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Acoustic Emission Signal Classification in Condition Monitoring Using the Kolmogorov-Smirnov Statistic

L. D. Hall, D. Mba and R.H. Bannister
School of Mechanical Engineering, Cranfield University, Bedfordshire, UK, MK43 OAL

Abstract

Acoustic emission (AE) measurement at the bearings of rotating machinery has become a useful tool for diagnosing incipient fault conditions. In particular, AE can be used to detect unwanted intermittent or partial rubbing between a rotating central shaft and surrounding stationary components. This is a particular problem encountered in gas turbines used for power generation. For successful fault diagnosis, it is important to adopt AE signal analysis techniques capable of distinguishing between various types of rub mechanisms. It is also useful to develop techniques for inferring information such as the severity of rubbing or the type of seal material making contact on the shaft.

It is proposed that modelling the cumulative distribution function of rub-induced AE signals with respect to appropriate theoretical distributions, and quantifying the goodness of fit with the Kolmogorov-Smirnov (KS) statistic, offer a suitable signal feature for diagnosis. This paper demonstrates the successful use of the KS feature for discriminating different classes of shaft-seal rubbing. A hierarchical cluster algorithm was employed for grouping extracted KS values. AE rub signals were simulated with various metallic seals and measured at the journal bearings of a test rig rotating at approximately 1500 rev/min. Also, the KS classification results were directly compared with more established AE feature vectors.

Introduction

Measurement of high frequency acoustic emissions (AE) has become a viable technique in the condition monitoring of many types of rotating machinery (McFadden and Smith, 1983; Sato, 1990; Holroyd and Randall, 1992; Mba and Bannister, 1999; Choudhury and Tandon, 2000;). Due to its superior sensitivity over conventional low frequency vibration analysis, AE measurements can provide an earlier indication of incipient faults such as fictional rubbing. In addition, time-synchronous measurement from more than one AE transducer often allows the location of rubbing to be estimated.

However, in real operational machinery it is often only practical to take AE measurements from non-rotating members, at or on the bearing housing. Consequently, AE signals originating from the rotating shaft will incur significant perturbation across the transmission path to an AE receiver attached at the bearing housing. This can be related to inhomogenities and scatterers within the structure, reflections at acoustic boundaries, interference and attenuation effects across the bearing interfaces. Moreover, the AE signal will be further coloured by the characteristic frequency response of the AE transducer itself. In light of these factors, interpretation of the AE signals is not trivial and often departs from the classic AE signal model (Mitrakovic and Grabec, 1985; Venkatesan, 1996).

In recent years various signal processing and pattern recognition techniques have been successfully applied to AE signals for diagnosing the severity and location of defects in various types of rotating machinery. Notably artificial neural networks (ANN) (Li, 1989) and clustering (Ono and Huang, 1994) have been adopted for AE signal classification. Regardless of the classification engine employed, it is invariably identification of the key resolving features or descriptors within the AE signal that is paramount for successful classification. Generally, the size of the feature vector chosen depends upon the specific application and recognition requirements. Previous studies (Chan, 1985) employed relatively large feature vectors for the AE signal classification problem. However, for discriminating between different classes of rub signatures, it was considered useful to define a feature vector with a minimum number of parameters (often assessed by a quality index). This can be related to the stability of the classification result in a clustering algorithm and is justified by 'the curse of dimensionality' (Bishop, 1999) within an ANN approach.

Typical features extracted from AE signatures in condition monitoring include peak or total energy, standard deviation, median, AE counts, RMS voltage and duration. However, these are all related to absolute energy levels of the measured waveform or rely upon pre-set amplitude thresholds. As such, the quantities exhibit considerable variability from one bearing measurement to the next and are thus extremely dependent upon factors such as background noise, in addition to AE transducer positioning and coupling. Consequently, it is believed that such features are not ideal for AE waveform classification, especially in cases where several measurement positions are required.

Alternative features more related to the amplitude statistics of the measured AE waveforms and independent of absolute energy levels have also been considered. Notably, the fourth statistical moment known as kurtosis and the ratio of peak to RMS voltage known as crest factor have been applied for condition monitoring in rotating machinery. However, laboratory tests conducted as part of this research have indicated both of these quantities to be unsuitable for classification.

Spectral analysis techniques, such as the FFT have found numerous applications in acoustic signal classification (Chan, 1985; Liangand and Dornfield, 1987). Although some success has been reported in using certain spectral information within specified bands for AE classification, it is not generally believed to provide robust classification results. This is primarily because of the intrinsic broadband nature of measured AE activity and the frequency characteristics of the measurement system. Alternatively, transformations that do not involve a total averaging of time information such as wavelet transforms, spectrograms or the Wigner-Ville distributions could yield more suitable AE signal features.

