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Classification of acoustic emission signals using wavelets and Random Forests : Application to localized corrosion

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ABSTRACT

This paper aims to propose a novel approach to classify acoustic emission (AE) signals deriving from corrosion experiments, even if embedded into a noisy environment. To validate this new methodology, synthetic data are first used throughout an in-depth analysis, comparing Random Forests (RF) to the k-Nearest Neighbor (k-NN) algorithm. Moreover, a new evaluation tool called the alter-class matrix (ACM) is introduced to simulate different degrees of uncertainty on labeled data for supervised classification. Then, tests on real cases involving noise and crevice corrosion are conducted, by pre-processing the waveforms including wavelet denoising and extracting a rich set of features as input of the RF algorithm. To this end, a software called *RF-CAM* has been developed. Results show that this approach is very efficient on ground truth data and is also very promising on real data, especially for its reliability, performance and speed, which are serious criteria for the chemical industry.

1. Introduction

Acoustic Emission (AE) is the transient elastic sound waves produced when a material undergoes stress, caused by the release of localized stress energy. AE can typically be detected in frequency ranges within 50 kHz to 1 MHz, and one major application is health monitoring of structural materials (bridges, pressure containers, pipe lines, etc.). Different kind of evolving damages can be detected by AE technique, but special attention was paid to localized corrosion processes during the last two decades [1–5]. In these works, specific AE sources associated to corrosion damage were identified to be gas evolution (mainly H_2 produced by cathodic reactions), corrosion products formation and rupture, and stress corrosion cracking initiation and propagation. Localized corrosion phenomena, such as crevice corrosion, mainly affect passive metals and alloys in chemical and oil industries. Corrosion degrades the useful properties of materials and structures including strength, appearance and permeability to liquids and gases. Thus, real time detection and understanding the electrochemical processes involved in these phenomena are fundamental when it comes to implement a forward-looking strategy of operational maintenance of facilities. Over the past eighteen years, several studies have been conducted regarding the identification and the classification of different types of corrosion. In 1996, Barton et al. [6] developed an artificial neural network (ANN) to identify the onset and classify the type of localized corrosion from electrochemical noise (ECN) spectra. In 2004, Van Dijck et al. [7] presented a pattern recognition system to classify corrosion processes from ECN time series using the continuous wavelet transform (CWT), a Bayesian classifier and a genetic algorithm. In 2009, Piotrkowski et al. [8] applied

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wavelet analysis (WA) and bispectrum analysis (BA) to AE signals for damage identification and evaluation of corroded galvanized steel whereas Griffin et al. [9] performed both Short-Time Fourier Transform (STFT) and Wavelet-Packet Transform (WPT) on AE signals extracted during burn and chatter anomalies, using genetic programming as a classifier algorithm. In 2010, Zhao et al. [10] classified AE signals in composite laminates using wavelet packet analysis (WPA) and support vector machine (SVM). In 2011, Van Dijck and Van Hulle [11] used a hybrid filter-wrapper genetic algorithm and a naïve Bayes classifier to identify the absence of corrosion, uniform corrosion, pitting and stress corrosion cracking. In 2012, Yu and Zhou [12] proposed a classification method of AE signals deriving from oil storage tank damage, combining SVM and an optimized grid search algorithm whereas Li et al. [13] studied the classification of AE signals of 304 stainless steel during stress corrosion process based on K-means clustering. Except the latter work, all of these researches are based on supervised learning algorithms but, to our knowledge, no attempt using decision trees has been made so far.

Considering the crevice corrosion process, emitted bubbles coming from chemical reactions generate AE activity, which can be recorded by sensors located on the surface of the specimen. Since AE signals associated to crevice corrosion are characterized by low energy content, it is very difficult to separate those signals from the environmental noise [14]. Thus, an in-depth work has been realized to preprocess the corresponding waveforms and a major motivation was to find the most relevant set of features. Chosen classification algorithm must be fast, reliable and not very sensitive to a mislabeled learning database (due to real-time and reliability industrial constraints). Moreover, it is preferable to provide a confidence level for the final decision.

This paper is organized as follows: waveform preprocessing and some details about the extracted features are given in Section 2. In Section 3, the RF algorithm is explained before an in-depth analysis is performed on ground truth data in Section 4. Classification results on real cases involving noise and crevice corrosion are shown in Section 5. Finally, some conclusions are drawn and improvements will be proposed.

2. Feature extraction from preprocessed waveforms

2.1. Waveform preprocessing

This important preliminary step is performed on waveforms directly acquired from sensors. The motivation here is to normalize those AE signals for consistent comparison. It is possible to discard useless information, numerically store the waveforms for further analysis and denoise them. The waveform preprocessing consists in the four following steps.

2.1.1. Pre-trigger removing

Pre-trigger removing simply deletes samples from the waveform corresponding to the very first points of the acquisition process. The pre-trigger value to be removed is totally customizable, depending on experiment conditions. This step is useful to remove digital noise from acquisition.

2.1.2. Tail cutting

Tail cutting resides in dynamically cutting the end of the waveform according to an energy criterion. For each point in the waveform, the cumulative energy computed from the beginning is compared to the energy contained in a 10 μs length window following that point. If this energy is less than a certain threshold T (in %) of the cumulative energy, then the corresponding point represents the end of the signal (Fig. 1).

This step is especially useful when it comes to remove the “zero-padding” which may have been applied at the end on some waveforms during the acquisition process (for length normalization purpose), thus removing useless information.

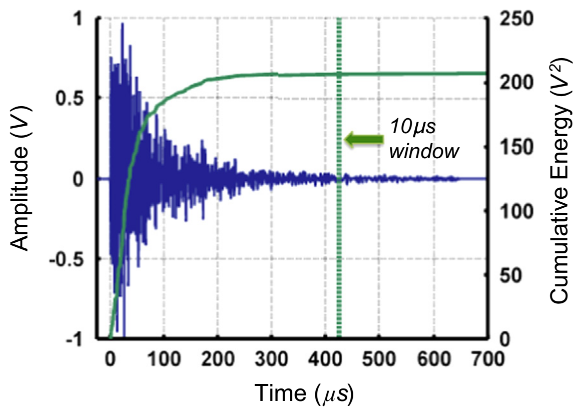

Fig. 1. Illustration of the tail cutting process on a waveform.