. The circuit is floating on the same voltage as the rotor to protect it from high voltage. A differential amplifier is used for taking the difference of the reflected waveforms.

The twin-signal sensing method has proved to be successful in detecting shorts

- in simple units like autotransformers [1], and
- for localizing shorts in a downed rotor [2].

No excitation was present in these tests so the effect of loading on the signature signals was unknown. Rotation also causes noise from the slip-rings/brush interface. There is also a different impedance sensitivity in the windings for rotating units. The shape of the signature signal can be significantly altered because of this.

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Signal Pre-selection and Outlier Detection

Siganture signals from rotating units can be corrupted by interference from "jumps" at the slip-ring/brush interface. A method of outlier detection is therefore necessary to avoid training the detector on irrelevant waveforms. Outlier detection is used to detect the signatures that differ markedly from a set of previous signatures. A given batch of signature signals is gathered (50 signatures in our case) from which an average and standard deviation are calculated. All signatures landing within three standard deviations from the average are declared as valid and used to train the novelty detector. The signatures in the first average are then re-checked. The resulting average is then used to test the incoming signature's outlier status. The outliers are far from signature signals for both the shorted-turn and no-short cases. Their elimination is therefore straightforward.

Novelty Detection

In *novelty detection*, the status quo signal "fingerprint" of healthy operation is monitored. If the fingerprint samples remain in the a region normally prescribed for healthy operation, there is no reason for alarm. If the fingerprint drifts significantly from status quo, however, something *novel* has occurred. Degradation - in our case the forming of a winding short - is suspected.

Novelty detection is useful in cases where data corresponding to "unhealthy" system conditions is unavailable. Such is the case for detection of shorted windings. Obtaining signature signals for operating rotors with shorted windings is prohibitively expensive.

Novelty detection can be conceptually viewed as a method of grouping all signals of a given training set and comparing future samples with this group. The underlying assumption is that the training set is statistically representative of all status quo operating conditions and that the system from which the samples are obtained is not time variant. View each healthy signal as a point is signal space. A surface is imposed around these points. If a new signal lies within this surface, it is status quo. Otherwise, it is novel.

Surfaces that can be placed around the healthy data include

- a *spherical boundary*,
- an *elliptical boundary*,
- a rectangular boundary formed by the extrema of the data, or *min-max* surface, and
- *nearest neighbor* boundaries.

In the first two methods, incoming signatures are compared to a given prototype signature. The result is declared novel if the signal exceeds a given distance from this prototype. For the spherical boundary, the distance is a standard Euclidean measure and is therefore equivalent to a matched filter. When an elliptical boundary is determined along the data's eigenvectors, the Mahalanobis distance from the prototype is being used. (The Euclidian distance is a special case corresponding to equal eigenvalues.)

For the min-max technique, the smallest possible box containing all of the healthy data is used. The dimensions of the box are determined by the minima and the maxima of the signature signals. This is equivalent to finding upper and lower bounds for all of the healthy data. These two signals uniquely define the box by its vertices. After the box is defined, each linear dimension of the box may be proportionally enlarged or compressed depending the desired performance of the min-max novelty detector.

The nearest neighbor novelty detector allows for more general data topology. Here, minimum Euclidean distances are found between each point and its closest neighbor. The distance proportional to the maximum of these distances is then used as a decision parameter. Every incoming point is compared to every point in the healthy training set. If the new point is at a greater distance from each of the healthy points than the decision parameter, it is declared to be novel.

Novelty detection can be couched in the paradigm of hypothesis testing.

H_0 : status quo (no winding shorts)

H_1 : a winding short is present.

The binary hypothesis test considers a given hypothesis H_0 that is to be proved, versus an alternative hypothesis H_1. In our case, H_0 is the hypothesis that the rotor is healthy. H_1 is the alternative hypothesis that the rotor has shorts. In marking a decision, two types of error can occur. The *false alarm probability* is

α = Probability[H_1 is announced given H_0 is true]

= Probability[a short is erroneously announced].

and the *detection probability* is

β = Probability[H_1 is announced given H_1 is true]

= Probability[a short is correctly announced].

