ACTIVE IR THERMOGRAPHY PROCESSING BASED ON HIGHER ORDER STATISTICS FOR NONDESTRUCTIVE EVALUATION

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ABSTRACT

Active infrared thermography is a nondestructive method for evaluating defects in artworks. A conventional excitation radiation heats the sample and the photothermal response is recorded by an infrared (IR) camera. Classical pulsed excitation has shown the feasibility of such a detection system, but the energy deposition for a long period of time can alter samples. Random excitations can prevent such problem, but signal processing methods should be implemented to extract the useful information. We propose a processing method that combines Singular Value Decomposition (SVD) and Higher Order Statistics (HOS). The former decomposes the dataset in several subspaces, allowing to remove the influence of the acquisition environment and system. The latter is used to build up from the useful information one or two images for diagnostic. We show on a mural-type "laboratory" and on a *in situ* artwork that this method allows good identification of defects, providing a complementary detector to classical analysis.

Index Terms— Active infrared thermography, Higher Order Statistics, Skewness, Kurtosis, Singular Value Decomposition, Subspace decomposition.

1. INTRODUCTION

Traditional assessment of defects is the manual inspection called "acoustic sounding". It is realized by tapping lightly with the fingers the artworks. The quality of diagnosis depends however on the capacity of perception and experience of the specialist [1].

Thermal properties of materials can provide quantitative information regarding the state of artworks. Active infrared (IR) thermography is one method that enabled nondestructive testing assessment of properties of materials. It has been used for example to establish microclimatic conditions inside churches in Rome [2], to observe the level of conservation and the impact of visitors on paintings after restoration [3], to study masonry structures [4], etc. Active IR thermography has been also proved as a reliable method for nondestructive evaluation of porous carbon fiber reinforced polymers or plastic [5,6] and for the investigation of art and historic artifacts [7]. In these recent applications, a step heating was used as excitation and the increase of surface temperature was recorded by an IR thermal camera. Measured signals (heating and/or decay) as a time response in each pixel, governed by physical processes (thermal conductivity, thermal diffusivity, etc.), were modeled in order to extract different parameters and hence to assess defects [6,7]. Another approach was to estimate Higher Order Statistics (HOS) from the recorded signals, in each pixel, in order to construct maps of the analyzed sample and use them for the detection of defects [5]. However, the HOS were estimated on exponential decay signals. Such estimation is not appropriate as signals represent realizations of non-stationary processes. For such signals, estimation of parameters represents a more direct way.

The main disadvantage of the step heating method is that the energy is deposited for a continuous period of time, which may alter the artworks. Another solution is to use a Pseudo Random Binary Sequence (PRBS) excitation in order to deposit the same amount of energy, but randomly distributed over time. As processing method, the impulse response of the sample in each acquisition pixel is usually estimated (for example by correlation or parametric analyses [8,15]) and defects can thus be detected. This response includes heating and decay information, the processing being done during the application of the PRBS and not only heating or decay as in the step excitation case.

The use of HOS is more straightforward for random signals, but in our application the recorded signals are strongly influenced by several factors: the mean response of the analyzed sample (usually a sum of exponential signals); the environment (relative position of camera versus sample and excitation sources, ambient temperature, etc.); the recording instrument, etc. Due to influence of these factors, a direct application of HOS may lead to improper interpretation. The Singular Value Decomposition (SVD) is a useful tool to perform a separation of the initial dataset in complementary orthogonal subspaces by extracting decorrelated vectors [9,10]. It has been already used as an efficient preprocessing step to remove the ground response influence in the detection of anomalies in dikes [11,12].

The goal of this paper is to present a signal processing scheme for nondestructive active infrared thermography. The SVD is used to remove the influence of useless factors. This operation allows exploiting the HOS of recorded signals as they can be interpreted as realizations of a stationary (supposed ergodic) random process. Applications on a mural-type "laboratory" and *in situ* artworks show that the use of PRBS excitations, combined with this processing scheme, allows a very good identification of defects. This result is complementary to the classical one obtained by pulsed excitation, the in-depth defects being detected.

2. SYSTEM AND DATA DESCRIPTION

The acquisition system created by the GRESPI laboratory is presented in Fig.1. It consists of two conventional radiative sources (halogen lamps), which are excited with a PRBS signal (top left).

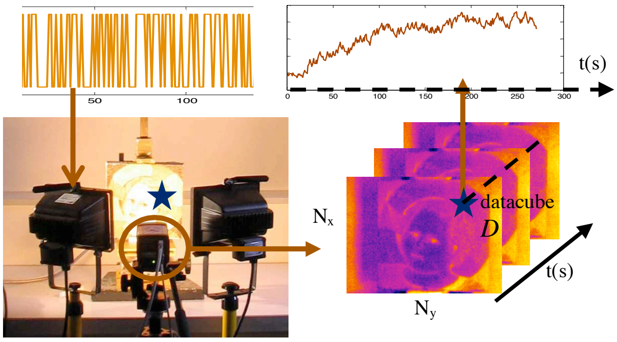

Figure 1: Data acquisition system. Top: excitation and sample of a recorded signal. Bottom right: recorded datacube *D*.

The IR thermal camera records images (bottom right) of size N_x x N_y pixels, with an acquisition frequency of F_a Hz. Images are recorded during a time T, resulting in $N_t = T{\cdot}F_a$ samples per pixel. An example of a signal recorded in one pixel is presented in the top right of Fig.1. The recorded data is thus a datacube:

$$D(x,y,t) \quad \text{with} \quad x \in [1, N_x], y \in [1, N_y], t \in [1, N_t] \quad (1)$$

As we are not interested in this work in the relation between adjacent pixels, we can unfold the datacube into a matrix format, D(k,t), with k an index depending of x and y. A signal recorded in one pixel thus represents one row of D.

3. SUBSPACE DECOMPOSITION BY SVD

The Singular Value Decomposition (SVD) of the data matrix is defined as [9-11]:

$$D = \sum_{i=1}^{N} \sigma_i u_i v_i^T, \quad (2)$$

where N = min{Nt, NxNy}, σ_i represent the singular values arranged in a descending order, while u_i and v_i are the left and right singular vectors. The vectors v_i represent the temporal variations, while the vectors u_i their variation in the image plane.

The SVD can be used to separate the recorded data into orthogonal subspaces. In our case, the data matrix is affected by an energetic mean response of the analyzed sample (a sum of exponentials as illustrated in Fig. 1 for one recorded signal). This response depends on the acquisition pixel due to the configuration of the system and the environment (relative position of camera versus sample and excitation sources, ambient temperature, etc.). This information can be extracted by the most energetic subspace. Such kind of analysis has already been done in other applications, as for example the extraction of the ground response in the problem of leakage detection in dikes [12]. On the other hand, the recorded data is polluted by noise (electronics, etc.). As the noise is supposed white and uncorrelated, it is generally modeled by the least energetic subspace. The decomposition of the matrix data D in the corresponding subspaces is given by:

$$D(k,t) = D_{trend}(k,t) + D_{useful}(k,t) + D_{noise}(k,t) = \quad (3)$$
$$= \sum_{i=1}^{m} \sigma_i u_i v_i^T + \sum_{i=m+1}^{n} \sigma_i u_i v_i^T + \sum_{i=n+1}^{N} \sigma_i u_i v_i^T,$$

where: the subspace D_{trend} constructed with the first more energetic m vectors models the mean response of sample and the environment; the subspace D_{noise} constructed with the last N-n vectors characterizes the uncorrelated white noise; the useful information is spanned by the rest of vectors into the D_{useful} subspace.

4. HOS AS DIAGNOSTIC TOOL

Higher-order statistics (HOS) are descriptive measures of probability distributions and sample distributions [13,14]. These statistics have been already used in different applications for defining signal processing tools. For example, a criterion based on kurtosis was used to identify meteorological changes from temperature data recorded by optic fibers buried into the ground [11].

In order to use HOS as processing tools, signals are supposed to be realizations of a stationary random process. This is not the case for this application because the recorded signals present an increasing trend due to the accumulation of energy by the sample, as illustrated in the upper right of Fig. 1. Interestingly, the high energetic signal subspace D_{trend} estimates a mean trend of the response of the analyzed sample. This allows access to variations around this mean trend as the PRBS excitation is a random one. The useful information in the D_{useful} subspace can be interpreted as realizations of a stationary (supposed ergodic) random process. HOS can thus be estimated in each acquisition pixel. The third and fourth order normalized statistics are considered here, namely the skewness $\kappa_3(k)$ and kurtosis $\kappa_4(k)$, "k" being the index depending of position (x,y):

$$\kappa_3(k) = \frac{\widehat{\underset{t}{cum}}\left(D_{useful}(k,t), D_{useful}(k,t), D_{useful}(k,t)\right)}{\left[\widehat{\underset{t}{cum}}\left(D_{useful}(k,t), D_{useful}(k,t)\right)\right]^{3/2}}, \qquad (4)$$

$$\kappa_4(k) = \frac{\widehat{\underset{t}{cum}}\left(D_{useful}(k,t), D_{useful}(k,t), D_{useful}(k,t), D_{useful}(k,t)\right)}{\left[\widehat{\underset{t}{cum}}\left(D_{useful}(k,t), D_{useful}(k,t)\right)\right]^{2}}$$

where the 2nd, 3rd and 4th order cumulants should be estimated by using the unbiased estimators: the k-statistics [13,14], considering $D_{useful}(k,t)$ as realizations, over t, of a stationary and ergodic random process. It should be mentioned that variances of skewness and kurtosis only depend on the number of elements used to estimate them, namely the number of time samples in our application.

5. PROPOSED SCHEME

The methodology adopted for the nondestructive investigation of artworks is now schematized. As a first step, the datacube $\mathcal{D}$ recorded by the IR thermal camera using a PRBS random excitation (see Fig. 1) is unfolded into a matrix format D.

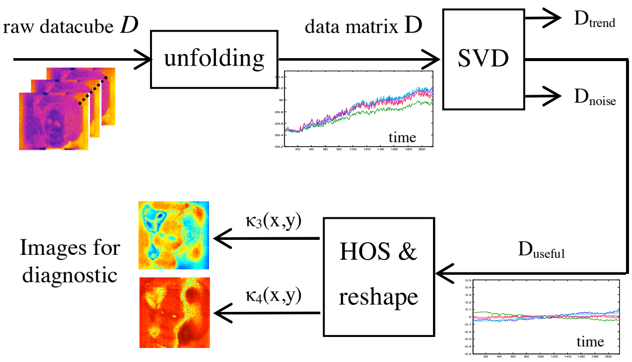

Figure 2: Proposed scheme based on the SVD and HOS of IR response at PRBS random excitations for nondestructive investigation of artworks.

As defects provide responses different of a normal area, their thermal signatures are not coherent and will not be revealed in the first few vectors obtained by SVD. On the other hand, the analyzed sample presents an increasing trend due to the accumulation of energy, which can be estimated by the first few SVD vectors. The noise related to the recording system (electronics, etc.) may provide a bias in the estimated HOS values. This noise can be removed by the last SVD vectors. The result of SVD is analyzed in terms of choice of the number of singular values, m and n, to be kept for constructing the useful subspace D_{useful}. The choice of these values is made on the basis of energies of the resulting subspaces, which are dependent on the recorded signals.

HOS estimators are then computed on this subspace, allowing estimation of skewness and kurtosis values in each acquisition pixel. These values can then be reshaped in a matrix format indexed by the coordinates (x,y), providing two images for the diagnostic of artworks.
Summarizing the above discussion, the proposed scheme for the nondestructive identification of defects in artworks is presented in Fig. 2.

6. APPLICATION

A partial replica of St. Christopher carrying the Christ Child, Florentine artwork of the late fourteenth century from the Campana collection of Louvre, was created in laboratory according to the technique of the Italian primitives [1]. This first artwork, shown in Fig. 3(a), was used to test the proposed scheme as nondestructive investigation method. Five defects illustrated in Fig. 3(b) were introduced during its manufacture: (A) is tilted with depth varying from 3 to 10 mm; (B) is located at 5 mm depth; (C) and (D) at 3 mm, while (E) at 10 mm. Defects (C) and (D) are of same type, different from (A), (B), and (E) which are of another type.

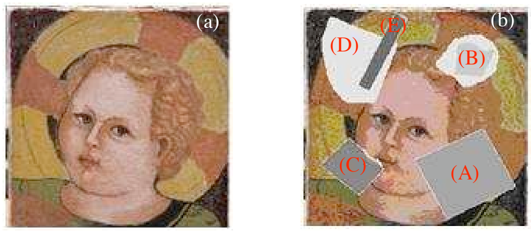

Figure 3: Replica of St. Christopher artwork (a); Defects introduced during its manufacture (b).

Data acquisition was realized with the system presented in Fig.1. The halogen sources of 250 W were excited with a PRBS signal. The IR thermal camera was used to records images of size N_x = 240 x N_y = 320 pixels. The excitation and the IR thermal camera were synchronized, the total acquisition time being T = 256 seconds with an acquisition frequency of 1 Hz. However, the interesting area representing the St. Christopher replica being of 218 x 224 pixels, only this information was considered. The raw datacube $\mathcal{D}$ is thereby of size 218 x 224 x 256, which gives after unfolding a data matrix D of size 48832 x 256.

The SVD allows to decompose the data matrix D into N=256 singular vectors with no vanishing singular values. The ratio $\sigma_1/\Sigma\sigma_i$, with i=1..N, represents 93.5%, meaning that the first vector extracts a high energetic subspace. We can thus choose m=1 to construct the first subspace that models the mean response of the sample and the environment. In order to choose the value of n, we have arbitrarily imposed that the D_{useful} subspace shall represent half of the energy of the subspace obtained after the removing of the first one, meaning n=39. This value does not substantially change the final result and should be properly estimated in future works on a large database.

After identifying the high energetic signal subspace ($m = 1$), mainly representing the trend of the response of the analyzed sample, as well as the noise subspace ($n = 39$), the D_{useful} subspace can thus be obtained using Eq. (3). This subspace contains the information related to defects and provides signals that can be interpreted as realizations of a stationary, supposed ergodic, random process. To illustrate this idea, Fig. 4(a) presents responses over time recorded by the IR camera in 1000 pixels chosen randomly (i.e. 1000 lines of data matrix D). The vertical axis represents the temperatures. Fig. 4(b) shows the signals after removing the trend and the noise (i.e. the lines at same positions but from data matrix D_{useful}).

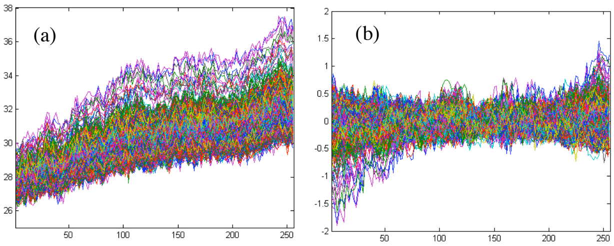

Figure 4: Several responses over time recorded by the IR camera (a); Signals after removing trend and noise (b), which can be interpreted as realizations of a stationary process.

Descriptive measures of these signals can thus be estimated by using HOS. Estimators of skewness and kurtosis were computed for each row "k" of the subspace D_{useful}. The estimation was done by employing k-statistics [14]. This means that the estimators are unbiased with variances only depending on the number of time samples, i.e. 0.023 for skewness and 0.092 for kurtosis.

After reshaping these values in a matrix format indexed by the coordinates (x,y), the obtained results on this dataset are shown in Fig. 5.

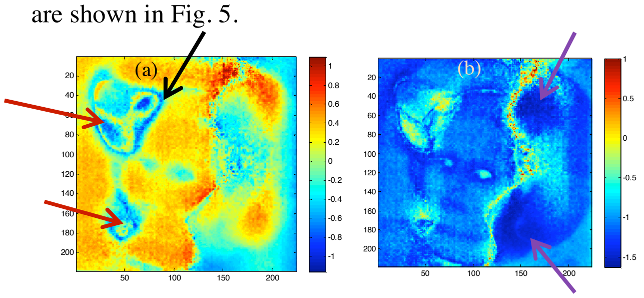

Figure 5: St. Christopher artwork, estimator of skewness (a) and kurtosis (b). Defects (C) and (D) of same depth and type are indicated by red arrows. The more in-depth defect (E) indicated by the black arrow changes the values of the skewness, imposing an important heterogeneity. Defects (A) and (B), of same type but different depths, are indicated by purple arrows in the kurtosis map. The defect (A), having a varying depth, imposes an interesting heterogeneity.

The skewness identifies defects (C) and (D), indicated by red arrows, which are of same type and same depth. Interestingly, this measure presents heterogeneities, which could be related with the type of defects. For defect (D), it could be linked with the presence of a more in-depth defect (E) shown by the black arrow. This result is very interesting and has never been obtained before, as discussed thereafter in the comparison paragraph.

The kurtosis identifies defects (A) and (B), shown by purple arrows, which are of same type and about same (average) depth. The defect (A) is tilted with depth varying from 3 to 10 mm, while (B) is located at a constant 5 mm depth. The defect (A) exhibits an interesting heterogeneity into the estimator of kurtosis, opening consideration for depth estimation of defects by the proposed scheme.

We have chosen to compare these results with the ones obtained on the same artwork in previous studies but using "usual" methods. The Fig. 6(a) shows the IR image recorded 160 seconds after the end of a step heating excitation. It represents the best result we can obtain with such kind of excitation, the intensities of the presented image being scaled to optimize the contrast [15]. Fig. 6(b) presents the result of a parametric analysis of the response to a PRBS excitation, as it was detailed in [15-17]. Presentation of these methods is outside the scope of this paper as well as the analysis of the influence of different parameters. What we are interested here is to compare at a glance the proposed scheme with usual analyses in the nondestructive investigation domain. An immediate observation is that the defects are better localized in both HOS measures. Another remark is that defects respond differently depending on their types, being highlighted by either the skewness or the kurtosis. The last is the presence of heterogeneities in the HOS estimators that could be used to quantify valuable information about the depth of defects.

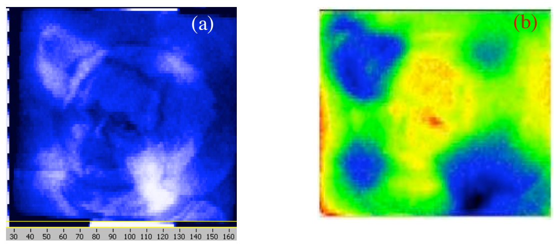

Figure 6: Defects estimation with other methods [15-17]: best contrasted image from an acquisition with a classical step heating excitation (a); results of a parametric analysis of the response to a PRBS excitation (b).

The second analyzed artwork is the St. Martin of the church of Bonnet from the 19th century. This time we deal with *in situ* acquisition. Fig. 7(a) shows the acoustic sounding (finger tapping) analysis, manually realized by the specialist. Due to the limited place, we present only the kurtosis map, in Fig. 7(b), which has been estimated with the same processing scheme. More information and discussions can be found in [18].

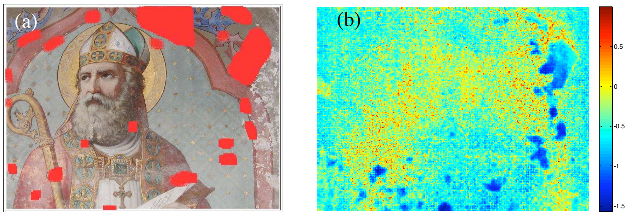

Figure 7: St Martin artwork, acoustic sounding analysis (a) and estimator of kurtosis (b). Kurtosis provided similar results to those obtained by acoustic analysis, being insensitive to pictorial layer.

Fig. 7(b) shows that the kurtosis can identify the defects, except for the upper and left sides. This was also the case with other methods of signal processing, including the step excitation case, being probably related to the acquisition settings. With the proposed scheme and wising PRBS excitation, defects are precisely localized, the final result being insensitive to pictorial layer, which can be an advantage but also a disadvantage [18].

7. CONCLUSION AND PERSPECTIVES

We have shown that the active IR thermography using a random PRBS excitation can be efficiently used for nondestructive investigation of artworks. In order to detect defects, we have proposed a processing scheme based on SVD and HOS. The decomposition of the raw data in 3 subspaces allows identifying a high energy subspace, mainly representing the trend of the response of the analyzed sample, as well as the noise subspace. The SVD can thus be used to extract the useful information related with the defects, providing signals that can be interpreted as realizations of a stationary random process. These signals can be further analyzed by HOS tools, namely skewness and kurtosis. These tools are very efficient to localize the defects, the accuracy being better than the state of the art methods. Moreover, the in-depth defects can be highlighted by this method, inducing interesting heterogeneities in the values of the skewness. The proposed scheme also permits to distinguish between different types of defects and to open consideration for further work dealing with the depth estimation.

Further work will also concern investigation of values of m and n in respect with parameters of the PRBS excitation (total time, amplitude, total energy, minimal energy of a pulse, etc.) as well as other methods to estimate and remove the trend or adaptation of methods insensitive to trend such as ICA-wavelet decomposition [19].

8. REFERENCES

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