In contrast, it has been shown that modelling an AE signal as an autoregressive stochastic process, as described by Melton (1982) and later Mba (1999), can provide good AE classification results. However, the use of AR coefficients as signal features approximating the shape of the signal has some disadvantages. Primarily, it is always necessary to determine the number of AR coefficients necessary to adequately represent each AE signal. Although numerous algorithms exist for determining the model order, it should be noted that the classification results could be sensitive to the AR model order. Secondly, it was evident from this study that AE signal classification using AR model coefficients was severely impaired when the measured AE signals was modulated by small levels of background acoustic noise.

In light of this discussion, it is postulated that a robust AE signal feature based upon amplitude statistics and independent of absolute energy levels or pre-defined thresholds, and less effected by pre-signal processing, can be a useful addition to AE signal classification. This paper proposes that the standard Kolmogorov-Smirnov statistic can provide such an AE waveform feature parameter for classifying different types of rubbing in rotating machinery. To demonstrate this, classification results are presented from rub experiments conducted on a journal bearing test rig that rotates at 1500 rev/min (rpm). In addition, classification performance of this technique was tested by modulating the measured AE signals with background noise taken from bearings of an operational 550 MW turbine unit.

Acoustic Emission and Rubbing in Rotating Machinery

The AE approach to condition monitoring in slow-speed rotating machinery is well-established (Choudhury and Tandon, 2000). Reasons for this include the obvious unsuitability of conventional vibration analysis at very low rev/min, the relatively low levels of background noise in such plant and the possibility of direct measurement upon the shaft. In contrast, application of AE to faster rotating machinery (i.e. >1000 rpm) has been less researched. This can be attributed to the proven success of vibration analysis and potentially higher levels of background noise. However, Sato (1990) reported that AE measurement can provide a valuable complementary tool for diagnosing rubbing in fast rotating plant such as turbine generators. For this investigation, signatures were measured at frequency bands greater than 100 kHz, overcoming mechanical background noise whilst increasing the probability of direct rub detection.

Fundamentally, a light frictional rub between the central shaft and surrounding stationary components, such as the seals within a turbine, will cause microscopic perturbation and a transient release of broadband strain energy referred to as stress waves (SW). Although originating from a different mechanical process, this wave motion is in practice extremely similar to the wave energy that propagates from microscopic cracks within solid structures, known as acoustic emissions (AE). Hence rubbing, although strictly a pseudo-AE source, is invariably associated with this term.

A number of reasons can be identified for the onset on light rubbing in a rotating plant. These include thermal effects, foundation movement, component movement, rotor unbalance or misalignment. Regardless of the exact relationship between cause and effect, the existence of rubbing is unwanted as it can often develop into more significant mechanical distress. Two main categories of light rubbing can be identified. Primarily partial rubbing constitutes distinct or intermittent rub events occurring instantaneously within the period of the shaft rotation. Secondly continuous rubbing involves more sustained contact between shaft and surrounding components. Although the mechanisms by which rub phenomena escalate are complex, it is suggested that for machinery of higher rotational speeds, a high concentration of partial rub events can lead to more sustained rubbing, which in turn can induce more serious vibration via mechanisms such as thermal bending of the shaft. Consequently, it is considered in this paper that an AE system capable of diagnosing individual partial rub events might promote the early diagnosis of impending mechanical distress.

Unlike the AE waveforms measured from continuous rubbing, partial rub events induce time-resolved AE waveforms. Propagation of such discrete rub signals departs from the elementary theory of plane wavefronts and they are considered to approximate discrete accumulation of point source transients that can propagate via both the metallic volume and surface. The latter of these modes is considered to be predominant in propagation along the shaft and is known as Rayleigh surface waves. This elliptical wave motion is slower than both longitudinal and transverse modes and penetrates to only a few wavelengths (Pollard, 1977).

To detect rubbing using AE, it is generally advantageous to minimise both the physical distance and number of interfaces between the location of rubbing and the AE receiver. This is because significant acoustic attenuation will occur, especially at higher frequencies (>100 kHz), due to frequency-dependent absorption, geometric spreading losses and reflection at interfaces. In some slow rotating cases, it is possible to place transducers directly on the rotating shaft, (Mba and Bannister, 1999). However in many types of operational rotating machinery, such as in turbine-generators, it is only practical to make measurements remotely at the bearing housing. In such cases, AE signals produced by rubbing on the shaft will incur considerable attenuation as the signatures propagate along the shaft surface to the bearing, across an oil film and into the bearing housing. This attenuation issue is considered to be the limiting factor for AE in many examples of large-scale machinery.

Both commercially available resonant and wideband piezoelectric ceramic transducers are primarily used to measure the AE response from mechanical rub events on account of their sensitivity. Although resonant devices possess some advantages in terms of sensitivity and cost, it is considered that broadband ceramic devices are generally more suited to partial rub signal classification and are used in this paper. The primary reason for this is the superior fidelity achieved by broadband transducers allowing the motion of the impinging acoustic wave to be reproduced as a voltage signal more accurately and less influenced by the transducer response. Finally, AE techniques have significantly benefited from the exponential improvement in signal acquisition and computing power.

Fig. 1 A shaft-seal rub induced AE signal measured at the journal bearing of a test rig.

3. Theory

Figure 1 shows an example AE signal measured at the bearing housing of the test rig whilst rotating at ~1500 rpm. This signature was a result of simulating a partial rub on the shaft with a steel seal fixture. Clearly, the AE burst shows some resemblance to the shape of a classic AE waveform produced by crack propagation or a Hsu-Nielson source, although it is not possible to identify individual extensional and flexural wave modes as can be often obtained by the Modal AE approach in thin plates. A notable feature of this rub waveform is the initial onset of acoustic energy through the succession of initial high energy peaks prior to the exponential decay. Therefore, it might be inferred that useful signal features might include kurtosis or crest factor as they describe the extreme values in the amplitude distribution. However, investigation of numerous rub signatures has shown considerable inconsistency in these parameters under stable experimental conditions. Consequently, they are not considered suitable parameters for classifying rubbing.

Alternatively, it is conceived that the Kolmogorov-Smirnov (KS) test statistic (Press et. al., 1993) might provide a more appropriate feature vector for classifying AE rub signals. In essence, this standard goodness-of-fit test quantifies the difference between the amplitude statistics of the measured AE signal and a specified theoretical distribution function model. It can be defined in equation (1) as the maximum absolute difference (D) between the empirical cumulative distribution function $S_{N2}(x)$ and a hypothesised theoretical distribution function $S_{N1}(x)$.

$$D = \max_{-\infty < x < \infty} \left| S_{N1}(x) - S_{N2}(x) \right| \tag{1}$$

As $S_{N1}(x)$ and $S_{N2}(x)$ are non-decreasing and $S_{N2}(x)$ is considered to be constant between the defined values of amplitude x, as illustrated in Fig. 2, the maximum deviation between the two curves will occur at one of the defined observation points $x_1,x_2,x_3 \ldots x_n$. It should also be noted that the distribution of D, in the null hypothesis, can be calculated to give the significance of any observed non-zero value of D. Moreover the statistic is invariant under reparametrisation of x. For example, the same significance exists under x as for log (x).

Fig. 2 D is the greatest distance between an empirical distribution $S_{n2}(x)$ and the theoretical distribution model $S_{n1}(x)$.

Fig. 3 A schematic for the AE classification algorithm.

The basic algorithm devised for this paper is summarized in Fig. 3 and was implemented using MATLAB V5 and incorporated functions from the Statistics Toolbox. Primarily, each digital AE signal was decimated by a factor of 5 to reduce the KS computation time. However, it should be noted that this decimation in AE information was not expected to degrade classification results because of the high initial sampling rate used in the analogue-to-digital convertor (ADC) (4 MHz). Following this stage, theoretical Gaussian distribution models for each of the AE signals were derived, assuming the null hypothesis that each signal belongs to this candidate family of distributions. These theoretical cumulative distribution function (CDF) curves were derived directly by the method of moments as opposed to a maximum likelihood approach. That is to say, the mean μ and variance σ^2 of each input signal was determined and the model estimate of the CDF evaluated using the two parameter equation for the Gaussian distribution family given in equation (2).

$$f(x \mid \mu,\sigma) = \frac{1}{\sqrt{2\pi}\sigma}\int_{-\infty}^{x} e^{\frac{-(t-\mu)^2}{2\sigma^2}}\,dt \qquad (2)$$

In addition to the Gaussian fit, each AE signal was modelled using theoretical Rayleigh and exponential distributions (D'Augostino and Stevens, 1986). as defined in equations (3) and (4), respectively. Therefore, it was possible to evaluate three D values for each of the AE signals, which in effect constituted three independent measures of amplitude statistics for an AE signal as illustrated in Fig. 4. These values provided the feature vector input used for classification.

$$f(x \mid b) = \int_{0}^{x} \frac{t}{b^2} e^{\left(\frac{-t^2}{2b^2}\right)}\,dt \qquad (3)$$

where f(x|b) is Rayleigh CDF with parameter b derived from the mean or variance.

$$mean = \frac{4-\pi}{2}b^2 \quad or\ variance = b\left(\frac{\pi}{2}\right)^{\frac{1}{2}}$$

$$f(x \mid \mu) = \int_{0}^{x} \frac{1}{\mu} e^{-\frac{t}{\mu}}\,dt \equiv 1 - e^{-\frac{x}{\mu}} \qquad (4)$$

where f(x|μ) is the exponential CDF with parameter equal to the standard deviation (μ).

Fig. 4 Modelling the CDF of an AE signal with respect to three distribution families.

As shown in Fig. 3, rub signal classification involved hierarchical clustering (Chan, 1985; Murthy, 1987; Bently, 1988; Anastassopoulos and Philippidis, 1995), although it is believed that other approaches could equally demonstrate the use of the KS descriptor. Clustering describes 'the action of partitioning a set of objects into natural groups so that the profile of the objects in the same cluster are very similar and the profiles of objects in different clusters are quite distinct ‘. It is proposed that AE signatures from the same rub category (e.g. partial steel rubbing, partial brass rubbing, etc…) could be clustered in well-defined groups. This involves sequential stages of:

I Similarity, in which the Euclidean distance between every pair of KS signal vector was determined within the similarity matrix and

II Binary Linkage; in which a series of binary clusters of increasing size are made using the information in the similarity matrix, starting with the closest two signal objects, until all the objects are linked together in a hierarchical tree.

This is represented graphically within this paper using an agglomerative dendrogram plot, in which individual signals are labelled on the x-axis whilst the distance between the centroids of clusters are shown on the y-axis. The classification procedure described was used to assess whether KS features associated with AE signatures was sufficiently robust to cluster known rub classes into the correct natural groups. It should be noted that hierarchical clustering can be susceptible to undesirable early combinations involving class outliers and this can lead to spurious results.

1. Experimental

Figure 5 A schematic of the AE measurement system

The AE signal measurement system employed for this study is shown schematically in Fig. 5. The broadband piezoelectric transducer was a commercially built WD device from PAC© with a measurement bandwidth of 100 kHz-1 MHz. This ceramic sensing element was differentially connected to a 40 dB gain pre-amplifier, in order to effect an immediate improvement in the measured signal level and to reduce electromagnetic noise through common mode rejection. Moreover the separate pre-amplifier incorporated a plug-in analogue high-pass filter to suppress low frequency acoustic noise components and exhibited better temperature performance than could be achieved using an integral pre-amplifier. The signal output from the pre-amplifier was connected (i.e. via BNC/coaxial cable) directly to a commercial data acquisition card that occupies one of the ISA slots within a Pentium host PC. This AEDSP card also from PAC provided up to an 8 MHz sampling rate and incorporates 16-bit precision ADCs giving a dynamic range of more than 85 dB. Moreover, an extended local memory allowed the sequential recording of signals containing up to 256,000 samples. This corresponded to the continuous measurement over more than 0.06 s at a sampling rate of 4 MHz. Prior to the ADC, the card employs anti-aliasing filters that can be controlled (i.e. the band-pass altered) directly in software.

Figure 6 (a) depicts the rotating test rig. As shown, the shaft is supported by two journal bearings. A wave-guide made contact with the inner bearing housing and the receiving AE transducer was attached to the other end, ensuring a direct transmission path. Throughout the experimentation high temperature acoustic couplant was applied to ensure a good acoustic contact between transducer and the wave-guide and between wave-guide and the bearing housing. The rub simulation mechanism is positioned between the third and forth of five steel discs shrink-fitted on to the central shaft that rotates at up to ~3000 rpm. Figure 6 (b) illustrates how partial rubs are simulated using this device. Essentially, a non-concentric dummy shaft fixture is attached to the rotor so as to rub against a supported seal fixture on every shaft rotation. The seal fixtures employed were initially machined in mild steel or brass. The reaction pressure[1] exerted by the seal upon the incident shaft was set by masses applied to the rub fixture as shown in Fig. 6(b). These masses applied a force of approximately 140 N throughout the measurements.

(a)

(b)

Figure 6 (a) The journal bearing test rig, (b) The rub simulation mechanism.

5 RESULTS AND DISCUSSION

Using the aforementioned system, AE signals were recorded from different types of partial shaft-seal rubbing. Primarily burst signals from the partial rubbing of steel and brass seal fixtures were taken. Secondly, partial rub signals were taken from three steel seal fixtures exhibiting different states of wear. This section presents results pertaining to the use of the KS statistic to classify the defined rub classes by employing hierarchical clustering. By comparing the results to alternative AE feature extraction methods, the potential of the KS statistic is demonstrated.

5.1 Seal Material Classification

Figure 7 Steel and brass seal fixtures

In condition monitoring of rotating machinery, a technique that predicts the types of material rubbing on the shaft is potentially useful. Specifically, it might infer whether rubbing on the shaft is significant and should be acted upon or could provide information pertaining to the location of rubbing. To illustrate the use of the KS statistic in discriminating between rubbing from different materials, partial rub AE signatures were measured from the test rig using the identically shaped brass and steel seal fixtures shown in Fig. 7. In each case, fifteen AE signatures are recorded under the same experimental conditions, i.e., the shaft period and the load applied to the rub simulation mechanism remained constant. Examples of the AE signals produced from steel and brass seal rubbing are shown in figure 8.

(a)

(b)

Figure 8 Examples of the AE signals produced using (a) steel and (b) brass seal fixture

[1] Calculation of the normal reaction pressure applied by the seal upon the rotating shaft is not trivial. It depends upon:- the incident forces of the rotating shaft, the weight distribution of the entire upper section of the rub simulator (the moving components), the contact area of the seal-fixture and the supporting screws and the coefficient of friction between the vertical motion guidance posts and the upper section.

Table 1 lists mean and standard deviation values for extracted AE features for the example steel and brass signals, see Appendix for full table. The KS values were obtained using the Gaussian, Rayleigh and exponential distribution families. Gaussian KS values for each of the signals multiplied by two were also shown and it should be noted that these values are not significantly different to the Gaussian KS values obtained from the original signals. Although many established AE signal features were considered, only the RMS, median, kurtosis and autoregressive (AR) coefficients are represented in Table 1 as they proved more significant rub indicators.

Table 1 KS values for brass and seal rubbing

SIGNAL /MATERIAL	KS-Gauss	KS-Rayl	KS-Exp	KS-Gauss ×2	RMS	Med	Kurt	AR (1)	AR (2)	AR (3)	AR (4)	AR (5)	AR (6)	AR (7)	AR (8)
Steel Mean	0.106	0.616	0.825	0.106	0.008	0.016	10.948	-1.999	1.234	0.059	-0.123	-0.030	-0.070	0.058	0.062
Steel STD	0.012	0.008	0.017	0.011	0.003	0.003	1.101	0.014	0.025	0.020	0.007	0.017	0.024	0.017	0.006
Brass Mean	0.053	0.580	0.881	0.054	0.006	0.014	7.849	-2.006	1.186	0.117	-0.100	-0.066	-0.068	0.044	0.068
Brass STD	0.008	0.004	0.009	0.008	0.002	0.001	0.617	0.017	0.040	0.028	0.010	0.016	0.031	0.021	0.006

Primarily, use of the KS values derived from the Gaussian, Rayleigh and exponential models for all thirty signals are considered as the input vector to the clustering algorithm, i.e., three values per vector per signature. The achieved clustering results are depicted using the dendrogram plot in Fig. 9. As shown, the x-axis represents the steel fixture rub signals by labels 1 to 15 and the signals produced using the brass fixture as signals 16 to 30. Moreover, the y-axis shows the Euclidean distances between the input KS values. It is evident that the two main clusters do discriminate between the brass and steel rub classes. Moreover, ignoring signal-6 and signal-12 corresponding to steel rubbing, the separation is relatively pronounced.

Figure 9 Gaussian KS discrimination, single-linkage (nearest neighbour)

It should be noted that the algorithm used to determine KS values involves the generation of a random reference signal and hence produces slight changes in the result for a given AE signal over repeated calculation. However, this variability was not seen to prevent adequate separation between brass and steel signals over many independent experiments. Moreover, it was apparent that using a signal feature vector that constitutes repeated KS evaluations for a specified reference distribution could improve the clustering results. Figure 10 shows the clustering achieved using a feature vector consisting of four independent KS evaluations assuming the Gaussian model. In this plot, the Ward's method of clustering is employed in preference to the single-linkage (i.e., nearest neighbor). This is a procedure in which the similarity used to join two clusters is calculated as the sum of squares between the two clusters summed over all variables. It is effective in increasing the 'within cluster' homogeneity and prevents chaining.

Figure 10 Gaussian KS discrimination, Ward's method

In contrast to the robust KS results, clustering of the thirty partial rub signals using established AE signal features such as peak energy, total energy, RMS, median, standard deviation, counts and peaks within an FFT revealed poor separation between brass and steel signals. The most appropriate of such features was the signal kurtosis. As indicated in Table 1, this energy independent measure of signal spikiness generally yielded larger values for steel rubbing signals than from brass rubbing. However, repeated tests revealed a number of spurious clustering results. This was attributed to the large spread of kurtosis values obtained across all of the AE signals measured.

