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Statistical analysis of IR thermographic sequences by PCA

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Abstract

Automatic processing of IR sequences is a desirable target in Thermal Non-Destructive Evaluation (TNDE) of materials. Unfortunately, this task is made difficult by the presence of many undesired signals that corrupt the useful information detected by the IR camera. In this paper the Principal Component Analysis (PCA) is used to process IR image sequences to extract features and reduce redundancy by projecting the original data onto a system of orthogonal components. As a thermographic sequence contains information both in space and time, the way of applying the PCA to these data cannot be straightforwardly borrowed from typical applications of the PCA where the information is mainly spatial (e.g. remote sensing, face recognition). This peculiarity has been analysed and the results are reported. Finally, in addition to the use of the PCA as an unsupervised method, its use in a "learning and measuring" configuration is considered.

Keywords: IR image sequence; Principal component analysis; Learning and measuring; Data compression; Feature extraction

1. Introduction

PCA is a quite old method, originated in 1901 by Pearson [1] and later developed by Hotelling [2]. It has found its application in various fields such as face recognition, remote sensing, and image compression and is a common technique for summarizing data of high dimension. It is a classical multivariate analysis that is useful for data compression and detection of linear relationships. It is essentially equivalent to Karhunen–Loeve transformation and closely related to factor analysis. All these methods are based on second order statistics of the data. Recently, the PCA technique was introduced in the thermal non-destructive evaluation (TNDE) field for discriminating between optical and thermal effects in open-crack detection [3]. In such an application, the PCA was used to qualitatively enhance the thermal signal due to the open-crack and to reduce the optical effects regarded as false alarms. A more recent application called Principal Component Thermography (PCT) [4] has been proposed as a method for defect depth characterization. In this quantitative approach, a link between some principal components and the thermal contrast was found. This made it possible to formulate a calibration function for the defect depth estimation. These first applications of the PCA to thermal data

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showed some interesting potentialities that it is worth investigating. The question is whether the PCA can be straightforwardly borrowed from its typical fields of application, or there is a better way to take advantage of the specific nature of the thermal signal. Indeed, a set of IR images coming from a dynamic thermal test contains useful information both in space and time. Furthermore, most of the processing algorithms in TNDE are based on the analysis of the thermal contrast evolution in time, while spatial analysis is rarely used. This peculiarity makes thermal sequences different, for instance, from multispectral images used in remote sensing. This paper reports on the possible ways of applying the PCA to IR sequences captured in transient TNDE procedures. The example of application to experimental data will be reported. It will be shown that the signal decomposition operated by the PCA provides good, but generally not predictable results. This is acceptable for qualitative analysis carried out by an operator, but prevents the use of the PCA in automated environments. To overcome this problem and take a step toward quantitative applications, a learning phase is introduced.

2. Basic principles of PCA

The PCA is a linear projection technique for converting a matrix $\mathbf{A}$ of the dimension $m \times q$ to the matrix $\mathbf{A_p}$ of the lower dimension $s \times q$ ($s < m$) by projecting $\mathbf{A}$ onto a new set of principal axis. This can be done by the matrix multiplication $\mathbf{A_p} = \mathbf{U}^T\mathbf{A}$ where the columns of $\mathbf{U}$ are the projection vectors that maximize the variance retained in the projected data $\mathbf{A_p}$. This operation can be also seen as a linear transformation that minimizes the reconstruction error or a procedure to obtain uncorrelated projected distributions. Each principal axis corresponds to the normalized orthogonal eigenvector of the scatter matrix $\mathbf{S} = (\mathbf{A} - \mathbf{A}_{\text{mean}})(\mathbf{A} - \mathbf{A}_{\text{mean}})^T$ of $m \times m$ elements. One simple approach to the PCA is to use singular value decomposition (SVD) of $\mathbf{S}$:

$$\mathbf{S} = \mathbf{U}\mathbf{D}\mathbf{U}^T = [\mathbf{U}_s \quad \mathbf{U}_n]\begin{bmatrix} \mathbf{D}_s & \\ & \mathbf{D}_n \end{bmatrix}[\mathbf{U}_s \quad \mathbf{U}_n]^T \quad (1)$$

where $\mathbf{U}$ is the eigenvector matrix (i.e. modal matrix) and $\mathbf{D}$ is the diagonal matrix whose diagonal elements correspond to the eigenvalues of $\mathbf{S}$ (in descending order). Then the PCA transformation from m-dimensional data to s-dimensional subspace (with $s + n = m$) is given by choosing the first s column vectors. The matrix $\mathbf{A_p}$ taking into account the first s principal components is given by:

$$\mathbf{A_p} = \mathbf{U}_s^{\mathrm{T}}\mathbf{A} \quad (2)$$

The choice of s is based on the desired amount of the variance proportion retained in the first s eigenvalues:

$$r = \frac{\sum_{i=1}^{s} d_i}{\sum_{i=1}^{m} d_i} \cdot 100 \quad (3)$$

where d_i is the ith element (eigenvalue) of the diagonal matrix $\mathbf{D}$. In many cases more than 95% of variance is contained in the first three to five components.

3. PCA applied to IR image sequences

Let us consider a typical thermal non-destructive test: a sample front surface is heated and the transient thermal process is observed by an IR camera. The acquired sequence of n_t IR images ($n_x \times n_y$ pixel) represents the source data volume $\mathbf{V}$ to be processed with the PCA algorithm. A pre-processing phase is needed to structure this three-dimensional data set in a way convenient for performing SVD. Before doing that, it is worth explaining the meaning of the columns and rows of the above mentioned matrix $\mathbf{A}$ with $m \times q$ elements. $\mathbf{A}$ represents a set of q measurements of m-dimensional data. To make the PCA work properly, the average value across each of the data dimensions must be subtracted to compute the matrix $\mathbf{S}$. Hence $\mathbf{A}_{\text{mean}}$ is an $m \times 1$ vector that is subtracted column-wise from $\mathbf{A}$.

As the information contained in the original volume $\mathbf{V}$ is both in space (e.g. defects geometry and location) and time (thermal contrast evolution), there are two possible ways to convert **V** into the matrix **A**.

Case 1: regarding **V** as a sequence of thermograms, $\mathbf{A}_1$ has $n_x \cdot n_y$ rows (each column is an unrolled image) and n_t columns. The data dimension is $n_x \cdot n_y$ and the number of cases (or measurements) is n_t.$\mathbf{A}_{1\text{mean}}$ is the mean image. From a dimensional point of view, the principal axes are images and the projected data are temporal profiles.

Case 2: **V** is considered as a sequence of thermal contrast profiles, $\mathbf{A}_2$ has n_t rows (each column is a time profile) and $n_x \cdot n_y$ columns. The data dimension is n_t and the number of cases is $n_x \cdot n_y$.$\mathbf{A}_{2\text{mean}}$ is the mean temporal profile. Dimensionally speaking, the principal axes are temporal profiles and the projected data are images.

3.1. Computational aspects

From the computational point of view the main difference between Cases 1 and 2 is the dimension of the matrix **S**. As an example, let us consider a sequence of 150 images 320×240 pixels each. In the first case $\mathbf{S}_1$ is a huge matrix of 76,800×76,800 elements which requires an amount of RAM hardly available in normal computers, in the second case $\mathbf{S}_2$ is a much smaller 150×150 matrix. In practice, it is always possible to use the second approach because there is a simple relationship to recover the eigenvector matrix of the Case 1 from that obtained in the Case 2:

$$\mathbf{U}_1 = (\mathbf{A}_1 - \mathbf{A}_{1\text{mean}})\mathbf{U}_2\mathbf{D}_2^{-\frac{1}{2}} \quad (4)$$

where $\mathbf{U}_2, \mathbf{D}_2$ are, respectively, the eigenvectors and eigenvalues related to the second case. It is worth noting that Eq. (4) is based on the assumption that

$$(\mathbf{A}_1 - \mathbf{A}_{1\text{mean}}) = (\mathbf{A}_2 - \mathbf{A}_{2\text{mean}})^T. \quad (5)$$

