Spatial-temporal characterization of noise in web cameras.

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Abstract:

Web cameras are widely used as an image acquisition systems that are cheap, available and easily configured. Their settings are implemented electronically and the software drivers have a limited access to the internal characteristic of the cameras. These settings are prepared to cover the most common of the illumination conditions and scenes. The images provided by these cameras not only have to do with the physical characteristics of the detector array, but also with the compression algorithm used to present the images onto a display. In this contribution we apply the principal component analysis to a set of frames obtained by web cameras. This method allows to extract different spatial-temporal patterns of the noise of the cameras.

1. Introduction

Web cameras are widely used nowadays as a cheap image acquisition system. Most of them use some type of compression algorithms to encode the captured images in order to produce files for easily transmission through internet or other computer networks. This produces that the types of artifacts seen in the image are very different and with different types of correlation among them. Then, it is expected that not only temporal noise appear on the image, but other artifacts depending on the interaction of compression algorithms with the spatial content of the image. Recently some methods to deal with these types of spatial-temporal structures has appeared in the literature1,2. One of these methods is the principal component approach (PCA). To use this method, the data to be analyzed is a set of N frames, F, containing M pixels. This frame set can be transformed into another set having zero mean, that is better adapted to the case of the analysis of the noise by means of the PCA. A given pixel can be seen as having a value at each frame. These different signals of the same pixel can be seen as the coordinates of a point within an N dimensional space. When all the pixel of the frame set is represented in this N dimensional space, an scatter plot is obtained. The covariance among the frames is, in general, non negligible. The PCA expands the set of frames in terms of independent variables. Then, the contribution of each independent variable to the noise can be better analyzed. Actually, the analysis of the noise structure becomes an analysis of the distribution of the cloud of dots representing the pixels in this N dimensional space. By using the PCA the actual data are expanded in terms of a new set of data: the eigenimages, Y. The covariance matrix of the eigenimages is diagonal. These eigenimages explain, in decreasing order, the variance of the original data. They are linear combinations of the original set of frames. The method can be expressed as the following eigenvalue equation written in matricial form,

$$SE_{\alpha} = \lambda_{\alpha} E_{\alpha}$$

where S is the covariance matrix, \( \lambda_{\alpha} \) is the eigenvalue and \( E_{\alpha} \) is the eigenvector. These eigenvectors can be arranged as a N x N matrix \( E = \{E_1, E_2, \ldots, E_N\} \) to produce the eigenimages as follows,
Each eigenvector describes a direction in the scatter plot representing the pixels. The first eigenvector, associated with the highest eigenvalue, describes the direction over which the spread is the largest. The rest of eigenvectors describes the directions of spread in the scatter plot in decreasing order. Therefore, this method produces a set of $N$ eigenvalues ($\lambda$), $N$ eigenimages ($Y$), and $N$ eigenvectors ($E$) having $N$ components, being $N$ the number of frames.

An eigenvalue, $\lambda_i$, provides information about the importance, in the noise structure, of the corresponding eigenimage $Y_i$. The contribution can be given as a percentage when the eigenvalue is normalized to the sum of all the eigenvalues representing the total variance of the data. This eigenimage appears in a given frame $F_i$ having a weight given by the corresponding component $k$ of the eigenvector $E_i$. It is interesting to enhance that the PCA method provides images. These images, properly combined, produce the original data. This relation is written in matricial form as $\overline{F} = YE^T$ and also as the following sum

$$\overline{F}_i = \sum_{\alpha} e_{i,\alpha} Y_\alpha$$  \hspace{1cm} [3]

Besides, it is possible to obtain a filtered set of frames by taking into account a selected subset of eigenimages and reproduce the frame set by using only this selected subset\(^1\). This is done by selecting the indices in the sum of equation [3]. On the other hand, the components of an eigenvector can be seen as the time variation of the associated eigenimage in the actual set of frames. In our analysis we will consider that the rate of acquisition of the images is uniform, and the individual frames are spaced a given and constant time period along the set. A statistic analysis of the principal component decomposition allows to classify and group the eigenvalues (and the corresponding eigenimages) into processes. This is done by assuming that when a subset of eigenvalues, along with their uncertainty due to the sampling, can be consecutively undistinguishable they belong to the same process (see Appendix of Ref. 2 and Ref. 3).

A process is defined as a filtered set of frames generated by a subset of principal components being their eigenvalues consecutively undistinguishable by the sampling procedure\(^2\). Let us assume that we have two eigenvalues, $\lambda_1$ and $\lambda_2$, that are undistinguishable by the sampling. These two eigenvalues are associated with two eigenvectors, $E_1$ and $E_2$ that define a plane in the $N$ dimensional space of eigenvectors. All directions within this plane are equivalent to explain the same amount of variance represented by the sum of the corresponding eigenvalues. Then, it is possible to rotate these eigenvectors within that plane by a certain angle. By means of equation 3 a new set of frames is produced. It is easy to verify that the amount of variance due to the rotated eigenvectors is the same than before the rotation\(^2\). At the same time, the two set of frames reconstructed by the rotated and the non-rotated eigenvectors, exhibit between them a non negligible amount of covariance due to the inner connections given by eigenvector rotation procedure\(^2\).