Although the KS technique outperformed these established signal features dependent upon energy or extreme values within the amplitude distribution, it should be noted that application of autoregressive coefficients as input AE signal features also produced effective discrimination between brass and steel rubbing. This technique (Melton, 1982) involves modelling each AE signal as an N^{th} order linear stochastic process and using the subsequent AR coefficients within the clustering algorithm to represent the signal 'fine-scale' shape to within a certain accepted prediction error. The optimum order (N) for the AR model is often the lowest order at which the minimum mean-squared error becomes stationary and can be determined via the application of the final prediction error (FPE) and Akaike's information criterion (AIC) (Kay and Maple, 1981; Makhoul, 1975). However, it was considered that the success of subsequent AE signal clustering was extremely sensitive to the number of AR coefficients employed, as the optimum order varied for different classes of rub signal. In addition to this drawback, it became clear that the AR approach to partial rub classification breaks down when the measured rub signals are modulated by background acoustic noise.

To demonstrate the effect that background noise can have upon rub classification, acoustic noise from the bearings of an operational 500-MW turbine unit was superimposed upon the brass and steel rub signals. In this test, the same levels of turbine noise were added to the thirty rub signals and the same band-pass filter was applied. Figure 11 shows hierarchical clustering results achieved from fifteen noisy brass signals and fifteen noisy steel signals using a 20^{th} order AR coefficients as the signal descriptors. This dendrogram plot clearly demonstrates that the AR approach becomes inappropriate for brass and steel classification when even low levels of background noise are present. It is interesting to note that this lack of class resolution was also observed when attempts were made to remove background noise using an appropriately designed band-pass filter. In contrast, it became clear that KS-based rub classification is less affected by the addition of real noise, see Fig. 12. As shown, AE signal classification using KS descriptors is more suitable than that based upon the more established AR technique.

Figure 11 AR(20) discrimination with low levels of real noise measured from a 500MW turbine

Figure 12 KS discrimination with low levels of real noise measured from a 500MW turbine.

5.2 Seal Wear Discrimination

Figure 13 The AE signatures from steel V-Groove

It is proposed that some diagnosis of the 'wear state' of rubbing seals might be inferred from the measured AE data. Three mild steel V-groove seals at different stages of wear were prepared. These are shown in Fig. 13 and are referred to as unworn, mid-wear and worn.

Applying each of these fixtures to the partial rub simulator in turn, AE signatures were recorded at the bearings. Figure 14 shows examples of the signatures obtained for the three wear states at the bearing-1. By inspection, it is obvious that the unworn signal appears to be more complex[2] than the other two wear state signals. Specifically, it is clear that two smaller bursts appear in the tail of the unworn AE waveform. However, visually identifying the difference between the mid-wear and worn state is more difficult, especially as the peak amplitudes of all three are very similar.

(a) (b) (c)

Figure 14 Example AE signals from a V-Grooved steel seals exhibiting (a) No wear (b) Mid-wear (c) Extreme wear

To illustrate an automatic classification approach for these wear states, fifteen example signals were taken; five from each of the wear states. Initially, the AR model approach to clustering was applied. As in the previous section, inspection of the residual error plot, using the Akaike's Information Criterion, suggests that an AR order of 8 was sufficient to represent the signature shape. To test the applicability of the AR approach, a plot of the cluster achieved by measuring Euclidean distances between centriod values of AR coefficients associated with each signature is shown in Fig. 15. No clear pattern in the cluster was observed and it was deduced that the AR classification approach is not suitable for determination of the wear state of the rubbing seal.

Figure 15 Clustering achieved using 8 AR coefficients for unworn (signals 1-5), mid-wear (signals 6-10) and very worn (signals 11-15) shaft-seal rubbings.

To investigate using the KS statistic for distinguishing between the unworn, mid-wear and worn partial rubbing states, the same fifteen signals were used. The Gaussian distribution was used as the reference within the KS algorithm and the cluster result can be seen in Fig. 16. It is clear from this that reasonably good wear classification has been achieved. Primarily, the two major clusters discriminate between the unworn AE signals and the other two types. This can be justified in that the second and third smaller bursts within the unworn signals cause significant deviation from Gaussian amplitude statistics. Secondly, it is encouraging to observe that the Gaussian KS statistic is sensitive enough to separate mid-wear and very worn rubbing signals within the broader cluster group.

[2] This difference between the AE produced from 'sharp' surfaces rubbing and more planar contact is related to known asperity contact effects and is generally observed in low-speed rotating machines.

