Damages detection in cylindrical metallic specimens by means of statistical baseline models and updated daily temperature profiles

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Abstract. In previous works, damage detection of metallic specimens exposed to temperature changes has been achieved by using a statistical baseline model based on Principal Component Analysis (PCA), piezodiagnostics principle and taking into account temperature effect by augmenting the baseline model or by using several baseline models according to the current temperature. In this paper a new approach is presented, where damage detection is based in a new index that combine Q and T^2 statistical indices with current temperature measurements. Experimental tests were achieved in a carbon-steel pipe of 1m length and 1.5 inches diameter, instrumented with piezodevices acting as actuators or sensors. A PCA baseline model was obtained to a temperature of 21º and then T^2 and Q statistical indices were obtained for a 24h temperature profile. Also, mass adding at different points of pipe between sensor and actuator was used as damage. By using the combined index the temperature contribution can be separated and a better differentiation of damages respect to undamaged cases can be graphically obtained.

1. Introduction

Early damage detection in metallic structures is of main interest for different type of industries such as aviation, hydrocarbon, aeronautic, among others, in order to avoid potential future accidents [1]. Several approaches have been reported in literature for structural health monitoring (SHM) of metallic structures by using several techniques such as optical, vibration, guide waves [2]-[6]. In recent years, the use of guided waves for damage assessment in pipeline structures has been reported as successful [7]. Thus, by taking advantage of piezoelectric properties and guided waves, piezoelectric PZT devices are a cheaper technology with promising results for pipeline damage assessment [8]. In addition, the effectiveness of principal component analysis for structural damage detection algorithms has been demonstrated (for example in pipeline crack detection algorithms [9]). Although piezoelectric (PZT) devices have been reported as a promising technique to detect damages in metallic structures such as aircraft wings, pipelines and train rails, some limitations are presented during the travel of the generated wave, for example external disturbances such as temperature changes.

Some structural damage detection methodologies that account temperature variations have been reported in literature **[10]**, **[11]**, **[12]**, where for example several or augmented models are created for different temperature levels. However, they have taken into account temperature changes in steady state but not dynamic response of the wave travel during the transient changes or along a daily temperature profile.

By taking into account the above exposed limitation, this work proposes to detect damages in metallic cylindrical structures by combining environmental temperature measurements with statistical indices T^2 and Q obtained from a statistical baseline model for a reference temperature. First, a baseline statistical model is obtained by using Principal Component Analysis at a reference environmental temperature based on PZT responses at the end of a pipe section when a wave is generated by PZTs at the other end. Then, PZT responses are recorded during one or more days where temperature changes are presented. Finally, damages are emulated consisting of mass adding at different points of structure between actuation and sensing points. A first order model that relates statistical indices T^2 and Q with temperature is obtained, what is used to estimate undamaged statistical indices. They are subtracted from the current indices and the temperature effect is then compensated.

2. Damage Detection Methodology

The proposed methodology consists of detecting structural damages in metallic cylindrical specimens based on guided waves generated by PZTs and statistical indices obtained from a statistical PCA baseline model. Updated T^2 and Q statistical indices are computed by using both current and estimated, where estimation is based on current environmental temperature measurements. Figure 1 presents the main steps followed by the proposed methodology.
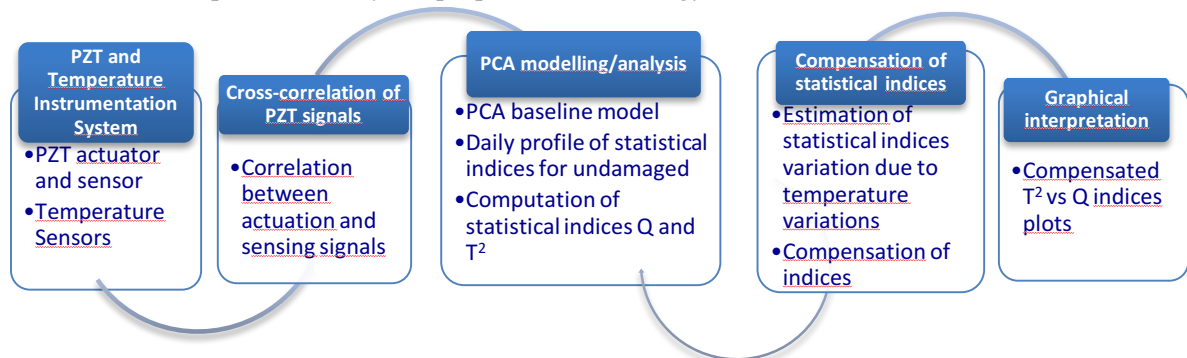