Mostly, the image noise is described in terms of the Fixed Pattern Noise (FPN) and the random noise. The FPN is described as an image appearing in all frames, while random
noise is a salt and pepper image changing from frame to frame\textsuperscript{4}. When FPN appears in the PCA, it is associated with an eigenvector having all its elements equal, and therefore describing an image with the same weight in all frames. Contrariwise, the random noise appears associated to eigenvectors perpendicular to the FPN one. Then, the FPN describes a set of frames whose correlation is one, and random noise represents a set of frames with zero correlation. However, Mooney \textsuperscript{4} describes different kind of noises with different levels of correlation between zero and one. Then, the PCA does not only classify the pure spatial (fixed pattern noise with temporal frequency equal to zero) and pure temporal noise (random variation of the signal or white noise), but it also describes noise terms that appear at intermediate time scales or correlations\textsuperscript{2}.

2. Application to web cameras

The previous scheme has been applied to the analysis of spatial-temporal response of a web camera, taken 15 frames per second through the USB port of a personal computer. The kind of studied images were scenes of horizontal frequency bars as those shown in figure number 1.

![Figure 1: Types of images taken with the web-cam. They consist in vertical bars with increasing frequencies in horizontal dimension.](image)

After taking the image with the CCD, the web-cam processes it in order to give a compressed image. These kind of images are easily sent through internet or recorded in the computer. This process is made through an internal mechanism of “adaptation”. It is shown in figure number 2. At the beginning, the camera explores the image looking for the optimum level of resolution to code it. This is shown in the display as a “decreasing number of squares” overimposed on the image till the level of correct resolution is reached.

![Figure 2: From left to right the number of squares overimposed on the image is decreasing till the right resolution is reached.](image)

Once the level is established, the previous mechanism is still operating in order to adapt it continually to movement images. This produces random variation of the images located, meanly, near the edges. With the application of Principal Component
Decomposition we expect to isolate this aspect of the noise from the white noise operating normally.

3. Experimental results

The method was applied to different data sets of images of vertical bars to produce different horizontal frequencies. The data set consist of 60 frames and only a small portion of the whole image is analyzed due to computer time problems.

In general, three different kinds of processes are found. One is a fixed pattern due to the image itself. The second one is a set of different processes associated to the adaptation mechanism. The third one is associated to properly random noise. The eigenimages (principal components) associated to each type of images are shown in figures 3 and 4 for the case of a low and high frequency.

**Figure 3:** From left to right, single image of frequency used, first principal component associated to a fixed pattern (image); next, the three principal component associated to three different processes all related with the image of the frequency used (compensation mechanism); next 5th to 60th principal components associated to a single process related with temporal noise of the camera. Low frequency example. In each image the whole scale is used to enhance the spatial structure.

**Figure 4:** From left to right, single image of frequency used, first principal component associated to a fixed pattern (image); next, the three principal component associated to three different processes all related with the image of the frequency used (compensation mechanism); next 5th to 60th principal components associated to a single process related with temporal noise of the camera. High frequency example. In each image the whole scale is used to enhance the spatial structure.

In the previous images is shown how the second group of principal components are associated to the type of frequency (P1). They show a clear structure that resembles the structure of the original image. Finally, the second group (P2) forms a single process with 56 principal components. In both cases (high and low frequency) they are associated to random temporal noise.
After classifying the processes it is possible to build a new set of frames by means of the reconstruction of the images or rectification respect to a set of principal components. This has been done for the principal components of the groups P1 and P2 and for 6 different frequencies among frequencies of figure 3 and 4. For each one of these groups a 3D noise analysis is made. It is possible to see how both types of principal components are associated to temporal noise, mainly. For both, P2 is process mainly related to pure temporal noise for all frequencies (high TVH).

![Graphs showing 3D noise values for different frequencies.](image)

Figure 5: 3D noise values for the frames reconstructed with the principal components of the group P1 and P2. From up to down and left to right frequency 1 to 6. Frequency 1 corresponds to the image of figure 3 and frequency 6 to the image of figure 4.

Another possible analysis is to calculate, for each set of rectified frames, the value of the rms of the image. Each set consists of 60 frames. Due to this, it is possible to obtain an uncertainty for the rms value, too. The results are shown in figure number 6.
Figure 6: Values of rms for the set of frames reconstructed with the principal components of the set P1 and the set P2. It is possible to see how the process associated to the frequency component of the image has a lower value than temporal noise.

From the previous figure it is possible to see how the part of the images associated with the principal components of the group P1 have a lower rms value than the temporal noise. Even in this case, the method of principal component decomposition is able to extract this artifact from the whole data set.

4. Conclusions

The method of principal component decomposition is applied to a set of frames coming from a web camera and seeing different spatial frequency pattern. The method is able to extract three types of images from the whole data set. One of them involves the image itself. The other two are related with the temporal noise of the camera. One is due to the temporal noise and the other comes from the interaction of compression mechanism with the image. The structure of these types of noise is analyzed with other methods (3D noise, rms), showing how the Principal component approach is able to separate artifacts even lower than temporal noise.

References:


