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# Principal Components Analysis for RGB and Intensity data reduction

168

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# PRINCIPAL COMPONENTS ANALYSIS FOR RGB AND INTENSITY DATA REDUCTION

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168

# Table of contents

## Introduction

The complete survey of a building facade can be carried out by acquisition of its geometry by means of a terrestrial laser scanning (TLS), which also provide radiometric information about the signal intensity, and characterization of the material by means of RGB data provided by calibrated camera, temperature data provided by thermographic camera, deformation maps provided by interferometry radar, and so on. Nevertheless, since the collected data are sometimes significantly redundant, their amount can be so large that the interpretation is difficult or also impossible. Similar problems affect a multiband survey of a rock wall.

In order to reduce the redundancy and to keep only the significant information, the use of suitable processing techniques, aimed to enhance the really interesting features of the observed scenario, is necessary. The principal component analysis (PCA) can be a good solution for the data amount optimization.

A simple approach to PCA-based image analysis is here described, in order to stress the method potentiality in the context of processing of radiometric data aimed to TLS data texturing.

In previous technical reports, Pesci et al. [2009, 2010] described the procedure for TLS point cloud texturing with intensity and RGB information, leading to a complete reconstruction of physical surfaces with captured details and features. The present paper is aimed to provide the next processing step in terms of data management for effectiveness information analysis.

## 1. PCA basic concepts

The Principal Components Analysis (PCA) is a method able to reduce redundant information about experimental data simplifying the recognition of details and hide features. It works similarly to a matrix diagonalization, leading to a new basis of the space of data whose component are totally independent. In order to clarify the concept, a classic simple example is proposed in figure 1. The data are distributed inside an elliptical area, along two preferential directions easily recognized corresponding to the major and minor ellipse axes. The recognition of these preferential directions strongly facilitate the data analysis. It is the case, for example, of the dispersion of GPS data, largely known in geodesy.

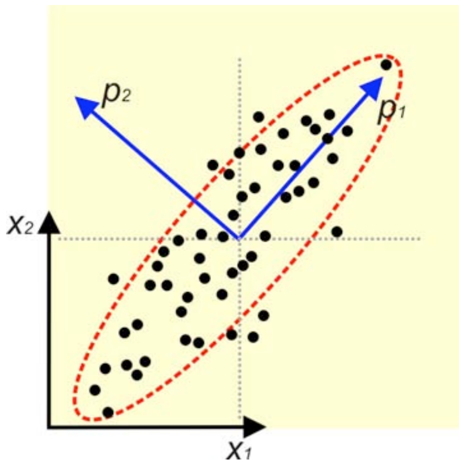


**Figure 1.** Reference frame transformation.

Let $X$ be a $n$-by-$k$ real matrix with $n \leq k$ (in data analysis, generally it is $n$ << k). The singular value decomposition (SVD) of $X$ is given as $X = UDP^T$ where $U$ is a $n$-by-$n$ orthogonal matrix, $P$ is a $k$-by-$k$ orthogonal matrix, and $D = \mathrm{diag}(d_1, d_2 \ldots, d_n)$ is a $n$-by-$k$ diagonal matrix with $d_1 \geq d_2 \geq \ldots \geq d_n \geq 0$. Since $D$ is in general not a square matrix, strictly speaking it is a matrix whose first $n$ columns are a $n$-by-$n$ diagonal square matrix whereas the remaining $k - n$ columns are all zero. The non-zero $d_j$ values are called singular values of $X$, whose number $r$ is the rank of the matrices $X$ and $D$, while the remaining, zero values can be discarded reducing the dimensionality of the problem. The SVD decomposition can be found for each matrix, although in general it is not unique (Golub and van Loan, 1980).

Let now $A$ be a $m$-by-$m$ square real symmetric matrix. It is diagonalizable, leading to the eigenvalue decomposition $A = P\Lambda P^T = \sum_{i=1}^{m} \lambda_i \mathbf{p}_i \mathbf{p}_i^T$, where $P$ is an orthogonal matrix whose columns $\mathbf{p}_1, \mathbf{p}_2 \ldots, \mathbf{p}_m$ are the eigenvectors and $\lambda_1 \geq \lambda_2 \geq \ldots \geq \lambda_n$ are the eigenvalues of $A$.

