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Classification Analysis of High Frequency Stress Wave for Autonomous Detection of Defect in Steel Tubes

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Abstract

Interpretation of propagated high frequency stress wave signals in steel tubes is noteworthy for defect identification. This paper demonstrated a successful new approach for autonomous defect detection in steel tubes using classification analysis of high frequency stress waves. Classification analysis using Principal Component Analysis (PCA) algorithm involved feature extraction to reduce the dimensionality of the complex stress waves propagation path. Two defective tubes containing a slot defect of different orientation and a reference tube are inspected using Vibration Impact Acoustic Emission (VIAE) technique. The tubes are externally excited using impact hammer. The variation of stress wave transmission path are captured by high frequency Acoustic Emission sensor. The propagated stress waves in the steel tubes are classified using PCA algorithm. Classification results are graphically illustrated using a dendrogram that demonstrated the arrangement of the natural clusters of the stress wave signals. The inspection of steel tubes showed good recognition of defect in circumferential and longitudinal orientation. This approach successfully classified stress wave signals from VIAE testing and provide fast and accurate defect identification of defective steel tubes from non-defective tubes.

Keywords: Principal component analysis, Classification analysis, Defect recognition, Stress wave, Impact excitation.

1. Introduction

Preventing tube failures is vital towards plant safety and reliability. Overlooking defect in the tubes can cause disruption to plant operation, production and containment losses, as well as safety hazard (Bulloch et. al., 2009; Cicero et. al., 2010; Allahkaram, Zakersafaee, & Haghgoo, 2011). Therefore, detecting the loss of tube integrity as early as possible while they are in service, to check for the presence of corrosion and other potential defects are the essential aspects in safety and continuity of processing plant operation. Many non-destructive testing (NDT) methods has been developed and widely used to inspect and assure the tubes are safe to operate. The inspection results are useful to characterise tube condition and support future decision in determining the structural integrity of the tubes.

The success of the NDT inspection methods is very dependent on the utilization of well trained personnel to administer, implement and interpret the inspection. Data interpretation of the NDT methods is a vital part in assessing the tubes' health. In industrial practice, only certified personnel are qualified to interpret the signals and draw conclusion on the structural health of the tubes. An accurate evaluation of the inspection results in the tube integrity assessment that enable a cost-effective maintenance planning (Teixeira et. al., 2008). However, the success of current interpretation method is highly dependent on inspector's ability to interpret the presence of defect. Apparently, large variation of results can be expected depending on the skills and experiences of qualified inspector to recognize and correctly interpret the defective signals. Hence, recorded signals can be easily misinterpreted as defects, therefore leading to unnecessary tube plugging or replacements.

Defect characterization is gradually evolving and where it enable practitioner to perform a more efficient and effective interpretation approach. There are plenty room for improvements as rapid growth in measuring industry. In recent years with the use of computers, the processing of recorded stress wave signals to improve the interpretation and identification of defect has become a major consideration. Easy and rapid detection of the defect in the tubes is persistent and becomes a challenge in inspection technologies. Moreover, qualified and certified inspector requires extensive trainings, and involved a lot of resources and cost (Carino, 2013). Hence, it is crucially important to be able to interpret and recognize defect at an efficient rate and cost-saving.

Various signal processing techniques have been successfully applied to high frequency stress wave signals for diagnosis of severity and location of defect in various structural application. Typically, the stress wave signals are classified according to: i) time of arrival, ii) single parameter such as amplitude, r.m.s. and frequency level, and iii) pattern recognition. Conventionally, defect recognition in steel tubes employed the first two techniques, and most of the open literatures on the pattern recognition were focused mainly on visual comparison of recorded signals of the inspected tubes and calibration tubes by certified inspector (Wilson & Tian, 2007; Yang & Li, 2013; Zhang, Ye, & Xu, 2007). In addition to these primary findings, studies on the pattern recognition are still needed for better understanding of autonomous defect detection.

Accordingly, this study proposes a signal-based classification approach using high frequency stress wave signals from Vibration Impact Acoustic Emission (VIAE) for defect recognition. The propagating high frequency stress wave signals in steel tube resulting from mechanical impact excitation would normally show a unique character and nature. There are several different phenomenon which are reflection, diffraction and attenuation that will occur during the propagation process due to the presence of disturbance in the tube structure. These phenomenon produce complex stress wave which is difficult to distinguish visually. Classification analysis as part of pattern recognition has wide application and is often used to get insight into the data distribution pattern. Thus, classification analysis can be the best alternative to improve defect characterization. This paper is served to automate the interpretation of defect using classification analysis. The proposed classification analysis using Principal Component Analysis algorithm is capable of extracting useful information from stress wave signal of VIAE as described in later sections of this paper.

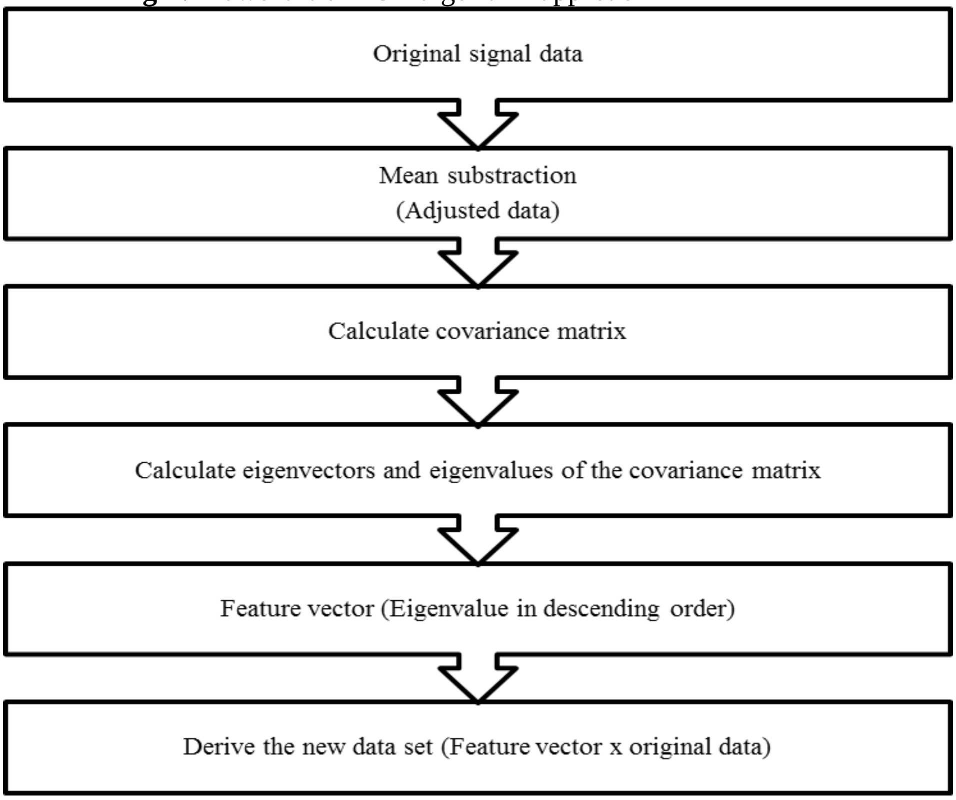
2. Principal Component Analysis

Principal Components Analysis (PCA) approach is based on reducing complex stress wave data to obtain relevant information and discover the hidden pattern in the signals data. Previous studies have successfully employed PCA model to distinguish complex data or signal structure. Omid et. al (2010) has applied the PCA to the emitting signals from impact acoustic testing on pistachio nuts. The results of this analysis have shown that the frequency domain of emitting signal has successfully sorted the nuts according to their sizes and condition. Moreover, Holford et. al (2009) were able to identified the location and source of fatigue crack in aircraft structures by using PCA. In the study, each signal resulting from different fatigue source can be properly classified.

The goal of classification analysis using PCA algorith is to propose an automated technique of defect detection for stress wave signals. Classification is done to find the similar characteristics between data and grouping similar data into clusters. Each data object has unique and similar characteristics within the same cluster that differentiate it between data objects in the other cluster.

PCA algorithm involve several sequential stages. A visualization of the sequential process is shown in the flowchart diagram as in Fig.1.