Figure 1. Damages detection methodology

2.1. PZT and Temperature Instrumentation System

PZTs should be attached to the monitored structure such that at least one (1) should be actuator and at least one (1) as sensor. Actuator(s) should be located at the end of the cylindrical specimen and sensor(s) at the other end such that any damage between both of them can be detected. At least one temperature sensor should be installed near to the structure (guide wave path should not be affected) to record environmental temperature at each experiment. Additionally, a signal recorder with capacity of storing 300 experiments (at least two signals recorded during at least 2 ms at a frequency greater than 1MHz, repeated approximately each 8s during at least 24 hours.

2.2. Cross-correlation of actuating and sensing PZT signals

The cross correlation analysis is used to exclude common external noise signals and then a better separation boundaries for damage conditions is obtained. Thus, actuation and sensing piezo-signals are correlated previously to apply the principal component analysis (Figure 2). The cross-correlation function between two signals $X(t)$ and $Y(t)$ is defined as:

$$R_{XY}(t, t + \tau) = \lim_{N \to \infty} \frac{1}{N} \sum_{k=1}^{N} X_k(t) Y_k(t + \tau) \qquad (1)$$

Where N is the number of signal samples and τ is the lag time interval used to compute the cross-correlation function.

2.3. PCA modelling and analysis

PCA is commonly used to obtain a reduced space representation for multidimensional, however in this approach it is used into two situations: Obtaining a statistical baseline model (modeling) and computing T^2 and Q statistical indices (validation). According to [16] PCA follow the next general procedure:

i. Normalize the original variables X by means of standard deviations $(\hat{\sigma}_j)$ and mean values $(\hat{\mu}_j)$

$$\hat{X} = \frac{X - \hat{\mu}_j}{\hat{\sigma}_j} \tag{2}$$

Where $\hat{X}$ corresponds to normalized data.

ii. Compute the covariance matrix of centered data matrix.

$$C_{\hat{X}} = \frac{1}{m-1}\hat{X}'\hat{X} \tag{3}$$

iii. Estimate the singular value decomposition for covariance matrix.

$$C_{\hat{X}} = \varphi\Sigma\varphi' \tag{4}$$

iv. Transform the original variables onto the orthogonal space defined by the Eigenvectors (φ) (loading matrix) of the covariance matrix.

$$Z = \varphi \cdot \hat{X} \tag{5}$$

v. Keep only the first r components in order to obtain a reduced representation for original variables. The variance for each new variable corresponds to their respective r eigenvalues.

$$Z_r = \varphi_r \cdot \hat{X} \tag{6}$$

Statistical baseline model corresponds to the loading matrix or eigenvectors obtained in iii. T2 and Q statistics are used to measure deviations of each experiment respect to the PCA baseline model (detection of damages), which are defined by equations 7 and 8.

$$T^2 = X^T\varphi_{und}(\Sigma^T\Sigma)^{-1}(\varphi_{und,})^T X \tag{7}$$

$$Q_i = \tilde{x}_i^T\tilde{x}_i, \quad \tilde{x}_i = [I - \varphi_{und} * (\varphi_{und})^T]X_i \tag{8}$$

Where $\tilde{x}_i$ is the residual projection for each experiment. T^2 statistics index is a variation measurement of each experiment within the statistical PCA model (undamaged model) and the Q statistics index is the squared 2-norm that measures deviations of the experiment respect to the lower-dimensional PCA representation [20].