If $X$ is an $n$-by-$k$ data matrix, the $k$-by-$k$ matrix $A = X^T X$ is symmetric and therefore is diagonalizable. For this reason it is $A = X^T X = PDU^T UDP = PD^2 P^T$ (note: $U^{-1} = U^T$ ). The elements of the diagonal $D^2$ matrix are $d_1^{\ 2}, d_2^{\ 2}, \ldots d_r^{\ 2}$, i.e. they are the $r$ non-zero eigenvalues of the matrix $A = X^T X$, with $r = rank(A) \leq n$.

If $X$ is a centered matrix of experimental data, i.e. a zero mean data matrix, $A = X^T X / (n-1)$ is the variance-covariance matrix of $X$. The PCA is the eigenvalue decomposition of the variance-covariance matrix $A$. Since a diagonal matrix is obtained, which implies that the covariance values vanish, the applied transformation provides a new reference frame whose directions are mutually independent.

## 2. PCA of a series of images

Let consider an RGB image consisting of 3 $l$-by-$m$ matrices $R$, $G$, $B$, corresponding to the red, green and blue channels respectively. The $3$-by-$k$ data matrix $X$, with $k = l \cdot m$, can be created by reshaping each one of the $R$, $G$, $B$ matrices in to the corresponding $k$-length row. For example, if the RGB matrix is a *128*-by-*128*-by-*3* matrix, the $X$ matrix is *3*-by-16384. Before the next step, the normalization of $X$ to obtain a zero-centered, 1-standard deviation matrix is carried out. Later on, the normalized version of $X$ is considered.

The PCA of $X$ leads to 3 independent directions, ordered for importance in data description. The first component value describes the maximum data variability, the second one describes the maximum variability of the remaining data and so on. If an eigenvalue is relatively low with respect to the first one, it can be discarded supposing its contribute is not relevant and probably related to the data noise only. If the first eigenvalue is normalized to 1, typically the threshold is 0.02 (see e.g. Jollife, 2002).

In general, the same procedure can be used for $n$ data matrices. For example, if an RGB image (three components), an intensity image (grey level data, i.e. one component) and a thermographic image (one component) are available, a 5-rows $X$ matrix is built and the PCA leads to 5 independent directions. One or more of these could be neglected because of their low corresponding variance.

Finally, the PCA allows the reduction of the dimensionality of the problem and the easy detection of the main features of the observed object.

A simple example for the PCA ability in redundant data reduction is here provided. Figure 2 shows the three color components $R$, $G$ and $B$ of a true optical digital image acquired in Piazza S. Stefano (Bologna, Italy). The original image is a 219-by-330-by-3 matrix whose rows results to be highly correlated. The PCA analysis results in an output matrix with 219-by-330 elements only. In fact, only the first eigenvalue, computed as 0.8 is accepted, while the remaining two eigenvalues are lower than the threshold 0.02. Figure 3 shows the final image, which is the first principal component and is composed of all the main interesting features extracted by input data.

Regarding to the computational cost of the procedure, the fact that the SVD of a $n$-by-$k$ matrix $X$ require the diagonalization of a $k$-by-$k$ matrix $A$, with large $k$, should be noted. In the case above shown, a 72270-by-72270 matrix is involved, since $72270 = 219 \cdot 330$.

**Figure 2.** The RGB image decomposed in the three *R*, *G* and *B* components. The correlation is evident, showing redundant data.

**Figure 3.** New 219-by-330 image obtained from PCA, containing all the significant information with no useless redundancy.

## 3. PCA analysis for TLS point clouds: "Corte Isolani" study case

In June 2010, an experimental survey was planned and executed to test the efficiency of Optech ILRIS 3D TLS (Optech, 2010) in architectural applications. In particular, the front of the Corte Isolani palace in Bologna city was measured.

