DETECTING FAULTS IN STRUCTURES USING TIME-FREQUENCY TECHNIQUES

Samuel Pon Varma, Antonia Papandreou-Suppappola, and Seth B. Suppappola

Telecommunications Research Center, Department of Electrical Engineering
Arizona State University, Tempe, AZ, 85287
samuel.ponvarma@asu.edu, papandreou@asu.edu, seth@blackbird.eas.asu.edu

ABSTRACT

In this paper, we investigate various methods of classifying time–varying signals. In particular, we are interested in detecting acoustic emissions that may occur in concrete structures during imminent failure. This important classification problem will result in detecting and separating the distress signal from other natural or man made acoustic signals. Due to the time–varying nature of the signals, we employ several time–frequency based classification methods proposed in the literature. We also propose a new automatic classification method that is based on the matching pursuit algorithm, and we demonstrate its superior performance using real data.

1. INTRODUCTION AND IMPORTANCE

There are numerous reasons why it is desirable to ascertain the condition of a structure to determine if failure is imminent. For example, failure of a structure may result in loss of use which usually implies loss of revenue. In addition, repair costs resulting from the failure of a structure usually far exceed the cost of preventive maintenance repair. Moreover, failure of certain structures may result in collateral costs that could conceivably exceed the cost of the structure itself. Although failure of a structure may seem sudden to the uninformed observer, there frequently are numerous warning signs which precede catastrophic failure. In order to perform preventive repairs it is necessary to not only look for these warning signs, but to detect and interpret them. Concrete structures containing reinforcing metal, in particular, lend themselves nicely to this type of diagnostic testing.

When a concrete structure is under distress due to corrosion of the reinforcing metal, acoustic emissions may occur which indicate the presence of this condition. These emissions may be caused by cracking of the concrete itself, or by breakage and/or slippage of the reinforcing metal. Acoustic monitoring of such structures is one technique which addresses the issue of actually looking for the distress. In addition to that, classification of any such recorded event can be a daunting task. When performing acoustic monitoring, many acoustic events can occur, most of which are undesirable and do not contain any information as to the status of the structure under test. These emissions can result for example from passing workers, birds, animals, machinery, automobiles or rain. In practical situations, far less than one percent of all recorded emissions will be of diagnostic value. Without some automated method of separating the valuable events from the clutter, the arduous task of manual classification becomes mandatory.

In this paper, we propose an automated method of classifying acoustic emissions to assist in the diagnosis of concrete structures. Due to the time–varying nature of these signals, we have used various time–frequency based methods as well as matching pursuit algorithms for their automatic classification. After briefly explaining some of these classification methods, we compare their performance using eight different acoustic events. Our main objective is to extract the acoustic signals due to distress in concrete structures so that the status of the structure can be ascertained. Note, however, that although it is highly desirable to identify this one class of signals, we do not wish to combine all remaining classes into a single class. This is the case because there often are several other classes capable of providing secondary diagnostic information.

2. CLASSIFICATION METHODS

There exist many classification methods which depend on the nature of the signals. In the following two sections, we discuss some methods that can be used for the classification of acoustic events of an acoustic monitoring system. The effectiveness of the methods are investigated by using them to classify eight different types of acoustic signals. Figure 1 shows the spectrogram [1] of a characteristic sample signal of these eight different types of signals. As seen from the figure, only class 1 and class 3 have high frequency components whereas all other classes consist of low frequency signals. These kind of signals are chosen because in an acoustic monitoring system, low frequency signals like machinery, human voice or automobile noises will be quite often recorded. Empirical data indicates that class 1 is the warning signal which usually precedes a catastrophic failure, and thus must be classified accurately.

2.1. Time-Frequency Classification Techniques

The authors in [2] discuss some time–frequency (TF) techniques that can be used for non-stationary signal classification. They consider each TF point of a TF representation as a Gaussian random variable whose probability distribution function is defined. Once the distribution is known, then it is easy to arrive at a classification rule [2]. Specifically, using binary classification, one can deduce that the test signal is in class 1 if[1]

$$\langle\langle \, \mathrm{TFR}_x, \overline{\mathrm{TFR}}_{x^{(1)}} \, \rangle\rangle > \langle\langle \mathrm{TFR}_x, \overline{\mathrm{TFR}}_{x^{(2)}} \rangle\rangle$$

where TFR_x is a TF representation of a test signal $x(t)$, $\overline{\mathrm{TFR}}_{x^{(j)}}$ is the average TF representation of class j, and $x^{(j)}(t)$ is a signal in class j. The average TF representation is obtained by averaging the TF representation of all the learning signals in class j. The average TFR of a class is calculated using

[1] Here, $\langle\langle \mathrm{TFR}_x, \overline{\mathrm{TFR}}_{x^{(j)}} \rangle\rangle$ defines the two-dimensional (2-D) inner product $\int\int \mathrm{TFR}_x(t,f)\, \overline{\mathrm{TFR}}^*_{x^{(j)}}(t,f)\; dt\; df$.