2.3.1. Modelling. Two models are obtained in this step:

i) Statistical baseline model. It consists of obtaining the loading matrix φ (Equation 4), by using 300 repeated experiments at a reference environmental temperature (T_0), for undamaged structure (no mass added). A $n \times m$ measurements matrix is organized, where m is the number of experiments (300) and n the samples number of correlated signal, which is used to obtain the mentioned loading matrix.

ii) $\Delta Q/\Delta T$ and $\Delta T^2/\Delta T$ transfer functions. They relate statistical indices variations ($\Delta Q = Q_k - Q_0$) and $\Delta T^2 = T^2_k - T^2_0$) due to environmental temperature variations ($\Delta T = T_k - T_0$). For this purpose T^2 and Q statistical indices are computed by using the baseline model and from experiments periodically achieved (each 8s) during at least 24 hours for the undamaged structure and environmental temperature. Based on the daily indices and temperature profiles, process identification technique is used to obtain the mentioned transfer functions parameters. Then, by using discrete transformation of

continuous system, a discrete linear equation that computes statistical indices variation at sample k+1 in function of index at instant k and environmental temperature variation at instant k.

2.3.2. Validation. During validation, this stage consists of: i) Obtaining the Q and T^2 indices by projecting the correlated signal of current experiment on the principal component space by means of statistical baseline model and then to compute the mentioned indices, according to PCA analysis. ii) Computing the variation of the statistical indices due to the environmental temperature variation by using the obtained discrete linear equation.

2.4. Compensation of statistical indices
This step is used during the damage detection. It consists of subtracting the indices variation previously computed from the computed T^2 and Q indices. Thus a new compensated statistical indice are obtained to distinguish between undamaged and damage conditions of monitored structure.

3. Experimental Results

3.1. Experimental Setup
Experimental tests were achieved on a metallic cylindrical specimen consistent of a carbon-steel pipe of 1m length, 1.5 inches diameter and 0.003 m thickness (see figure 2). A PZT as actuator is attached at one end of the pipe while another one as sensor at the other end. A metallic piece that can be attached and displaced along the pipe section is used to simulate mass adding at different distances respect to the sensor (Figure 3 depicts the simulated damages). The experiment consisted of applying a 9-pulse 100 KHz burst signal from the actuator and to record the travelled wave at the opposite end during 2ms at a sample rate of 3.47MHz. Also, environmental temperature is recorded for each experiment by means of two (2) LM35 sensors.
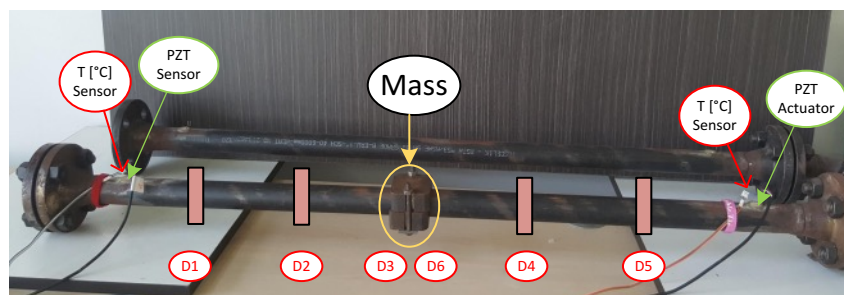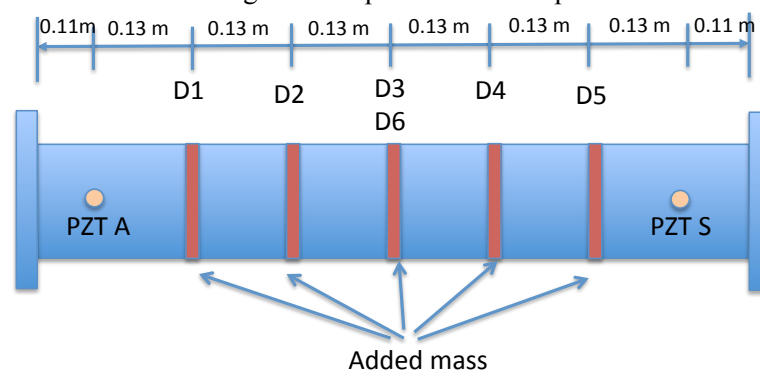

