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Technical Note

Development and comparison of spectral methods for passive acoustic anomaly detection in nuclear power plants

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ABSTRACT

We have developed spectral signal processing methods for passive acoustic anomaly detection in nuclear power plants. Furthermore, we compared the developed and existing methods by applying them to stationary sounds recorded in a controlled environment. Our new methods show significant improvement, in particular concerning robustness against false alarms. The results also demonstrate that clear detection of a given sound at a given signal-to-noise ratio is highly dependent on the distribution of characteristic frequency content in the spectrum in relation to the background noise and the spectral uncertainty. Since the frequency monitoring principle used here is quite rigid, we stress the need for research on more flexible methods, also taking into account differences between experiments and real reactor systems.

1. Introduction

Sodium fast reactors represent one possible option for reaching Generation IV standards in nuclear power plants. Some objectives of Generation IV reactor systems are to achieve better use of fuel resources, transmutation of long-lived radioactive waste products and excellent plant safety [1]. The latter requirement demands, e.g. fast and reliable detection of all accident precursors that otherwise would lead to more serious plant conditions. Two examples of such accident precursors for sodium fast reactors are local coolant boiling in the core and leaks between the primary and secondary side of the steam generators or heat exchangers. Acoustic detection methods have been studied for a relatively long time in this context [2]. So have possible alternatives such as neutron flux monitoring for local coolant boiling and chemical methods for leak detection [3,4], but the simplicity and prompt response of acoustic methods have made them an interesting option. Both active and passive acoustic methods may be envisaged, but in this study we limit ourselves to passive methods.

The passive acoustic signal processing methods studied so far may be crudely categorized into basic spectral methods using Fourier or wavelet decomposition such as [5], auto-regressive modeling as described in [6] and neural network methods, e.g. [7]. These techniques are not completely independent of each other as neural networks may take output from spectral methods or autoregressive models as input and the latter, in a general context, also can be viewed as spectral decompositions of a time domain signal.

For any pattern recognition problem, the detecting system may be divided into a signal acquisition part, a feature extraction part and a classification part which in this case provides the binary anomaly-or-not output [8]. A *feature* in this context, denotes a function of the raw input signal(s), defined in the time domain, intended to reduce the dimension of the problem and to provide a suitable input to the classifier. Whether a simple classifier such as a single threshold rule or a complex neural network with many input features is used, the performance of the whole system will be dependent on the features used. Still, not many comparative studies of the basic feature extraction schemes proposed in the literature have been made and it is an important aim of this work to start filling this gap.

One possible measure of the prestanda of a feature $g(t)$ is the *detection margin*, defined by the IAEA in [2] as:

$$DM[g(t)] = 20\log_{10}\left(\frac{\tilde{g}_+}{\tilde{g}_-}\right) \quad (1)$$

where $\tilde{g}_+$ denote the average value of $g(t)$ during the positive detection region of the signal, i.e. where the sound to be detected is known to be present. Similarly, $\tilde{g}_-$ denote the average value of $g(t)$ for pure background noise. Thus, it measures the ability of a feature to rise high above its background level at onset of the signal to be detected. For acoustic detection systems tested under experimental conditions so far it has been difficult to demonstrate detection capability at the low signal-to-noise ratios (SNR) present at full power conditions of a real reactor and high false alarm rates have been experienced. These facts suggest that developing new features with even higher detection margin is of interest.

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In this work we have performed an experimental comparison of detection margins of basic features from the literature by applying them to pre-recorded sounds generated in a controlled acoustic environment in the anechoic room of the Marcus Wallenberg laboratory at KTH, Sweden. We also present two new features that show considerably higher detection margin than the ones earlier reported. We have chosen to work with the power spectral density and the continuous wavelet transform, but all the features described here can be applied to any spectral decomposition of a signal. The techniques demonstrated are in principle also applicable to any binary classification problem at low SNR.

The signal processing techniques used are described in Section 2, covering the spectral transform methods, Section 3 which describes features already published in the literature and Section 4, describing the two new features presented in this study. Then, the experimental part of the work is described in Section 5 with results and discussion given in Sections 5.4 and 5.5 Conclusions are given in Section 6.