For problems where novelty detection is used, the detection probability can not generally be estimated. This is due to the unavailability of shorted winding signatures. In other words, we have no data corresponding to when "H_1 is true". The false alarm probability of the novelty detector, on the other hand, can be straightforwardly evaluated. After the novelty boundary is established using status quo *training* data, additional status quo *test* data is collected. The percentage of times a short is announced from the test data is an estimate of the false alarm rate. The law of large numbers assures convergence as the cardinality of the test set increases.

There is an inherent tradeoff between the false alarm rate, α, and detection rate, β. As one increases monotonically, so does the other. Each of the novelty detectors described has a parameter that allows tuning of this tradeoff. In the spherical and ellipsoidal cases, it is the choice of radius (Mahalanobis distance). As the radius increases, both the detection and false alarm probabilities increase monotonically. For the nearest neighbor detector, the tradeoff is similarly determined by the ball drawn around each training data point. The α and β parameters for the min-max detector are tuned by the choice of padding about the detection box region.

The only way of controlling the performance in novelty detection is to define an acceptable false alarm rate not to be exceeded by the training set (see e.g. [12]). An alternate method for setting the threshold, not considered here, requires the finding of threshold from the allowable false alarm probability from parametrical estimators. This method requires an assumption about the probability distribution of the data.

Other types of novelty detection have been suggested. One, often referred to as the *novelty filter* [3], compares the orthogonal complement of the linear space spanned by the training set to a threshold. In geometrical terms, this method tries to fit a hyperplane to the data. Only the orthogonal distance to the hyperplane is considered. Such an approach is useful only when the healthy data are known to lie in a hyperplane. Other approaches assume that the healthy data lie in clusters. These were also not applied to our problem since the healthy data appeared in one large cluster. One example is use of *radial basis neural networks* [9,11] as a method of a non-parametric estimation of the data's *a priori* distribution have also been applied to novelty detection [4]. A statistical semi-parametric estimation technique defining several hyperellipsoidal clusters is described in [5] and applied, extended, to novelty detection in [6]. This is an extension of the elliptical boundary detection to multiple clusters. A robust statistical method for finding elliptical clusters is defined in [7]. Nonlinear statistical estimation is applied in [8] where a neural network is trained to recognize a mapping of any given probability distribution to an uncorrelated Gaussian distribution. This is done with an information preservation criterion, and a simple spherical boundary detection is then applied. Other methods exist such as ART clustering techniques (see e.g. [11]), which automatically defines new clusters as something new is observed.

Which novelty detection approach works best? The answer depends on the structure of the healthy data. We will show that the elliptical novelty detector gave the best performance on the healthy data collected for our system operating rotor under load. In the test of the performance of the elliptical filter, there was rare availability of shorted winding signatures. This allowed testing for the short detecting capability of the novelty detectors.

Short Detection of Excited Running Rotor

The 4 pole rotor used for this test was constructed in the CIA Lab at the University of Washington to simulate the effect of rotation and voltage load in larger rotors. Even though the luxury of shorted winding data will not be available for operational rotors in the field, the prototype rotor was constructed to allow collection of such data. A set of signatures was gathered for the rotor at several operating stages. Three operating speeds were examined separately.

1. stopped rotor,
2. turning-gear speed, and
3. rotor running at a full speed.

The stopped rotor situation is similar to off-line testing except that the signature signal is obtained through the brushes (see e.g. [2]). The rotor is in turning-gear when it is rotating very slowly - in our case at 30-60 rpm. The fast rotating rotor ran at the synchronous speed, 1800 rpm, to simulate a four-pole turbine-generator in full operation.

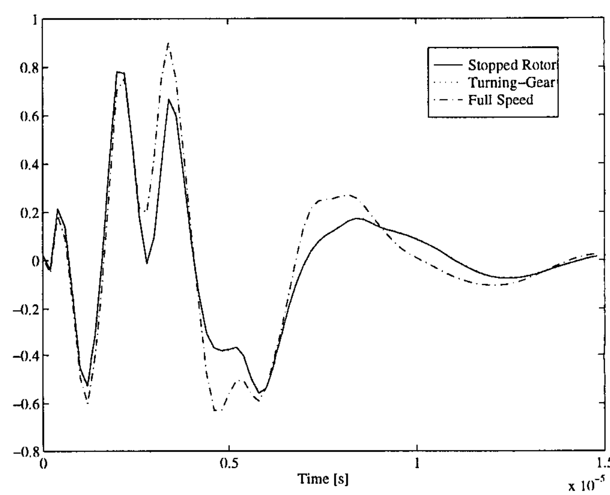

Figure 1: Typical signatures signals for different rotor speeds under no load. The variations were sufficiently different to require separate novelty detectors for each speed.

Three different novelty detectors were constructed corresponding to speed. This approach was motivated by the observation that the signature signal changed significantly for varying speeds (see Figure 1). The full-speed rotation provided by the external machine strongly affects the signature waveform through slip-ring noise and general impedance change in the windings at the higher frequencies. However, the stopped rotor and turning gear signatures seem to coincide. Due to the similarities, combining the stopped rotor and turning gear ratio novelty detectors into a single detector is a possibility in future studies.

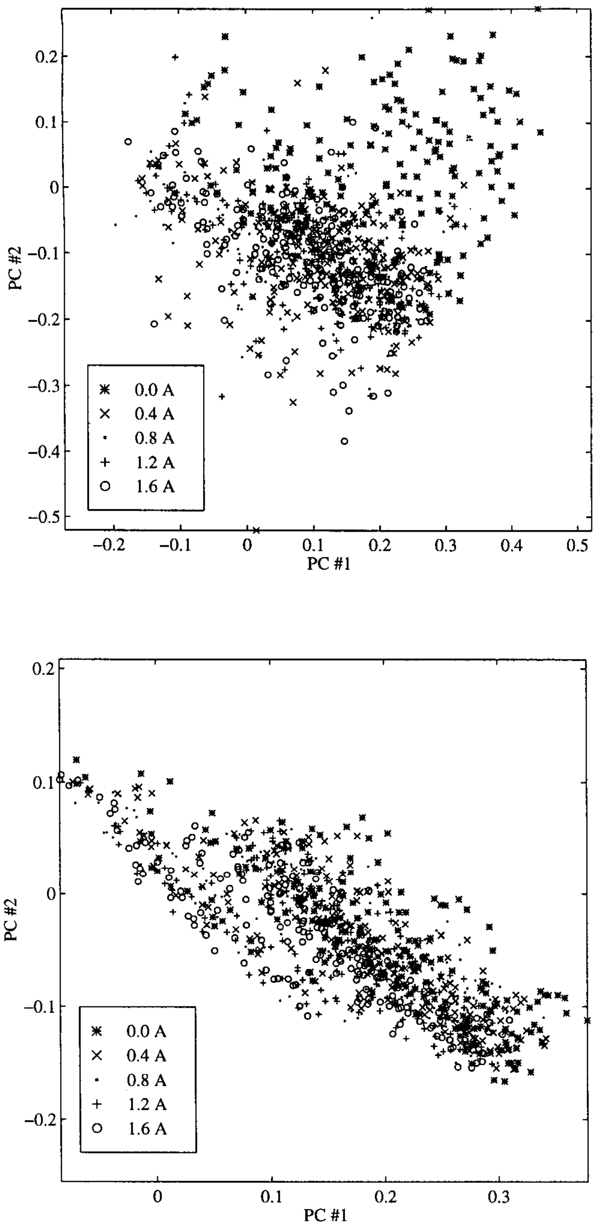

Figure 2: Signature signals of healthy status quo signals obtained from a rotor operating at full speed (top) and stopped (bottom) under different loads. The two dimensional plane for both cases is obtained from the two largest principal components of the data. Although there is minor drift, the data in both cases clusters nearly independent of the load. For a given operating speed, this is the case generally. Thus, the shorted winding novelty detector need not be parameterized by load.

A given novelty detector was expected to perform over a large range of loads. The variation of the signature signals under varying loads at the same speed, as shown in Figure 2, was not as significant.