Figure 2. Experimental set-up

Figure 3.Graphical description of simulated damages

3.2. Set of experiments
Three sets of experiments were achieved.

i) Obtaining of statistical baseline model. A set of 300 repetitions of the experiment was achieved at a reference environmental temperature of 23.3ºC and for the undamaged structure. Stages 2.2 to 2.3.1 were achieved and loading matrix or statistical baseline model was obtained.

ii) Statistical indices and environmental temperature daily profile. Experiments were achieved each 8.84s during 24 hours for the undamaged condition (no mass addition), thus vectors of 9763 elements for Q, T^2 and T were obtained and are presented in figure 4. Based on these curves, step 2.3.1 to obtain two first order transfer functions ($\Delta Q(s)/\Delta T(s)$ and $\Delta T^2(s)/\Delta T(s)$) of the form:

$$G(s) = \frac{K}{\tau s + 1} \tag{9}$$

Where parameters for $G_Q(s) = \frac{\Delta Q(s)}{\Delta T(s)} = \frac{k_Q}{\tau_Q s + 1}$ are $k_Q = 1.4$, $\tau_Q = 4450$ s and for $G_{T^2}(s) = \frac{\Delta T^2(s)}{\Delta T(s)} = \frac{k_{T^2}}{\tau_{T^2} s + 1}$ are $k_{T^2} = 3500$, $\tau_{T^2} = 2450$ s. The differential equation resulting from the first order transfer function is of the form:

$$\tau_Q \dot{\Delta Q}(t) + \Delta Q(t) = k_Q \Delta T(t) \; ; \; \tau_{T^2} \dot{\Delta T}^2(t) + \Delta T^2(t) = k_{T^2} \Delta T(t) \tag{10}$$

The equivalent discrete representation of the continuous firs order transfer function is of the form:

$$\Delta Q(k+1) = e^{-\frac{Ts}{\tau_Q}} \Delta Q(k) + k_Q \left(1 - e^{-\frac{Ts}{\tau_Q}}\right) \Delta T(k) \tag{11}$$

$$\Delta T^2(k+1) = e^{-\frac{Ts}{\tau_{T^2}}} \Delta T^2(k) + k_{T^2}(1 - e^{-\frac{Ts}{\tau_{T^2}}}) \Delta T(k) \tag{12}$$

Where Ts is the sample time (8.84s). The resulting discrete equations are:

$$\Delta Q(k+1) = e^{-\frac{Ts}{\tau_Q}} \Delta Q(k) + k_Q \left(1 - e^{-\frac{Ts}{\tau_Q}}\right) \Delta T(k) \tag{13}$$

$$\Delta T^2(k+1) = e^{-\frac{Ts}{\tau_{T^2}}} \Delta T^2(k) + k_{T^2}(1 - e^{-\frac{Ts}{\tau_{T^2}}}) \Delta T(k) \tag{14}$$

Figure 5 presents the comparison of the measured against estimated T^2 and Q statistical indices by using the above discrete equations, where it can be observed an acceptable error for compensation purposes.