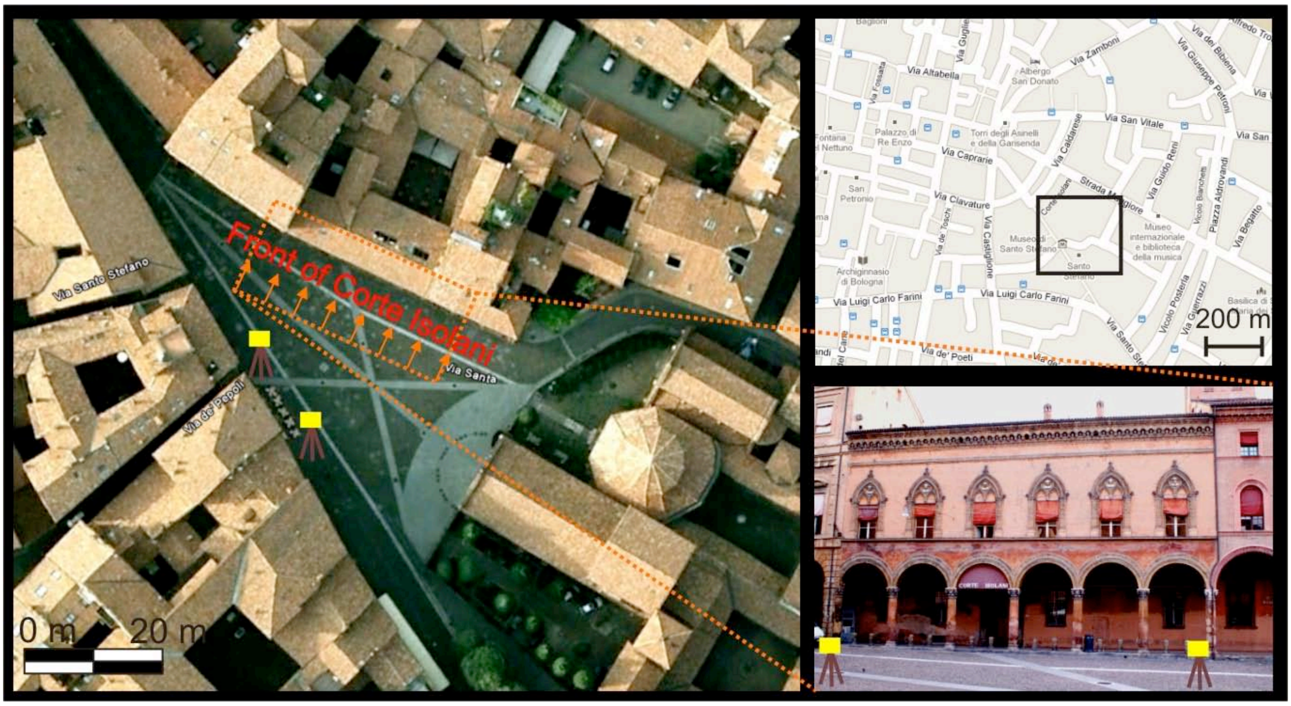


**Figure 4.** Panorama of S. Stefano square in Bologna. The front of the Corte Isolani palace is zoomed in the left bottom part of the figure. The arrows schematically show the acquisition direction from the two base points of the scanner.

This kind of long range instruments is conceived for the acquisition at ranges of the order of some hundred meters and is especially designed for the monitoring of natural surfaces like volcanic craters, landslides, glaciers, quarries and so on (see e.g. Vosselman and Maas, 2010). The survey was performed to acquire both the intensity and the RGB information, by means of a calibrated camera mounted on the top of the scanner. The Nikon reflex D50, which is characterized by 28-mm focal length and 8.0 mega-pixel resolution was used.

The standard procedure for data texturing was carried out by using Innovmetric PolyWorks software package (Innovmetric, 2010), providing both the metric and the radiometric information to the point clouds (figure 5).


**Figure 5.** Intensity and RGB textured point clouds. The images are snapshots of the point cloud managed by using PolyWorks, subsequently processed to have the same resolution.