2. Transform methods

2.1. Power spectral density

An estimate of the power spectral density (PSD) of a signal $x(t)$ during a time window of length T is given by

$$\mathrm{PSD}(f,T) = \frac{1}{T}\left|\int_{-T/2}^{T/2} x(t)e^{-j2\pi \mathrm{ft}}\mathrm{d}t\right|^2 \quad (2)$$

This is a density function, which expresses the (generalized) power present in each frequency of the signal. Since the time window is finite, the signal values in the beginning and at the end of the window will have more uncertain frequency, yielding a quite noisy representation of the spectrum.

A common method of overcoming this problem by decreasing the uncertainty contribution and thereby smoothing the resulting spectrum is the Welch method [9]. In this method, the PSD estimate of the main time window is computed as an average of several estimates of overlapping sub-windows. The signal $x(t)$ is in each sub-window also multiplied with some weighting function aimed to give increasingly higher weight to signal values closer to the middle of the sub-window.

2.2. Wavelet transform

The continuous wavelet transform (CWT) of a signal $x(t)$ in a time window of length T is given by

$$WX(a,b) = \int_{-T/2}^{T/2} x(t)h\left(\frac{t-b}{a}\right)dt \quad (3)$$

where $h(t)$ represents the mother wavelet. Different mother wavelets have been used for this and similar applications. E.g. [5] used the Daubechies-04 mother wavelet whereas [11] used the complex morlet, which is stated to be suitable for acoustic signals.

At each level a the wavelet decomposition defines a signal $X_a(t_n) = X(a,b_n)$ for each time sample $t_n = b_n$. To create features from these level signals, we use the square-root of sum of the squares during the time window as an intermediate step, i.e.

$$X(a) = \sqrt{\sum\nolimits_n WX^2(a,b_n)} \quad (4)$$

3. Existing feature extraction methods

Let any transform of a signal $x(t)$ taken over a time window T be $X(c,T)$, where c is the independent variable in the transform domain, e.g. frequency for the PSD. We will from now on denote this transform only by $X(c)$, implicitly assuming that the transform will be continuously updated for each time window during the monitoring/detection procedure.

3.1. Sum

In [10,5] the PSD is used to create a feature called *power spectral density sum*, or *PSDSUM*, which is defined as the sum of preselected frequency components. Denote the transform by X (e.g. PSD as defined in (2) or CWT as defined in (4)). Let the pre-selected transform components be $c_1, c_2, \ldots, c_N$. Then, a generic sum feature may be written as

$$XSUM = \sum_{i=1}^{N} X(c_i) \quad (5)$$

where the $X(c_i)$ are updated in each new time window.

3.2. Direct and normal spectral distance

The direct and normal spectral distance features were proposed in [12], measuring the distance change of the whole spectrum vector. The direct spectral distance, (*DSD*) is defined as

$$DSD = \left|\vec{X}_{\mathrm{ref}} - \vec{X}(c)\right| \quad (6)$$

where $\vec{X}_{\mathrm{ref}}$ is a reference spectrum of the pure background noise and $\vec{X}(c)$ is updated. The normal spectral distance (*NSD*) is given by

$$NSD = \vec{X}(c)\cdot\vec{X}(c) - \frac{\vec{X}_{\mathrm{ref}}\cdot\vec{X}(c)}{\left|\vec{X}_{\mathrm{ref}}\right|} \quad (7)$$

which measures only the part of the spectral change that is orthogonal to the background noise vector.

3.3. Functions of the covariance matrix

In principle, detection could be performed simply by monitoring sums and distance measures of the selected frequency components. However, when reaching sufficiently low SNR, the increase in each transform component at onset of the sound to be detected will be of the order of the spectral uncertainty. A solution is to monitor covariance between the selected components. Consequently, scalar functions of the covariance matrix, such as the trace and determinant were suggested in [10], with the determinant showing the highest detection margins. The covariance matrix is given by

$$\mathbf{CM}(X(c_i),X(c_j)) = E[(X(c_i)-\mu_{X(c_i)})(X(c_j)-\mu_{X(c_j)})] \quad (8)$$

Here, the $\mu_{X(c_{i/j})}$ are averages taken over several PSDs from a negative detection (reference) region. During detection, the $X(c_{i/j})$ values are updated for each new time window. We will denote the features created by the trace and determinant of this matrix with *TRCM* and *DETCM* respectively.

4. New feature extraction methods

4.1. Square of determinant

At this point, we introduce two new features created from the covariance matrix. First, we note that squaring can be used to enhance feature differences, a fact that was used in the *twice-squaring method* presented in [13]. This suggests that simply taking the square of the determinant of the covariance matrix would yield