Fig-1. Flowchart of PCA algorithm approach



The stress wave signals are presented into a signal vector [X] to represent a starting point for PCA analysis. Then, the average value across each dimension is calculated using Eq. (1), and each of data is substracted with the mean.

$$Mean, \overline{X} = \frac{\sum_{i=1}^{n} X_i}{n} \qquad \text{Eq. (1)}$$

This produces an adjusted data set whose mean is zero. Next, the covariance between all the stress wave signals are calculated using Eq. (2). Covariance is a measure between 2 dimensions. If the data has more than 2 dimensions, there will be more than one covariance to be calculated. For an *n*-dimensional data set, the number of covariance values can be calculated is given by Eq. (3):

$$n_{cv} = \frac{n!}{(n-2)! \times 2} \qquad \text{Eq. (2)}$$

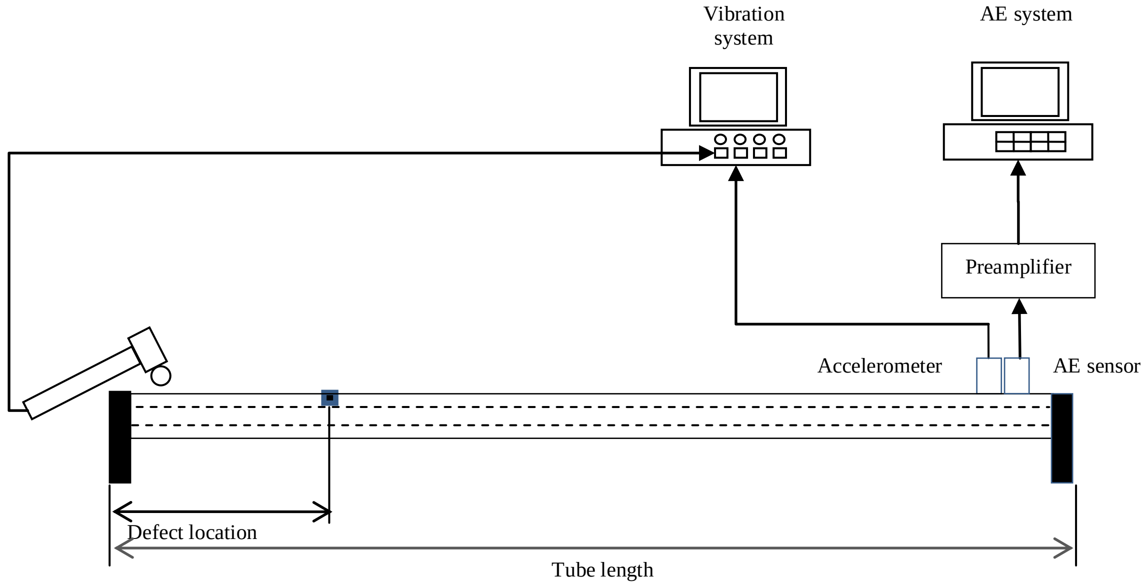
$$Covariance\ (X, Y) = \frac{\sum_{i=1}^{n} (X_i - \overline{X})(Y_i - \overline{Y})}{(n-1)} \qquad \text{Eq. (3)}$$

Once the covariance values have been calculated, the eigenvalues and eigenvectors for this matrix can be calculated. The eigenvectors and eigenvalues are rather important, as they disclosed useful information about the data. The eigenvalue is then arranged in descending order as feature vector, with the highest eigenvalue becomes the main principal component in the analysis. Finally, multiplication of the transposed feature vector and the original data produced a new data set. The PCA analysis has identified the statistical patterns in the data and presented the new data set in terms of the differences and similarities between them. The differences and similarities describe the relationships between the data. This is helpful to find patterns for each of stress wave signals.

3. Methodology

Vibration Impact Acoustic Emission (VIAE) method was employed in this study. Heat exchanger steel tubes A179 of 1m long tubes have a 19.05mm outside diameter and 2.11mm wall thickness. The measurement of stress wave was performed on three steel tubes RT, LS and CS. RT is a good reference tube, whereas LS and CS are defective tubes. Each defective tube has one artificial defect slot prepared by electrical discharge machining at 100mm from one of the tube ends. The slot is 5mm long and 1mm wide through the tube wall thickness. LS has a longitudinal slot defect parallel with the tube length. Whereas CS has circumferential slot defect transverse with the tube length. The experimental set-up is shown in Fig. 2.