Fig. 16 Clustering achieved using the KS-statistic for unworn (signals 1-5), mid-wear(signals 6-10) and very worn(signals 11-15) shaft-seal rubbings.

6. Conclusions

This paper introduces the use of the Kolmogorov-Smirnov (KS) test statistic as a useful signal descriptor in AE analysis. The KS results presented via hierarchical dendrograms indicate the potential of this statistic in classification of partial rubbing on shafts of fast rotating machinery. Moreover, the success of KS classification has been shown when the measured AE rub signals were modulated by background noise from a real operational 500-MW turbine.

It should be noted that the KS statistic tends to be more sensitive around the medium value (i.e., where $P(x) = 0.5$ within the CDF) and less sensitive at the extreme ends of the distribution, where $P(x)$ approach either 0 or 1. This is because the KS value does not have a probability distribution independent of amplitude (x). Therefore, it is postulated that while the KS statistic is good at finding shifts in the probability distribution, especially changes in medium value, it is not always so good at finding spreads, which more strongly affect the tails of the probability distribution. Consequently, it is concluded that the KS statistic is robust and not too sensitive to variability in amplitude outliers as is the case with the kurtosis statistic. Thus the KS statistic provides a suitably stable feature for broadband AE signals that characterises the entire amplitude statistics.

Implementation of this KS method for AE signal classification requires choosing the appropriate theoretical distribution families for reference. For the partial rub induced AE signals measured in this paper, the Gaussian distribution appeared to provide the closest fit, as indicated by the KS values given in Table 1. It is generally considered that the classification performance is increased by using reference distributions that are not rejected within the null hypothesis by exhibiting KS values that exceed the 5% significance level (Press, 1993). However, it can not be concluded from the results presented that the Gaussian distribution is the best amplitude statistics model for partial rub induced AE signals and other possible candidates include the log-normal (Lopez Pumarega et al., 1999) and t-distributions. Regardless of the distributions used for a specific classification task, it should be noted that determining the best set of reference distributions is the central consideration for the KS technique.

Interpretation of individual AE signal waveforms from partial rubbing is considered to be difficult. However, it is suggested that the general suitability of the Gaussian distribution and use of the KS statistic might infer more detailed information related to physical rub mechanisms. It is postulated that the Central Limit Theorem, as used for modelling ambient noise in underwater acoustics, might be adopted in AE condition monitoring. This could state that a rub induced AE waveform, which is formed by the addition of a number of temporally close but independent asperity contacts, has a probability density function, which approaches the Gaussian distribution, as the number of contributors or AE sources increases. Consequently, it is proposed that absolute KS values, assuming a Gaussian fit, might directly classify quantities such as rub severity.

The KS statistic essentially quantifies the difference between any two distributions. Therefore, in addition to diagnosing rubbing in fast rotating machinery, it is believed that the technique might find application in other condition monitoring applications. For example, the KS statistic could be useful for diagnosing tool wear or for detecting and classifying incipient faults in low-speed rolling-element bearings. In these cases, the KS value might indicate fault severity by quantifying the deviation of a measured AE signal from a known healthy-state signature. Moreover, alternative goodness of fit statistics could be applied if required for specific condition monitoring task. For instance, one way of increasing the statistic resolution out on the tails is to replace the KS statistic with a stabilised or weighted statistic such as the Anderson-Darling statistic D^*:

$$D^* = \max_{-\infty<x<\infty} \frac{|Sn1(x) - Sn2(x)|}{\sqrt{P(x)[1 - P(x)]}} \qquad (5)$$

Finally, it should be noted that these classification results were achieved using a high-fidelity wideband AE transducer. However, it is realised that the KS technique could break down using resonant devices due to low fidelity.