In this section the MATLAB$^{TM}$ package is used to perform the PCA of the RGB and intensity data via a SVD. The data processing is performed in the following steps:

1) Preprocessing of the RGB and intensity data to obtain images that can be analyzed together, i.e. a RGB image represented by $n$-by-$m$-by-3 matrix and the corresponding intensity image represented by a $n$-by-$m$ matrix. After the exportation of the snapshots from PolyWorks, the preprocessing is competed by using Corel Draw 11.
2) Since MATLB cannot manage square matrices that are greater than $p$-by-$p$, where $p$ depends on the MATLAB version, the operating system and the available RAM (for example, if MATLAB 7.0 is used under Windows XP and 2 Gb RAM are available, it is $p \approx 80$), each image is subdivided in square submatrices each having $p$ side.
3) Each submatrix is normalized to obtain a zero-centered, 1-standard deviation matrix.
4) The four corresponding $p$-by-$p$ matrices, three extracted from the RGB image and the fourth from the intensity one, are reshaped into $p^2$-length row vectors, and these row vectors are inserted into a 4-by-$p^2$ matrix.
5) The PCA is carried out on each of the obtained matrices. Since four components are processed, also the principal components (PCs), which are $p^2$-by-$p^2$ matrices, are four, but the components whose eigenvalues are lower than the chose thresholds (0.02) are discarded.
6) The output images, with are the PC of the input images, are built from the kept PCs of the $p^2$-by-$p^2$ matrices.

As a consequence of the subdivision of the input images into squared submatrices whose size is compatible with the MATLAB limitations, the trace of such a subdivision can be seen on the output image. This fact is not a limitation of the method because the PCA is not performed for aesthetic quality purposes, but its aim is the aid in recognition of significant features of the observed object. The PCA is not used in point cloud texturing, which is carried out by using either RGB or intensity information (or also other information, e.g. thermographic data) instead. For example, in architectural survey the PCA of the set of an RGB and of the corresponding intensity image can lead to an easy recognition of a crack that could be missed in a simple inspection of a RGB image. If a binary operator like the Sobel one is used to automatically perform an edge detection procedure, the borders of the subdivision could appear, but they can be easily removed because they are linear, regular features.

The MATLAB script, that can operate on MATLB 6.5 or later versions, allow the optimal choice about the squared submatrix subdivision on the basis of the user's needs and resources. The script can be freely requested to the authors (pesci@bo.ingv.it or giordano.teza@unipd.it).

The following analyses were carried out:
i) PCA of the three components of the RGB image (three input vectors);
ii) PCA of the RGB and intensity data (four input vectors);
iii) PCA of the $R$ component and of intensity data (two input vectors).

Figures 6 and 7 show the main results, whereas table 1 shows, for each case, the number of PCs larger than the threshold (the standard threshold 0.02 is used here). The fact that, in all the cases, the main features can be seen in the first PC should be noted. In any case, also in those cases where a second PC is larger than the threshold, the recognition of interesting features is strongly facilitated with respect to the direct analysis of four components.

Thanks to the merging of the intensity (in the near infrared band, 1535 nm wavelength, therefore particularly sensible to the effects of the moisture) and color information, the defects of plaster and the moisture spots can be better recognized in PCA than in the original images. This fact appears to be clear in figure 7, which is a zoom of the facade shown in figure 6. Although some important and large features can be recognized by using the RGB image (in general, the moisture acts on the plaster color), the recognition of the cracks is very hard if such an image is used. In particular, the cracks and some high spatial frequency features (i.e. features having sharp variation) can be easily detected if the second PCs are used (see figures 7.b and 7.c, right panels). Moreover, the borders of a zone of moisture, and the degree of moisture in various zones of the observed facade or structure, can be easily detected if the PCs are used. The fact that the zone of moisture in figure 6.a has unclear borders, whereas these borders can be see in the PCs should be noted.

Also in the case of the PCA of the set of red component and intensity image the plaster defects can be better observed in the retained PCs with respect to the case of RGB image. This is related to the fact that in the first case two partially correlated, but not strongly correlated, channels are studied, leading to two significant PCs (i.e. PCs having eigenvalue larger than the chosen threshold), whereas in the second one there are three highly correlated channels and large part of the significant information can be carried out by a channel only (i.e. only a significant PC is obtained).