Fig-2. Schematic experimental set up



Impact is introduced to the tubes to generate transient stress wave in the tube. The impact force load is quantified using BK PULSE Analyser as in Fig. 3. Consistent force loads are impacted on the tubes and demonstrated by coherency plot. Value nearing 1 indicates that the impact is consistent with each other. The coherency plot of each of the tubes are shown in Fig.4. The stress wave generated by the impact is captured at the other tube ends using Acoustic Emission (AE) technology. The AE sensor acquired high frequency stress wave propagated along the tube. The high frequency stress wave was used as the input for PCA algorithm. The detailed of experiment set up is explained in (Zakiah et.al., 2013).

Fig-3. Impact force load

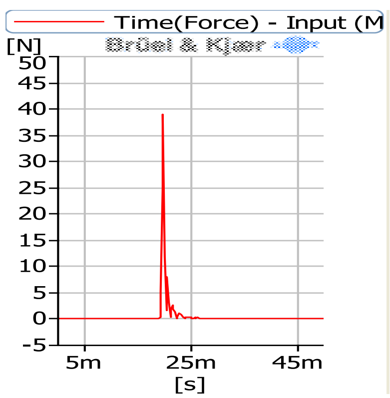
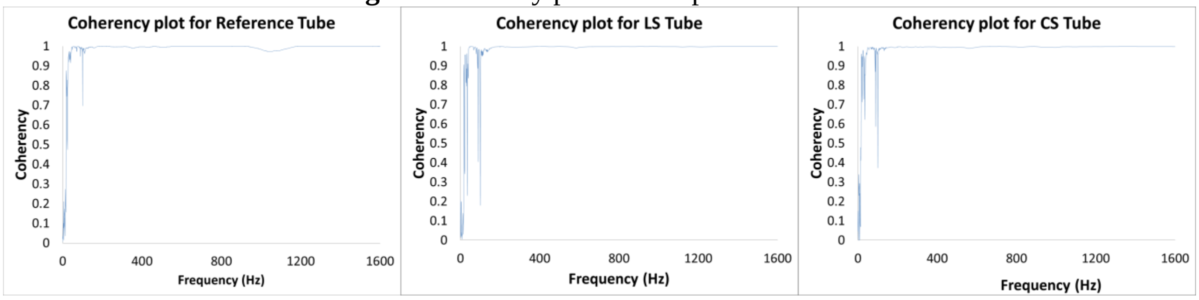


Fig-4. Coherency plots for Impact force loads



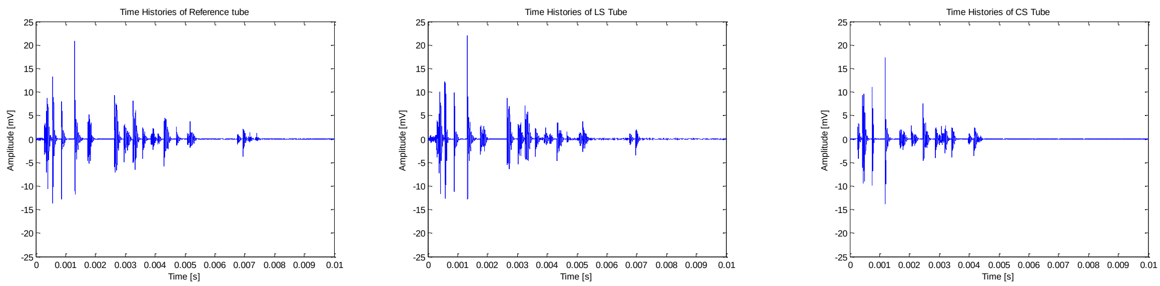
(a) Reference Tube (b) LS Tube (c) CS Tube