iii) Validation experiments set. A new set of experiments for about 2.5 hours was achieved, where mass was eventually added during 0.1 to 0.8 hours at different locations, time instants and environmental temperatures. In total six damages (explained in figure 3) that correspond to the same mass added at different locations between actuator and sensor, joint to undamaged conditions were registered during this step, whose statistical indices Q and T^2, and environmental temperature are presented in figure 6. By applying step 2.4 statistical indices were compensated by subtracting the statistical indices variations obtained by using the discrete equations obtained previously. New compensated indices are presented in figure 7, were it can be observed that new indices can differentiate undamaged respect to damage conditions. Finally figure 8 presents a graphical interpretation of new T^2 against Q indices, where a clear distinction of damage respect to undamaged case can be achieved. It can be observed that by using only compensated T^2 index D1 and D3 can be clearly distinguished from the undamaged condition and other damages, while D2, D4 to D6 are confused with undamaged condition. On other hand, by using only the compensated Q index, each damage can be differentiated respect to the undamaged case. Thus, for only detection purposes, compensated Q index could be effective and enough. However, if location of damage is necessary, a combination of both indices could be more effective. For example, damages D4 and D5 contain similar Q values, however by including T^2 index a separation of damages could be obtained for classification purposes.
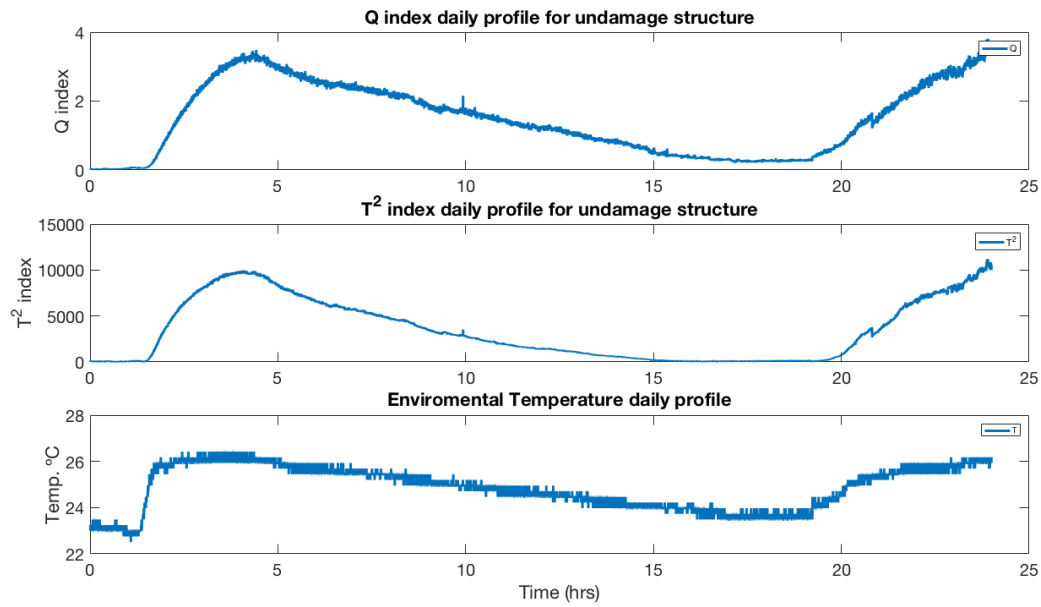
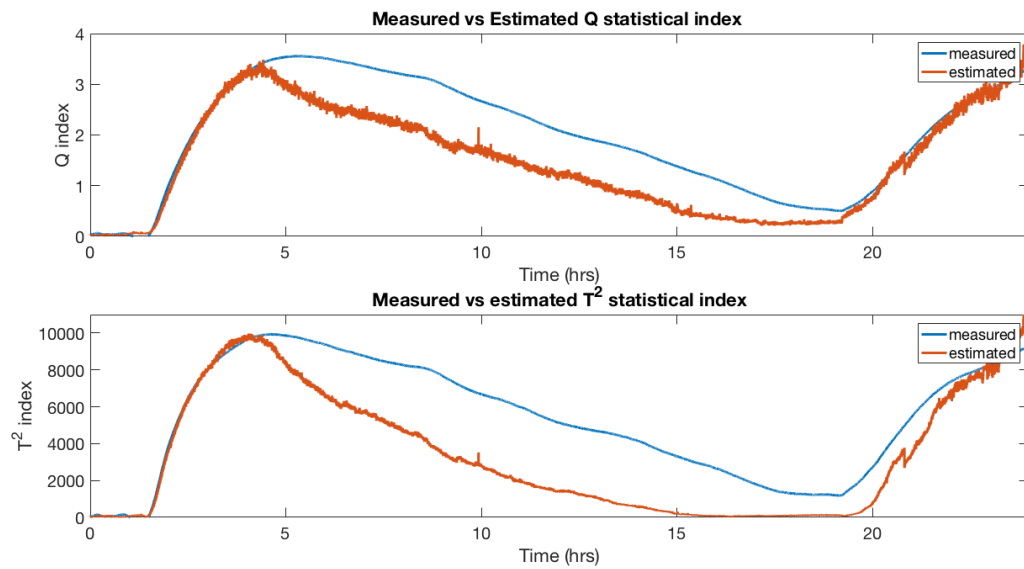Figure 4. Temperature and statistical indices daily profile