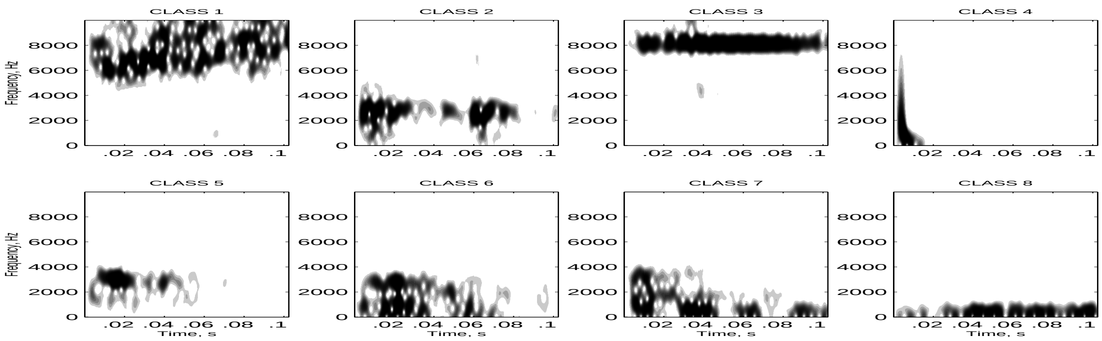

Fig. 1. Sample spectrogram for eight different classes of acoustic signals.

$$\overline{\mathrm{TFR}}_{x^{(j)}}(t,f) = \frac{1}{N_j}\sum_{k=1}^{N_j} \mathrm{TFR}_{x_k^{(j)}}(t,f), \;\; j=1,2$$

where $\mathrm{TFR}_{x_k^{(j)}}(t,f)$ is the TF representation of the k^{th} learning signal in class j and N_j is the number of learning signals in class j. Specifically, this rule corresponds to a 2-D matched filter [3]. The inner product between the TF representation of the test signal and the TF representation of the prototype/signature signal of class 1 and class 2 are used as the test statistic. The test signal will be assigned to the class whose 2-D correlation with the test signal is maximum. We applied this concept to our data consisting of eight different acoustic signals. In an 8-ary signal classification, the classification rule will be

$$x(t)\;\epsilon\; C_j \iff \arg\max_j \;(\;\langle\langle \mathrm{TFR}_x, \overline{\mathrm{TFR}}_{x^{(j)}}\rangle\rangle\;)$$

for j = 1,…,8, where C_j is the j^{th} class. We first choose the spectrogram [1] as our TFR, and then the reassigned spectrogram [7].

2.2. Ambiguity Function Classification Techniques

Auto Ambiguity Function
The narrowband Ambiguity function (AF) is the 2-D Fourier transform of the Wigner distribution [1]. The AF of a signal $x(t)$ can be written as[2]

$$\mathrm{AF}_{xx}(\tau,\nu) = e^{\frac{j2\pi\tau\nu}{2}}\int x(t)\,x^*(t-\tau)e^{-j2\pi\nu t}dt \;\; . \qquad (1)$$

In the AF domain, all the auto terms of a multicomponent signal $x(t)$ will be concentrated around the origin $(\tau,\nu) = (0,0)$, and all the cross terms will be away from the origin [1]. The AFs of the different signals to be classified are remarkably different. For example, Figure 2 shows the AF of a class 1 signal and a class 3 signal. It is clear from the figure that the AF of the first class signal is centered around $(0,0)$, while the AF of the third class signal has peaks all along the τ axis. Based on these distinct differences, we defined the test statistic as

$$\gamma_j = \langle\langle\; |\mathrm{AF}_{xx}(\tau,\nu)|,\; |\overline{\mathrm{AF}}_{x^{(j)}x^{(j)}}(\tau,\nu)|\;\rangle\rangle, \;\; j=1,\ldots,8$$

where

$$|\overline{\mathrm{AF}}_{x^{(j)}x^{(j)}}(\tau,\nu)| = \frac{1}{N_j}\sum_{k=1}^{N_j} |\mathrm{AF}_{x_k^{(j)}x_k^{(j)}}(\tau,\nu)|\;,$$

[2]Unless otherwise stated, limits of integration vary from $-\infty$ to $+\infty$.

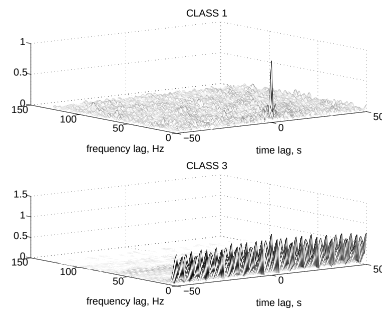

Fig. 2. The auto AF of signals from two different classes.

$|\mathrm{AF}_{xx}(\tau,\nu)|$ is the absolute value of the AF of the test signal, $|\mathrm{AF}_{x_k^{(j)}x_k^{(j)}}(\tau,\nu)|$ is the absolute value of the AF of the k^{th} learning signal in class j and N_j is the number of learning signals in class j. The classification rule in this case is

$$x(t)\;\;\epsilon\;\; C_j \iff \arg\max_j\;(\;\gamma_j\;), \;\; j=1,\ldots,8.$$

To the best of our knowledge this method has not been considered before in the literature.

Cross Ambiguity Function
Another classification method we used is based on the cross AF. The cross AF of the signals $x(t)$ and $y(t)$ is defined as

$$\mathrm{AF}_{xy}(\tau,\nu) = e^{\frac{j2\pi\tau\nu}{2}}\int x(t)\,y^*(t-\tau)e^{-j2\pi\nu t}dt \;\; . \qquad (2)$$

When $x(t) = y(t)$, the cross AF is the auto AF in (1). Using this basic argument, we can infer that when $x(t)$ and $y(t)$ are highly correlated, then it is not unreasonable to expect a maximum value at $(\tau,\nu) = (0,0)$ in the AF plane. This is because the maximum value of the auto AF occurs at the origin [1].

In this paper, we have made use of the above simple reasoning for signal classification. Let $x(t)$ be the test signal, and define

$$\overline{x}^{(j)}(t) = \frac{1}{N_j}\sum_{k=1}^{N_j} x_k^{(j)}(t), \;\; j=1,\ldots,8 \qquad (3)$$

where $\overline{x}^{(j)}(t)$ is the time averaged learning signal of class j, $x_k^{(j)}(t)$ denotes the time samples of the k^{th} learning signal in class j, and N_j is the number of learning signals in class j. We define the test statistic as

$$\gamma_j = |\mathrm{AF}_{x\overline{y}^{(j)}}(0,0)|, \;\; j=1,\ldots,8 \qquad (4)$$

where $\overline{y}^{(j)}(t)$ is the time shifted version of the averaged signal $\overline{x}^{(j)}(t)$ in class j in (3). The test signal may be the time shifted version of any one of the learning samples of the class where $x(t)$ belongs to. We have shifted the time averaged prototype signal in order to attain a maximum value at $\tau = 0$ in the AF plane which corresponds to the maximum possible time correlation between the test signal and the prototype signals. Note that if we substitute $(\tau, \nu) = (0, 0)$, (2) reduces to

$$\mathrm{AF}_{xy}(0,0) = \int x(t)y^*(t)\, dt.$$

Thus, (4) reduces to a time-sample correlation. The classification rule can be defined as

$$x(t)\ \epsilon\ C_j \iff \arg\max_j\ (\ \gamma_j\ ),\ \ j = 1, \ldots, 8.$$

3. A NEW MATCHING PURSUIT BASED APPROACH

The matching pursuit is an iterative algorithm which decomposes a signal into a linear expansion of waveforms selected from a redundant and complete dictionary. Mallat and Zhang in [4] used TF shifted and scaled Gaussian atoms as basic dictionary elements to decompose a given signal. In acoustic signal classification, a lot of iterations are needed to decompose a signal into basic Gaussian atoms. The authors in [5] suggest that it is also possible to use more than one type of basic atom in the dictionary. We modify the matching pursuit so as to use it in classifying acoustic signals. The difference in our approach from the approach in [4] is in the formation of the dictionary. Instead of using TF shifted and scaled Gaussian atoms as dictionary elements, TF shifted versions of the learning samples of each class constitute our dictionary elements as shown in Figure 3.