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Appendix

SIGNAL	KS-Gauss	KS-Rayl	KS-Exp	KS-Gauss ×2	RMS	Med	Kurt	AR (1)	AR (2)	AR (3)	AR (4)	AR (5)	AR (6)	AR (7)	AR (8)
Steel-1	0.108	0.618	0.839	0.103	0.007	0.013	10.176	-2.002	1.251	0.041	-0.126	-0.011	-0.094	0.081	0.052
Steel-2	0.114	0.622	0.846	0.113	0.005	0.011	10.690	-1.989	1.219	0.066	-0.124	-0.010	-0.104	0.077	0.062
Steel-3	0.103	0.609	0.832	0.100	0.006	0.015	11.159	-2.012	1.244	0.070	-0.132	-0.040	-0.054	0.043	0.067
Steel-4	0.097	0.613	0.833	0.108	0.012	0.016	10.644	-2.007	1.259	0.022	-0.106	-0.005	-0.104	0.064	0.068
Steel-5	0.130	0.629	0.828	0.124	0.010	0.012	12.443	-2.001	1.236	0.058	-0.120	-0.047	-0.047	0.047	0.062
Steel-6	0.083	0.605	0.849	0.089	0.009	0.014	9.3301	-1.973	1.180	0.099	-0.130	-0.039	-0.055	0.048	0.065
Steel-7	0.121	0.621	0.834	0.126	0.004	0.012	13.603	-2.012	1.248	0.065	-0.126	-0.058	-0.035	0.044	0.061
Steel-8	0.098	0.615	0.834	0.097	0.008	0.016	10.462	-2.010	1.263	0.032	-0.117	-0.027	-0.068	0.052	0.065
Steel-9	0.103	0.614	0.836	0.104	0.006	0.014	11.377	-2.020	1.271	0.041	-0.119	-0.048	-0.042	0.039	0.066
Steel-10	0.107	0.617	0.819	0.107	0.010	0.017	11.894	-2.003	1.233	0.068	-0.121	-0.035	-0.068	0.051	0.067
Steel-11	0.104	0.618	0.821	0.102	0.010	0.014	10.951	-2.005	1.245	0.051	-0.130	-0.011	-0.074	0.040	0.073
Steel-12	0.088	0.598	0.806	0.086	0.005	0.024	9.953	-1.975	1.198	0.066	-0.114	-0.016	-0.107	0.092	0.052
Steel-13	0.110	0.624	0.796	0.111	0.006	0.018	10.109	-1.987	1.208	0.079	-0.119	-0.048	-0.053	0.052	0.062
Steel-14	0.107	0.616	0.794	0.107	0.006	0.019	9.958	-1.998	1.221	0.080	-0.134	-0.039	-0.057	0.056	0.058
Steel-15	0.119	0.621	0.805	0.113	0.012	0.018	11.467	-1.995	1.237	0.049	-0.121	-0.016	-0.091	0.076	0.056
Brass-16	0.048	0.579	0.893	0.047	0.007	0.014	7.536	-2.003	1.163	0.141	-0.101	-0.071	-0.079	0.055	0.065
Brass-17	0.052	0.583	0.877	0.059	0.006	0.013	8.056	-2.015	1.209	0.097	-0.098	-0.070	-0.059	0.045	0.063
Brass-18	0.063	0.582	0.872	0.066	0.006	0.015	8.793	-1.984	1.143	0.126	-0.084	-0.029	-0.143	0.089	0.058
Brass-19	0.043	0.576	0.893	0.042	0.006	0.014	7.090	-2.028	1.236	0.082	-0.095	-0.087	-0.023	0.009	0.078
Brass-20	0.054	0.570	0.882	0.059	0.006	0.014	7.494	-1.979	1.118	0.163	-0.090	-0.068	-0.089	0.049	0.073
Brass-21	0.042	0.576	0.896	0.042	0.001	0.014	6.662	-2.010	1.192	0.121	-0.109	-0.069	-0.060	0.042	0.067
Brass-22	0.053	0.578	0.873	0.048	0.007	0.016	7.880	-1.991	1.155	0.142	-0.110	-0.062	-0.070	0.045	0.067
Brass-23	0.063	0.583	0.867	0.062	0.007	0.014	8.362	-1.998	1.170	0.133	-0.106	-0.079	-0.041	0.022	0.075
Brass-24	0.059	0.577	0.873	0.055	0.007	0.015	8.032	-2.017	1.218	0.079	-0.080	-0.075	-0.058	0.036	0.069
Brass-25	0.053	0.581	0.874	0.050	0.006	0.015	7.236	-2.041	1.264	0.073	-0.118	-0.056	-0.058	0.045	0.060
Brass-26	0.061	0.580	0.882	0.056	0.007	0.014	8.643	-2.015	1.206	0.103	-0.101	-0.066	-0.065	0.046	0.063
Brass-27	0.064	0.587	0.882	0.065	0.009	0.013	8.608	-1.996	1.162	0.141	-0.103	-0.088	-0.036	0.022	0.075
Brass-28	0.042	0.578	0.886	0.044	0.005	0.014	7.448	-2.017	1.217	0.095	-0.109	-0.051	-0.074	0.049	0.064
Brass-29	0.058	0.584	0.872	0.064	0.005	0.014	8.196	-2.006	1.188	0.110	-0.091	-0.080	-0.046	0.024	0.075
Brass-30	0.044	0.580	0.888	0.051	0.006	0.014	7.700	-1.986	1.143	0.143	-0.099	-0.043	-0.120	0.078	0.061