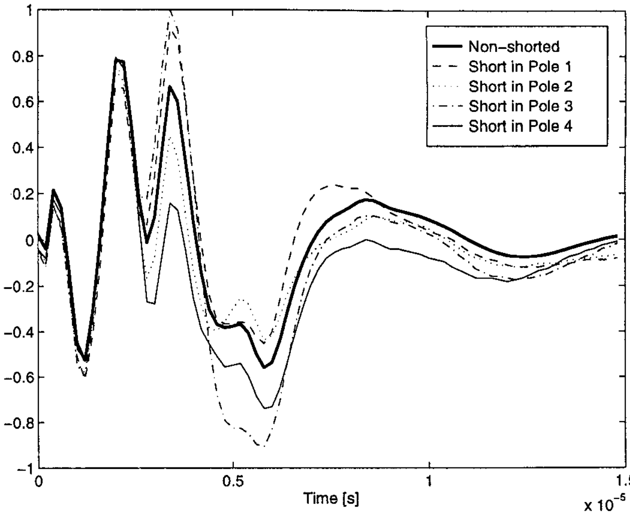

Figure 3: Signature signals for a stopped rotor with shorted turns

Five current levels between 0 and 1.6 A were used in all of the training sets. Every training set consisted of 1000 signatures, taken in sets of 50 each at different times during one day. The novelty detectors designed from this data were tested against five "healthy" test sets, taken over a period of 3 days. Each of these had 200 signatures, so a total of 1000 signatures of healthy data were tested. Shorts were induced around all the poles of the rotor, three for each inner winding and two for each outer. This was also done for all the same operating conditions described above. For each position of shorted turn and voltage level, 10 samples were taken or a total of 1000 signatures for each speed. Figure 3 shows examples of some shorted-turn signatures compared to a typical non-shorted one. The variation is significant enough to be detected.

Table 1: Detection results for voltage-excited running rotor.

	Stopped Rotor		Turning-Gear		Full Speed Rotor	
Detection Method	α %	β %	α %	β %	α %	β %
Spherical	0.0	83.8	0.0	85.3	0.0	65.0
Min-Max	63.6	100	32.9	100	0.8	92.8
Nearest Neighbor	56.2	100	0.0	100	0.1	79.3
Elliptical	0.0	100	0.0	100	0.4	91.0

The feature vector used is the time signature waveform, sampled at 20 MHz and decimated (downsampled) by 4 to reduce computation. Experience showed the decimation did not effect performance. Decimation gives 75 points in the signature. No additional feature extraction method was applied.

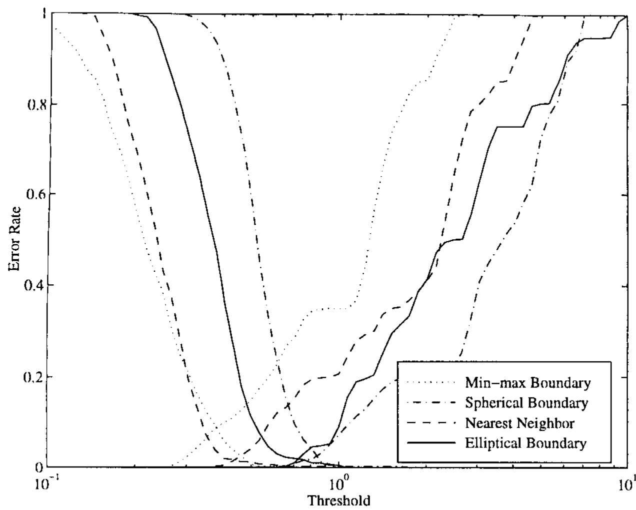

Figure 4: False alarm, α, and *miss rate*, 1–β, for different thresholds. This plot, shown for the rotor at full speed, is typical. The false alarm rate can be read from the curve on the left and the miss rate from the curve on the right. For novelty detection, the miss rate can not, in general, be measured as it is in this case. Thus, although there exists a threshold corresponding to low false alarm and miss rate for each detector, it can not, in general, be set by observing these curves.

Table 1 shows the detection results obtained for the different operating stages. The false alarm rate, α, is averaged over the five acquisition periods while the detection probability, β, is from signatures obtained over a 24 hour period. The best performance came from the elliptical novelty detector. The reason for the significant performance deviation will become obvious shortly.

Figure 4 shows us plots of α (left hand curves) and 1–β (right hand curves) for varying thresholds. All methods give good results for the proper threshold. In practice, however, the miss probability cannot be estimated since data for shorted windings is not available.

Discussion

The difference in performance among these grouping algorithms is considerable. For independent features, the min-max method is equivalent to N=75 two-sided hypothesis tests, where N is the dimensionality of the feature vector. For example, if the probabilities of exceeding each of the thresholds were 0.1% from a given distribution, there would still be 7.2% probability of being outside the "healthy region". The spherical threshold has lower detection rate than the other methods and suffers from being too general. The data, we will show, is spread in more of elliptical cloud. The sphere simply provides too large of a region for the status quo data.

How are different novelty detectors compared when the shorted winding detection rate can not be measured? One approach is to compare the volumes of the various status quo regions for a given false alarm rate. The region with the smallest volume can be interpreted as the most efficient representation of the status quo region. The elliptical boundary detection method confines the training set far better than the other methods, as measured by their volumes (see Table 2).

Table 2: A one-dimensional metric of confined volumes of detection surfaces. This is the N-th root of the volume where N=75 is the number of dimensions in the feature space.

Detection Method	Stopped Rotor	Turning-Gear	Full Speed
Spherical	0.279	0.244	0.372
Min-max	0.086	0.118	0.193
Nearest neighbor	≤ 0.051	≤ 0.105	≤ 0.188
Elliptical	0.042	0.060	0.092

Based on the metric of volume for as fixed false alarm probability, the elliptical boundary is much more efficient than the others. The reason becomes clear as higher order components are examined. Figure 5 shows a two dimensional slice of the data on the plane defined by the first two principal components[1] of the healthy training data. The healthy data, shown by small hollow circles, is tightly packed. Data from shorted windings is shown by ex's. The shorted winding data clusters in accordance to the location of the shorted winding on the rotor. Note, in Figure 5, the numerous small balls drawn around the status quo training data. These balls form the nearest neighbor novelty detection. The larger circle in Figure 5 corresponds to the spherical novelty detector. The ellipse from the elliptical novelty detector is so large in this plane that it is visible only in the corners of the figure box. The min-max novelty detector - not shown - is the smallest box that contains all of the healthy training data. In this figure, it appears that the elliptical novelty detector erroneously classifies some of the shorted winding data. This need not be true, however, for other dimensional slices of the ellipse.

The reason for the superior performance of the elliptical novelty detector is made evident in Figure 6. Here, data from the same problem is shown on the two dimensional plane defined by the 30th and 31st largest eigenvalues of the healthy test data. On this plane, the spherical novelty detector is so large that it shows only in the corners of the figure. The data in this planar slice is extremely compact. The nearest neighbor

[1] The N signature signals, $\{s_n | 1 \leq n \leq N\}$, are lined into N column vectors to form the matrix $\mathbf{S} = [\ s_1\ s_2\ s_3\ \ldots s_N]$. The eigenvalues and eigenvectors of the correlation matrix $\mathbf{S}^T\mathbf{S}$ are evaluated. The eigenvectors corresponding to the larger eigenvalues are the data's *principal components*.

balls are nearly aligned. The elliptical novelty detector boundary in this plane, almost circular, lies in the interior of the nearest neighbor balls. Shorted winding signatures, falsely classified by the nearest neighbors balls, are successfully categorized by the elliptical novelty detector.

Figures 5 and 6 reveal why the elliptical novelty detector surpasses the circular and nearest neighbor novelty detectors - it scales sizes in different dimensional slices. The spherical and nearest neighbor classifiers consist of balls. Balls have the same extent in all dimensions and are therefore unable to adapt in planes where the data becomes compact.

Lastly we note, as might be expected, that signature signals from a winding short in a given location tend to cluster. This is illustrated in Figure 7. On the top is shown the shorted winding data for the full speed operating rotor on the principal component plane. The separation for this case is even more dramatic when viewed on the plane specified by the tenth and eleventh largest eigenvalues. This is shown in the middle of Figure 7. As is shown on the bottom, the shorted winding data also clusters according to the short location when the rotor is stopped. We again emphasize that, in most novelty detection applications, shorted winding data will not be available.