4. Results and Discussion

4.1. Stress Wave Time-Domain History

The typical high frequency stress wave propagated along the tubes is illustrated in Fig. 5. Generally, the features shown by time-domain history for all three cases represent multiple repetitive burst characteristics prior to complete attenuation. Each burst has approximately 250µs period length. In addition, it is clearly shown that the stress wave has shorter attenuation in the defective tubes than the Reference tube. As illustrated in Fig. 5(a), the stress wave in Reference tube completely attenuated at 7586µs. Whereas, the stress wave in LS tube and CS tube completely attenuated at 7165µs and 4436µs, as shown in Fig. 5(b) and Fig. 5(c) respectively. CS tube has fewer number of burst signal and attenuated faster due to the orientation of the defect. Since CS tube has transverse defect, the stress wave diffracted easily from the original propagation path compared to LS tube. Even though the defective tubes have similar defect size, but the orientation of the defect affects the propagation of the stress wave in the tube structure. Thus, orientation of defect exist in the tubes affects the stress wave propagation in the tube structures. However, it is very difficult to differentiate the signals of CS tube from Reference tube by visual inspection. Hence, classification analysis was applied to discriminate the stress wave propagation pattern.

Fig-5. Typical stress wave history of the inspected tubes



(a) Reference Tube (b) LS Tube (c) CS Tube

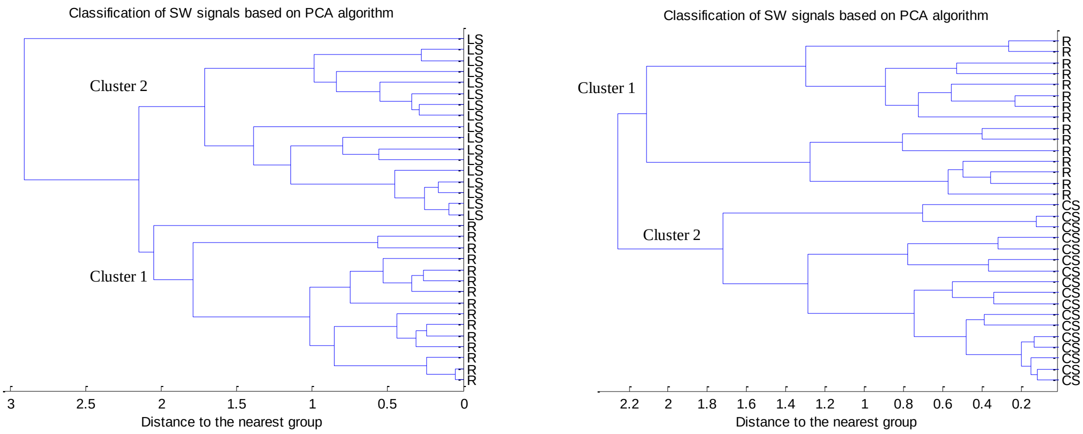
4.2. Classification Analysis

PCA algorithm was applied to automatically classify the high frequency stress wave signals in time domain acquired from all the three cases. Classification analysis is employed to get insight into the stress wave signal distribution pattern. The purpose of classification analysis is to put together similar characteristic signals into a group and dissimilar characteristic into another group. Each and every group has unique signal characteristic that differentiate one from another.

In PCA algorithm, all stress wave signals from the two tubes were collected in a matrix [X]. Generally, as all the stress wave signals attenuated completely by 0.01s, and each time domain signal was sampled at 10MHz. Thus, each stress wave signal will contain 100,000 number of data points, represented by a unit vector. Thus, the size of the matrix [X] is 20 x 100,000. Then, the covariance between 20 dimensions are calculated. For 20 dimensional data set, 190 covariance values can be calculated. The covariance values are represented in a covariance matrix. Then, the decomposition of eigenvectors and eigenvalues from the covariance matrix produced a feature vector. Since the vector is 20 dimensional, 20 eigenvectors are extracted and arranged in order of significance by eigenvalues, from highest to lowest. The eigenvector with the highest eigenvalue is the principle component of the stress wave data set. This is the most important stage in PCA analysis as it indicated the most significant relationship between the stress wave signals. Hence, decomposition of the eigenvectors of the covariance matrix revealed the characteristic patterns between the stress wave signals The rest of the steps involved transforming the data so that it is expressed in terms of the reduced dimensional data.