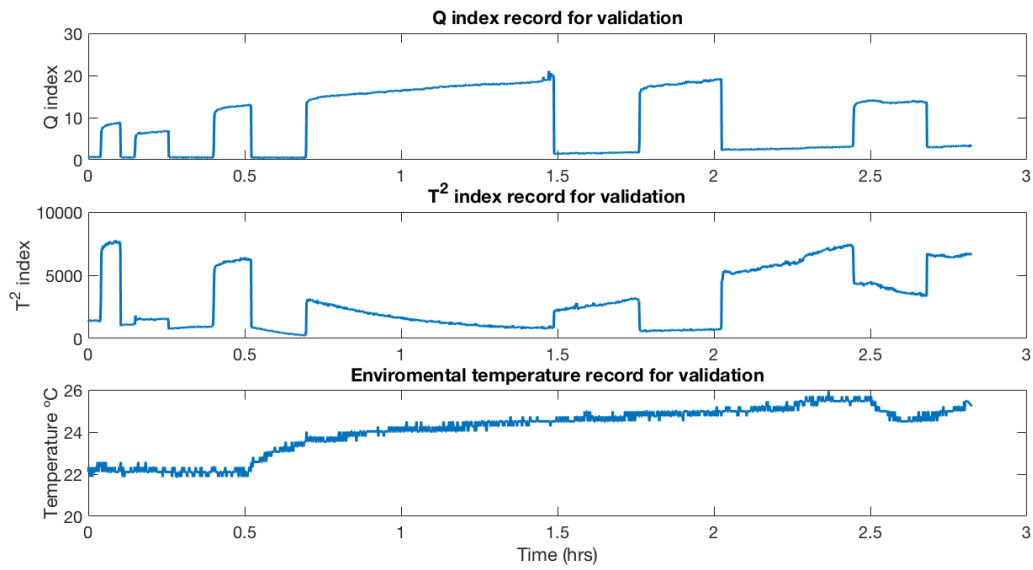Figure 5. Estimated vs measured statistical indices for a daily profile