| Case | N-PCA | PCA > 0.02 |
|---|---|---|
| RGB | 3 | 1 |
| RGB+INT | 4 | 2 |
| R+INT | 2 | 2 |

**Table 1.** Number of components and of principal components in the three studied cases.

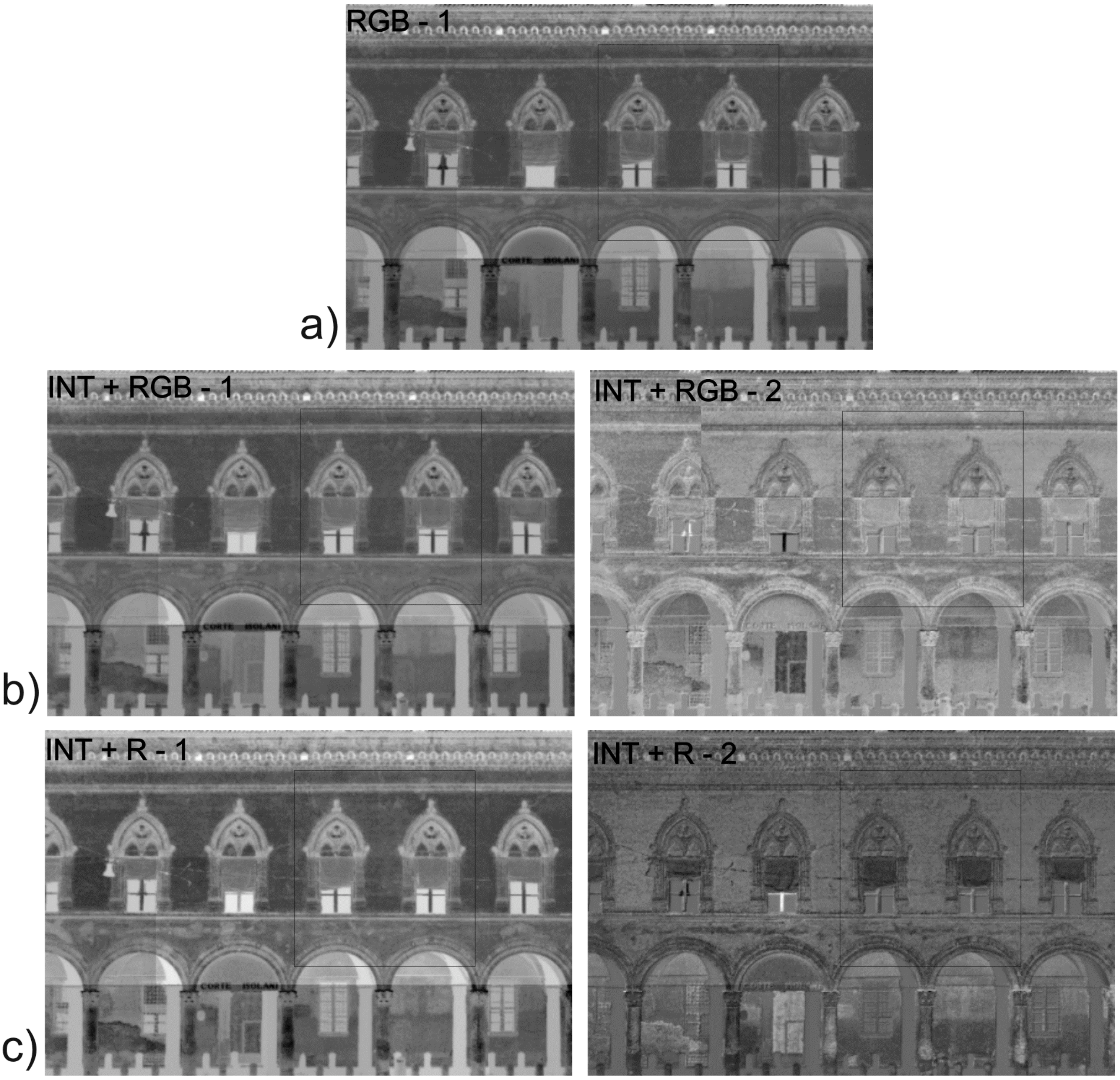


**Figure 6.** PCA results: (a) PCA of the RGB image (one PC only); (b) PCA of the RGB image and laser beam intensity image (two PCs); (c) PCA of the R component and intensity image (two PCs).