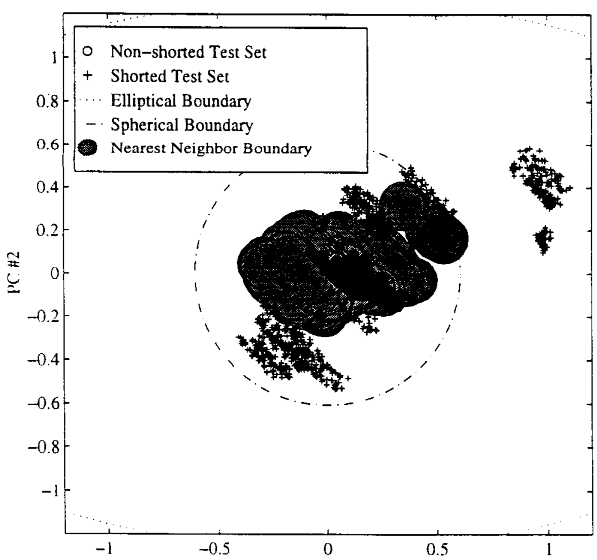

Figure 5: Stopped rotor data and boundaries projected onto the two principal components of the healthy training data.

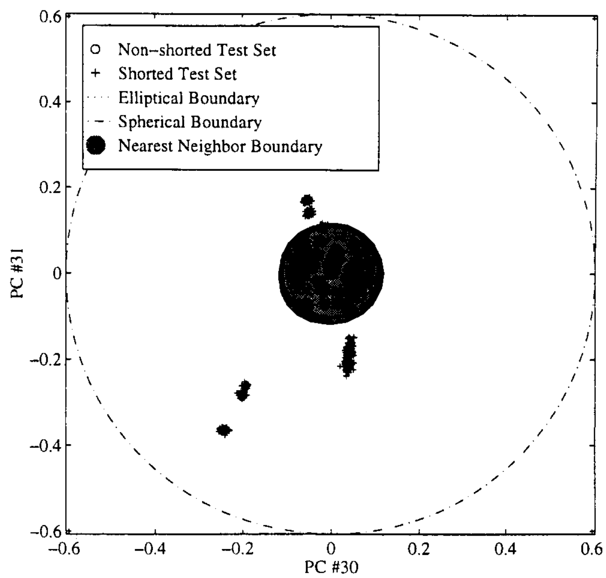

Figure 6: Stopped rotor data and boundaries projected onto higher order principal components. In this plane, the elliptical novelty detector is clearly the most discriminating.

Conclusions

On-line short detection in the field windings of operational asynchronous turbine generators will significantly improve maintainability. Twin-signal sensing for monitoring has the advantages of being simple, on-line and efficient. This paper shows twin signal sensing can result in superb detection performance. The novelty detector providing the lowest false alarm rate for the unit we considered is the elliptical grouping algorithm. It also generates the lowest volume in novelty detection space of those techniques considered. The result is less than 0.4% false alarm rate and at least 91% detection rate for a fully operational test-rotor.

In practice, healthy status quo test signal data should be taken and analyzed. The manner in which the data is distributed in signal space will suggest the best novelty detector for that specific case.

Acknowledgments

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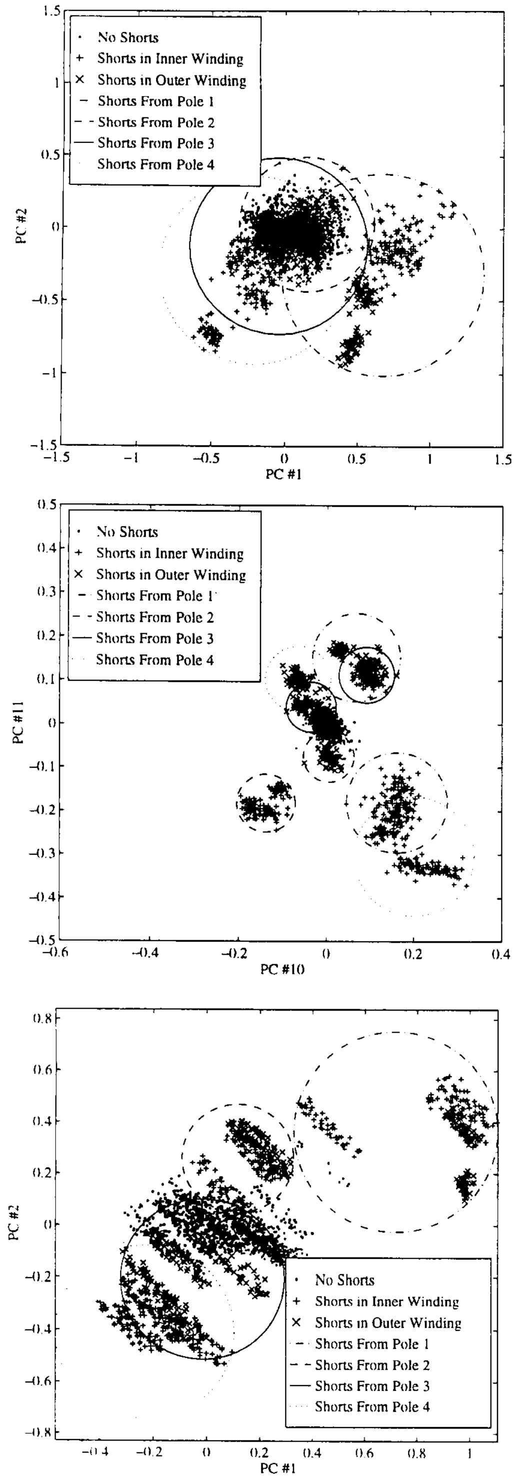

Figure 7. Signature signals from shorted windings tend to cluster in accordance to the location of the shorted winding. On top is the case is the principal component plane when the rotor is operating at full speed. More dramatic clustering on another two dimensional slice is shown in the middle figure. Similar clustering is shown on the bottom for the case of a stopped rotor.

References

[1] Robert J. Streifel, R. J. Marks II, M. A. El-Sharkawi, I. Kerszenbaum, "Detection of Shorted-Turns in the Field Winding of Turbine-Generator Rotors Using Novelty Detectors – Development and Field Test," *IEEE Trans. on Energy Conversion*, vol.11, no.2, pp.312-317, June 1996.

[2] M.A. El-Sharkawi, R.J. Marks II, S. Oh, S.J. Huang, I. Kerszenbaum, A. Rodriguez, "Location of Winding Shorts Using Fuzzified Neural Networks," *IEEE Trans. on Energy Conversion*, vol.10, no.1, pp.140-6, March 1995.

[3] T. Kohonen, *Self-Organization and Associative Memory, 2nd Ed.* Berlin Heidelberg: Springer-Verlag, 1988.

[4] J.A. Leonard, M.A.Kramer, "Diagnosing Dynamic Faults Using Modular Neural Nets," *IEEE Expert*, vol.8, no.2, pp.44-53, April 1993.

[5] Hans G.C. Tråvèn, "A Neural Network Approach to Statistical Pattern Classification by "Semiparametric" Estimation of Probability Density Fuctions," *IEEE Trans. on Neural Networks*, vol.2, no.3, pp.366-377, May 1991.

[6] S. Roberts, L. Tassarenko, "A Probabilistic Resource Allocating Network for Novelty Detection," *Neural Computation*, vol.6, no.2, pp.271-284, March 1994.

[7] J-M. Jolion, P. Meer, S. Bataouche, "Robust Clustering with Applications in Computer Vision," *IEEE Trans. on PAMI*, vol.13, no.8, pp.791-801, August 1991.

[8] L. Parra, G. Deco, S. Miesbach, "Statistical Independence and Novelty Detection with Information Preserving Nonlinear Maps," *Neural Computation*, vol.8, no.2, pp.260-9, Feb. 1996.

[9] Donald F. Specht, "Probabilistic Neural Networks," *Neural Networks*, vol.3, no.1, pp.109-119, 1990.

[10] Athanasios Papoulis, *Probability, Random Variables, and Stochastic Processes, Third Ed.* USA: McGraw-Hill Inc., 1991.

[11] Simon Haykin, *Neural Networks, A Comprehensive Foundation*. USA: Macmillan Publishing Company, 1994.

[12] Louis L. Scharf, *Statistical Signal Processing. Detection, Estimation, and Time Series Analysis*. USA: Addison-Wesley, 1991.