Hence, in such a condition, apart from the dimensional exchange between projection vectors and projected data, computing the PCA on $\mathbf{A}_1$ or $\mathbf{A}_2$ does not make any essential difference. For the sake of simplicity, from here on, the components having the same dimensions as the temporal profiles will be referred to as temporal components (TC) independently of their nature of principal vectors or projected data. Moreover, the first TC (TC1) will be that related to the largest eigenvalue and the following TC will follow the descending order of the respective eigenvalues. Analogously, the results of the PCA having the same dimensions as an image will be called spatial components (SC). All the following considerations will refer to the Case 2 without using any subscript to denote the matrix symbols.

3.2. Mean subtraction

Differently from the transposition of the matrix **A**, the way $\mathbf{A}_{\text{mean}}$ is computed influences the PCA results. As it was mentioned before, it is possible to subtract from each image the mean image or from each temporal profile the mean profile. To better analyse these two alternatives, experimental data are processed and results discussed. A test was carried out on a 3 mm thick steel plate with six circular bottom holes (10 mm in diameter) located at different depth, to simulate material loss due to corrosion from 50% to 2% of the total thickness. The sample was heated by two flash lamps delivering an energy pulse of 4800 J in 5 ms. An IR camera FLIR® SC3000 was used to image the specimen response. A sequence of 150 images was acquired at a frequency of 50 Hz amounting to an observation interval of 3 s.

3.2.1. Mean image subtraction

The first step was the normalization of the images by the second image in order to reduce the effects of a possible uneven heating pattern or absorption distribution. The choice of the second image instead of the first one available after the flash, was made to reduce the reflection signals coming directly from the heat source. Then the volume of raw data was reduced to a two-dimensional matrix **A** by a raster-like operation, the mean image (i.e. the averaged row) was finally subtracted from each row.

In such a way, the temporal profiles (columns of **A**) are the original temperature evolutions centered on zero (Fig. 1a). The PCA applied to **A** yields as a first result the TC (Fig. 1b) that represent the

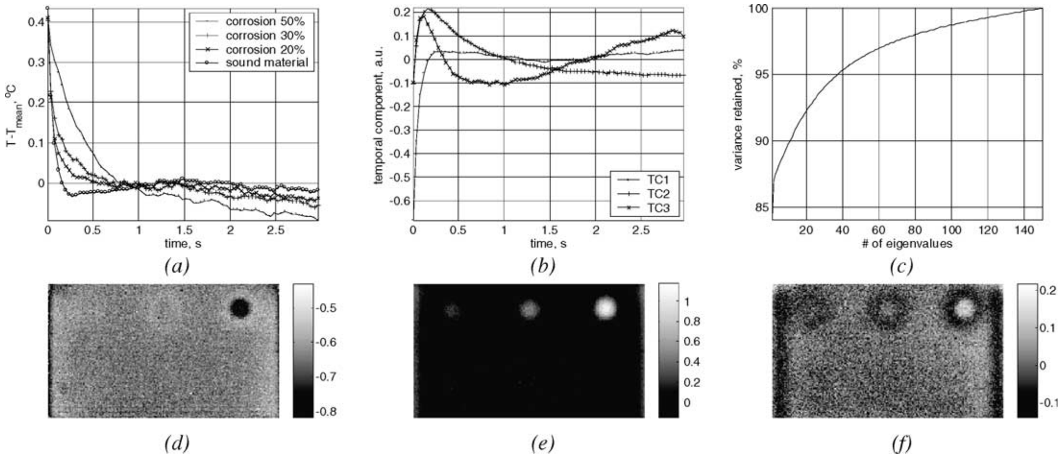

Fig. 1. Temperature profiles after subtracting the mean image (a); first three temporal components provided by PCA (b); dimensionality curve (c); first three spatial components (d, e, f).