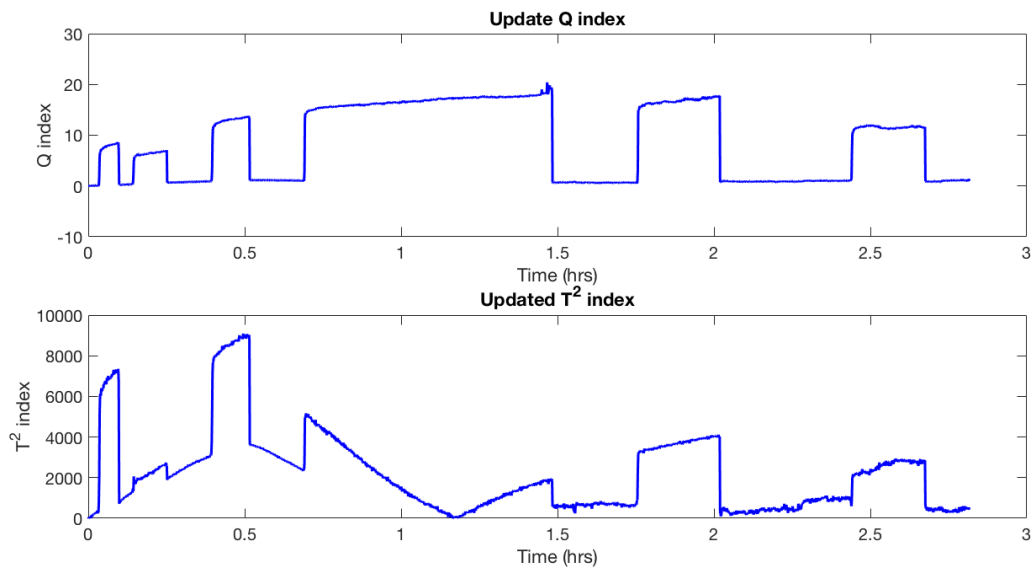Figure 6. Q, T^2 and T record for validation purposes
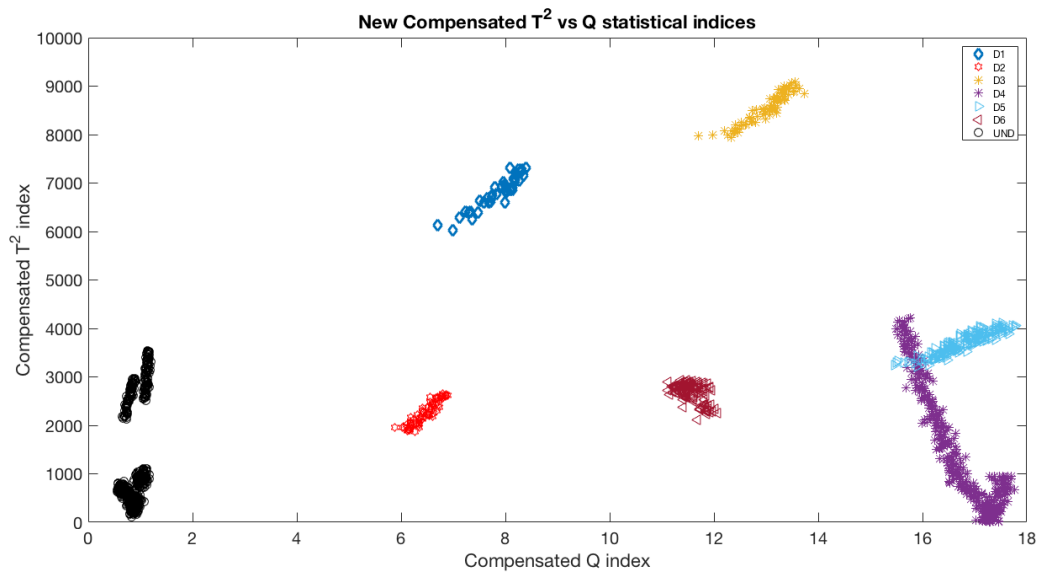

Figure 7. New compensated indices

Figure 8. New compensated T^2 vs Q indices for undamaged and damage cases

4. Conclusion

In this approach compensated statistical index is proposed for detecting damages in metallic cylindrical specimens by means of piezo-diagnosis principle and based on PCA. The novelty here was to compute the contribution of environmental temperature changes on the traditional T^2 and Q statistical indices and to exclude their effect for damage detection. The temperature variations corresponded to natural environmental temperature variations during a day and two first order models were identified and used to compute the mentioned contributions. Thus the proposed damage detection methodology becomes robust to detect damages front to temperature variations by using a compensated Q index. Additionally, by taking into account the graphical results is easy to distinguish types of damages (different location of added mass), thus at least a qualitative location of damage could be inferred by using a combination of both compensated indices T^2 and Q.

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