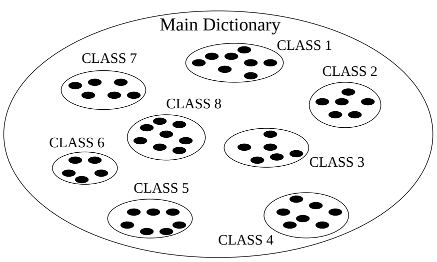

Fig. 3. The dictionary elements for the matching pursuit are the TF shifted versions of the learning samples in each class (shown in dark).

First, we start forming our dictionary by frequency shifting the learning samples of each class. Looking at the spectrogram of different classes in Figure 1, the range of frequency shifts of the learning signals of each class is limited. If we use a higher range of frequency shifts, then the misclassification rate may be higher. After this initial step, the following steps are followed to classify any given test signal.

Step 1 : Project the test signal onto all the dictionary elements.

Step 2: Select the dictionary element whose cross correlation with the test signal is maximum. Note that here we use a correlation and not an inner product in order to incorporate time shifts in the dictionary elements as well as frequency shifts.

Step 3: Subtract the chosen dictionary element from the test signal and store the class number of the chosen dictionary element. At the n_{th} iteration,

Class No.	No. of Learning Signals	No. of Test Signals
CLASS 1	50	342
CLASS 2	13	32
CLASS 3	10	30
CLASS 4	9	30
CLASS 5	11	14
CLASS 6	11	31
CLASS 7	13	37
CLASS 8	13	30

Table 1. Number of learning and test signals in each class.

$$x_n(t) = x_{n-1}(t) - \alpha_n^{(j)} d_n^{(j)}(t)$$

where, $x_n(t)$ is the residual signal at the n^{th} iteration, $d_n^{(j)}(t)$ is the best matched dictionary element at the n_{th} iteration and it belongs to class j. The correlation coefficient $\alpha_n^{(j)}$ at the n^{th} iteration that belongs to class j is given by

$$\alpha_n^{(j)} = \langle\ x_{n-1},\ d_n^{(j)}\ \rangle.$$

Step 4: The procedure is repeated until the remaining signal energy is only a small percentage of the overall signal energy or after performing a certain prescribed number of iterations. In our study, we set the energy threshold at 15% of the test signal energy and we used a maximum number of ten iterations.

Step 5: When the algorithm converges, the net contribution of the coefficients $\alpha_n^{(j)}$ in class j can be used as the test statistic. Specifically,

$$\gamma_j = \textstyle\sum_{k=1}^{K}\ \mid \alpha_{m_k}^{(j)} \mid$$

where m_k is the iteration number in which class j was chosen during the iterations, and K is the number of times that the class j was chosen. Finally, the unknown test signal will be classified in class j as,

$$x(t)\ \epsilon\ C_j \iff \arg\max_j\ (\ \gamma_j\ ),\ \ j = 1, \ldots, 8. \tag{5}$$

For example, for a test signal, if the matching pursuit yields the following correlation coefficients after 8 iterations, $\alpha_1^{(1)} = 0.9$, $\alpha_2^{(1)} = 0.8$, $\alpha_3^{(1)} = 0.7$, $\alpha_4^{(2)} = 0.6$, $\alpha_5^{(3)} = 0.5$, $\alpha_6^{(4)} = 0.4$, $\alpha_7^{(5)} = 0.3$, $\alpha_8^{(6)} = 0.2$, then the test statistics will be, $\gamma_1 = 0.9 + 0.8 + 0.7 = 2.4$, $\gamma_2 = 0.6$, $\gamma_3 = 0.5$, $\gamma_4 = 0.4$, $\gamma_5 = 0.3$, $\gamma_6 = 0.2$, $\gamma_7 = 0$, $\gamma_8 = 0$. Recall that $\alpha_3^{(1)}$ is the correlation coefficient from the third iteration that belongs to class 1 and γ_1 is the test statistic for class 1. Based on the classification rule in (5), the above example test signal will be classified in class 1.

4. REAL DATA ANALYSIS AND COMPARISON

The classification performance of the above discussed methods are compared using our empirical results. We always classify a given test signal into one of the eight different classes.