uncorrelated decomposed profiles. In Fig. 1c the percentage of retained variance (Eq. (3)) is plotted against the number of eigenvalues considered. It can be seen that considering three components the 87.5% of variance is maintained (37 eigenvalues are needed to keep 95% of variance). Moreover, TC1 appears to be very similar to the mean temperature decay of the sample, while the following components look like thermal contrasts. Fig. 1d, e and f show the SC related to the first three TC. The SC1 (Fig. 1d) is the quite uniform image, except for the shallowest defect already visible in the normalizing image. This means that the contribution of TC1 is about the same for all the profiles. The SC2 (Fig. 1e), on the contrary, exhibits low values for the background and higher values for defects (decreasing according to the severity of the material loss). Finally SC3 still shows the marks of the three largest defects (boundary effects on the edges of the sample are visible as well).

3.2.2. Mean profile subtraction

The same procedure has been applied to the same data set but subtracting the mean temporal profile instead of the mean image. Results are reported in Fig. 2. Fig. 2a shows how the input profiles are now similar to thermal contrasts. Indeed, after normalization, as the most part of the sample is defect free, the mean profile is very close to the normalized temperature evolution over a sound area. Hence, the curves in Fig. 2a could be regarded as normalized contrasts. With respect to the previous case, now the SC1 is noisier (Fig. 2d) and the three main defects are barely visible. No marked evidence of the upper-right defect is seen. While before the TC1 was similar to the mean thermal decay, in this case it is a quite constant profile (Fig. 2b). As for SC2 and SC3, the considerations of the previous case hold on. In particular the defect visibility in the SC2 was evaluated through the SNR in both cases and the results proved to be the same. The amount of variance retained considering three eigenvalues is now 68%. To keep the 95% of information 80 eigenvalues are needed.

3.3. Other examples of application

Let us consider now another example of application of the PCA to non-destructive testing of a 25 mm thick piece of opaque plastic with nine square shaped bottom holes having 25 mm on a side. The defects are located at different depths (from 1.6 to 14.4 mm). The test was carried out using another IR camera. The results are depicted in Fig. 3 where four SC are considered. In this case, the difference between the two cases is emphasized. It is worth noting that the SC4 shows

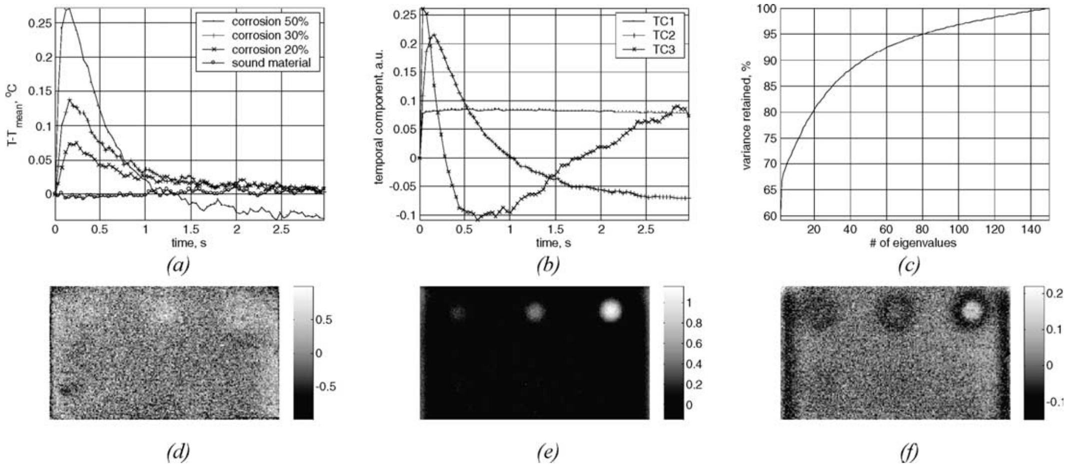

Fig. 2. Temperature profiles after subtracting the mean profile (a); first three temporal components provided by PCA (b); dimensionality curve (c); first three spatial components (d, e, f).

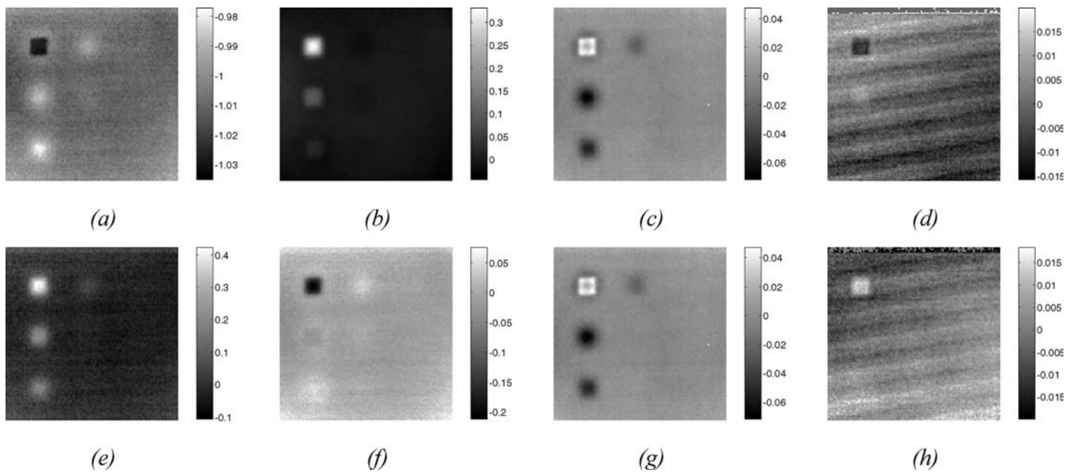

Fig. 3. TNDT of a plastic sample: spatial components provided by PCA after subtracting the mean image (a, b, c, d); spatial components obtained subtracting the mean temporal profile (e, f, g, h).

a very regular pattern probably caused by the malfunction of the camera synchronization device.

So far the examples reported above referred to a transient regime. In the following example, a 5 mm thick carbon fiber reinforced plastic (CFRP) plate is tested. Defects are simulated with nine square shaped Teflon® inserts having different sizes (12, 6 and 4 mm side length) and located at different depths (0.25, 1.25 and 2.5 mm).The sample was heated with a harmonic heat flux until the periodic regime was reached. Results are shown in Fig. 4. It can be noticed that in this case, compared to the transient tests, the two processing methods provide quite different results in both qualitative and quantitative aspects. For instance, the SC1 in the second row seems to show only the distribution of the uneven heating, while this information is totally absent in the first row.

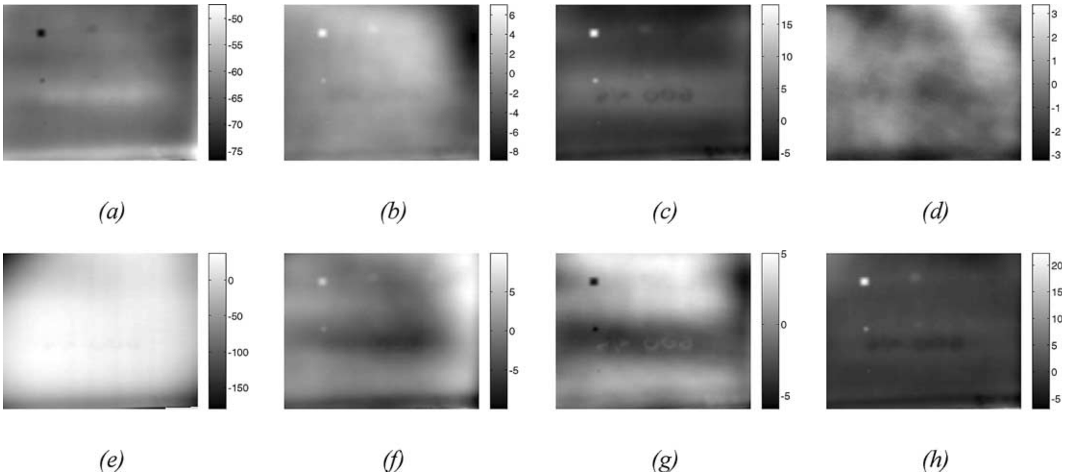

Fig. 4. TNDT of a CFRP in periodic regime: spatial components provided by PCA after subtracting the mean image (a, b, c, d); spatial components obtained subtracting the mean temporal profile (e, f, g, h).

4. Learning and testing

The PCA can be also used in a ''learning and testing scheme''. A training sequence is used to compute the new system of principal axes that, dimensionally, are temporal components. Afterwards, the training sequence is projected onto a specific subset of them so that each original profile is represented by its n coordinates, where n is the number of the projection vectors considered. These n-dimensional points (reference points) can be subdivided into subsets, each one having a specific meaning (for instance denoting a certain defect depth). A testing sequence is then projected onto the same principal vectors used before and the distances between each projected profile and the reference points are computed. The closest reference points will determinate the class assigned to the profile under test. This procedure was applied to the steel sample described before. The second and third TC were considered ($n = 2$). Classes from one to five represented the defect depths and the class 6 was related to the sound material. Two tests were carried out: one with the sample in a horizontal position (used for the learning phase) and one with the same sample rotated (testing phase). Fig. 5 shows the classification results. All the four defects were assigned to the correct class. This procedure, that can be easily made automatic, is useful when several tests have

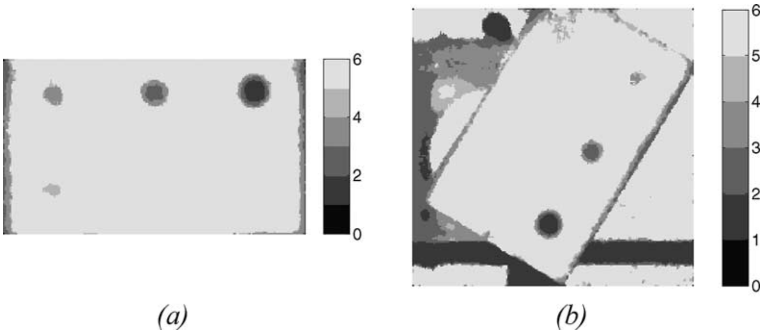

Fig. 5. Learning phase: after assigning the classes to defects depending on their severity, the training data were used for verification (a). Testing phase: result of the classification procedure applied to a testing sequence (b).

to be performed on the same kind of samples. Moreover, since a testing phase is based on matrix multiplication, it requires a very short computation time.

5. Conclusion

The application of the PCA to TNDT has been studied. The peculiarity of this application area stems from the fact that the information is in both space and time. This leads to the dual interpretation of the input data volume as a set of images or a set of temporal profiles. To better understand how the results are influenced by these two ways of thinking, the PCA has been applied to both cases. Some computational problems have been conditioned by the large dimensions of the scatter matrix. It has been shown that, in practice, this problem can be overcome thanks to the property of the eigenvectors matrix. The PCA technique has been then applied to the experimental data in both transient and periodic regime. It has been verified that considering the initial sequence as either a set of images or a set of temporal profiles influences final results. In any case, the PCA has showed its ability to extract features and condense information into a few images. Anyway, so far, no apparent connections have been found between the principal components and the physical processes involved in the test. Finally, the PCA technique was used for learning and testing. A preliminary training stage provided the principal components used as a reference system for implementing the classification algorithm. This procedure has been applied with promising results to the experimental data related to corrosion characterization.

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