Classification result for stress wave signals associated with the Reference tube and LS tube is displayed in Fig. 6(a). Hierarchcial clustering was employed to classify the eigenvalues. The Euclidean distance between the eigenvalues was measured. The two most closest signals was clustered together in a cluster. Then, when a new signal is added into the group, a new distance was calculated and a new cluster is formed. This step is repeated until all signals are added in the classification. It can be observed from the resulted dendrogram that the signals were successfully classified into two main clusters. The first cluster, namely Cluster 1 consist of stress wave signals associated with Reference tube and Cluster 2 consists of stress wave signals associated with LS tube. Similar outcome was observed for stress wave signals associated with the Reference tube and CS tube as indicated in Fig. 6(b). The resulted dendrogram demonstrated that the stress wave signals from the Reference tube were merged together in Cluster 1 while stress wave signals from the defective CS tube were assembled together in Cluster 2.

Fig-6. Classification analysis using Principal Component Analysis



(a)Reference tuve vs LS Tube (b) Reference tuve vs CS Tube

The results show that PCA successfully clustering the stress wave signals and gather it into respective groups. The classification results successfully classify the unique characteristic into recognize group. The clustering provided two groups segments, i.e reference tube and defective tube. The success of PCA algorithm to differentiate the stress wave signals associated with defective LS and CS tubes from the stress wave signals of Reference tube was primarily due to the unique stress wave signal patterns shown by the impacted tubes. Even tough all the stress wave have similar amplitude, the attenuation time are dissimilar. The unique stress wave signals pattern of the defective tubes was due to the energy loss mechanism in the tube structure, in which the stress wave is reflected, diffracted and dispersed in the presence of defect (Lin et.al., 2004). Moreover, as the orientation of defect transversely position with the tube length, more stress wave is reflected and diffracted in numerous direction and obstruct the propagation of stress wave. Thus, shorter attenuation of stress wave signals in the defective tubes.

It is obvious that these results have achieved the aim of classification. Primarily, the presence of two large groups discriminate the stress wave signals of the reference tube and the defective tubes. This can be justified by the fact that defective tubes have different transmission stress wave path compared to the reference tube. In summary, it can be proved that the signals that have the same structure and amplitude will be in the same group. Secondly, PCA algorithm has proven to be sufficiently sensitive to differentiate stress wave signals into the right cluster group using the the eigenvector decomposition analysis of covariance matrices. This signifies that PCA algorithm can distinguish stress wave signals between the defective tube and the reference tube. The PCA applications can also identify signals that have a high energy level at different attenuation time. Thus, it has proven that the time domain signals from different stress wave groups can be classified well with the PCA applications. Therefore, it can be concluded that the tube is in normal condition when the signal captured during inspection showed similar characteristic with the reference tube signals, otherwise defect is presence in the tube. This is important for the purpose of evaluation and monitoring of defect in the heat exchanger tubes through the observed stress wave signals during tube inspection.

Moreover, the application of PCA and dendrogram are very useful in autonomous tube assessment. The dendrogram permits easy interpretation of the nature of SW signals. The dendrogram illustrates the pictorial view of cluster formation of stress wave that aid in understanding the stress wave signals. The dendrogram becomes an alternative presentation to portray the stress wave signals compared to the current data interpretation practice. The data are summarized in dendrogram is employed to automate interpretation so that the results can be quickly and confidently interpreted. The PCA algorithm analysed the complex stress wave information and the dendrogram is used to help make better decision. Thus, this approach is suitable to adopt as an alternative method to evaluate and interpret defective signals.

5. Conclusion

The classification of stress wave signals based on PCA algorithm is to automate the identification and interpretation of tube inspection results of Vibration Impact Acoustic Emission (VIAE) technique. This approach successfully distinguish stress wave signals from defective tube structures using application of PCA. It was proved that the proposed PCA applications on complex stress wave data can succesfully and correctly identify defective signals and differentiate it from reference signals. Classification using PCA has been verified to automate the defect interpretation and evaluation without the need of prior knowledge of the condition of steel tubes and qualification of inspector. The dendrogram can be confidently interpreted and identified the presence of defect and prevent false interpretation. Recognition of defect in steel tube using PCA application on high frequency stress wave proved to be much easier compared to traditional method.

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