All the test signals we have used are sampled at the rate of 20 kHz. The duration of the test signals is 0.1024 seconds (2048 time samples). Table 1 shows the number of learning signals and the test signals used for each class. We have configured class 1 to be the major class of interest and the other events to be the undesirable events. For example, in an acoustic monitoring system, the desired event could be the precursor warning signs that precede catastrophic failures, and the undesired events could be passing workers, birds, animals, machinery, automobiles or rain.

Class No.	SPEC	RSPEC	AF	CAF	MP
1	13	14	13	28	3
2	4	3	2	1	2
3	0	0	0	0	1
4	0	0	1	0	0
5	0	0	3	3	0
6	6	6	7	9	5
7	1	1	5	4	3
8	0	0	1	1	0
No. of FA	0	1	28	0	2

Table 2. Number of misclassified test signals in each method.

Class No.	SPEC	RSPEC	AF	CAF	MP
1	0.96	0.96	0.96	0.92	0.99
2	0.88	0.91	0.94	0.97	0.94
3	1	1	1	1	0.97
4	1	1	1	1	1
5	1	1	0.79	0.79	1
6	0.81	0.81	0.77	0.71	0.84
7	0.97	0.97	0.87	0.89	0.92
8	1	1	0.97	0.97	1

Table 3. Probability of correct classification.

Table 2 shows the number of misclassified test signals for each class using different methods. It also shows the number of false alarms (FA) that corresponds to the number of test signals from classes other than class 1, that are classified as class 1. Table 3 shows the probability of detection of the test signals for each class using different methods. The methods used are 2-D matched filtering (cf. Section 2.1) using the spectrogram (SPEC) and the reassigned spectrogram (RSPEC), Ambiguity function techniques (cf. Section 2.2) like auto AF (AF) and cross AF (CAF), and finally matching pursuit (cf. Section 3) technique (MP). By inspection we can infer that the matching pursuit yields the best results in classifying the test signals belonging to the eight classes.

Considering the classification results for class 1, the matching pursuit misclassified only three of the class 1 test signals. The poor performance of the cross AF is expected, because the eight different types of signals considered are time-varying in nature and the method corresponds to a 1-D correlation as shown in (11). Since the main objective of the acoustic monitoring system is the premonition of the structural failures to be followed, it may not be advisable to use a classifier which misses between 13 and 15 of 342 test signals of class 1 (see Table 1). Thus, the matching pursuit method appears promising for acoustic monitoring systems. The misclassification of the two test signals of class 1 in the matching pursuit method is attributed to the presence of more dominant low frequency components along with the component of class 1. As expected, the matching pursuit classifies these test signals in class 8 which has more low frequency components. The number of false alarms are quite large in the case of the AF method. There are two false alarms in the matching pursuit method. However, this is not a major drawback of the matching pursuit method since a false alarm does not mean that a precursor warning event is overlooked, which is the case in misclassification.

If we compare the various methods by processing time, the matching pursuit ranks last. In the matching pursuit, for each iteration, it is necessary to find the inner product between the test signal and each element of the dictionary. As a result, it is computationally intensive. The processing time increases linearly with the number of dictionary elements. We can also infer from the results that the reassignment spectrogram performs similarly to the spectrogram for the classification of our signals.

5. CONCLUSION

Many papers suggest various methods for classifying non-stationary signals. We have used some of these methods as well as some new techniques to classify acoustic signals. This classification is very important in diagnostic testing of concrete structures. A method not discussed in this paper uses TF representation log deviation [2] as a test statistic to classify signals. Another test statistic is used in [6] which depends upon the inverse of the TF points of a TF representation. Note that it is very difficult to use these two methods in signal classification when the signals to be classified have no common non-zero values in a band of frequencies, which is exactly the case in the eight classes that are used in this paper. Moreover, the log deviation method limits the type of TF representation, because only positive TF representations like the spectrogram [1] or the reassigned spectrogram [7] can be used. For signals similar to those of our eight classes, the matching pursuit provides promising results for signal classification. We have demonstrated with real data that the matching pursuit method performs better when compared with the other methods discussed in the paper. Further studies can be made on the possibilities and the efficacy of preprocessing the data before classifying it using the matching pursuit method. This will cause the algorithm to converge quickly, which in turn will reduce the processing time.

6. REFERENCES

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