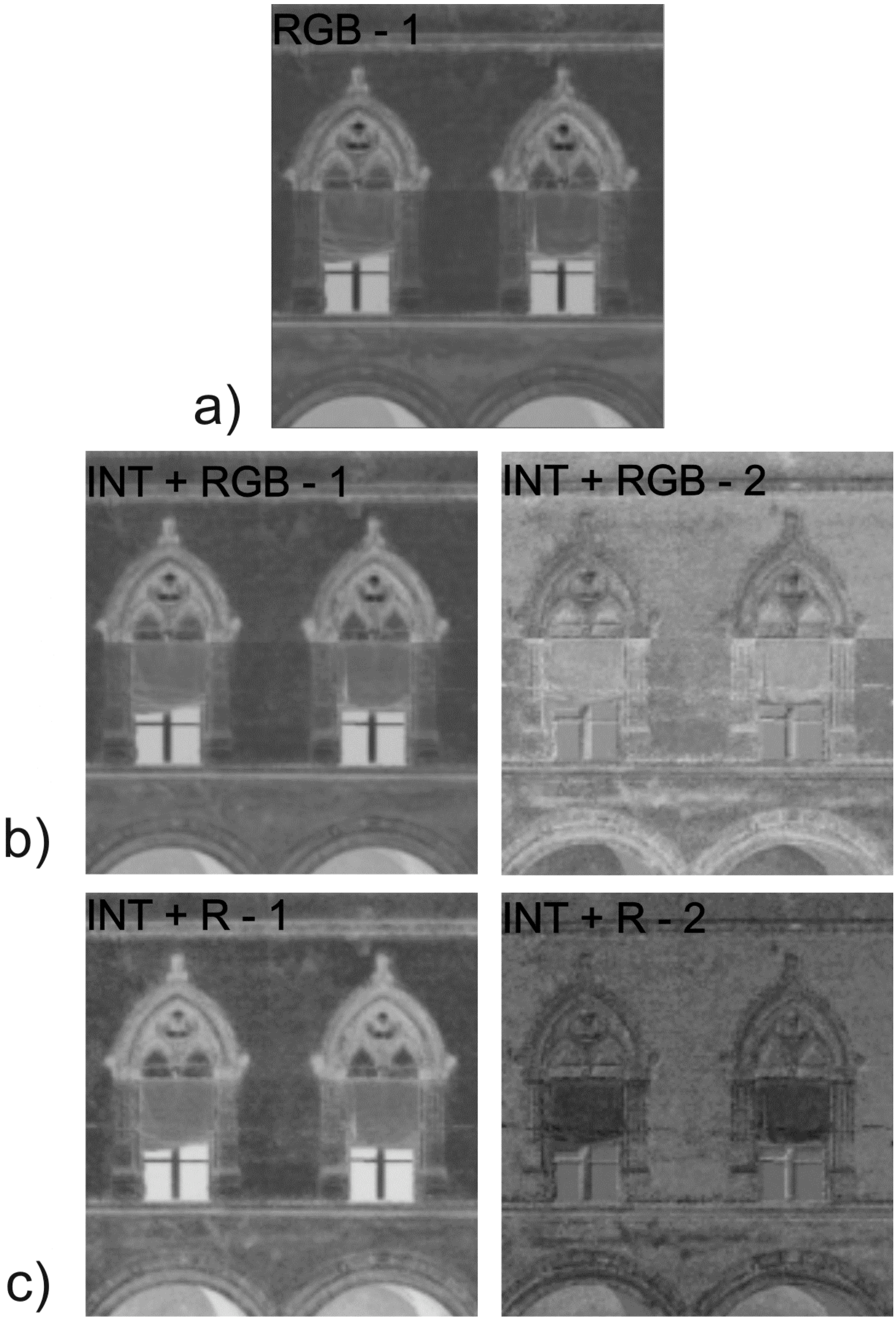


**Figure 7.** Particular of the PCA results for a portion of the facade shown in Figure 5: (a) PCA of the RGB image (one PC only); (b) PCA of the RGB image and laser beam intensity image (two PCs); (c) PCA of the R component and intensity image (two PCs).

## Acknowledgment

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