Characterization of artifacts in fully digital image-acquisition systems: Application to web cameras

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Abstract. We apply principal component analysis (PCA) to the characterization of artifacts in a digital image-acquisition system containing image-compression algorithms. The method is successfully applied to web cameras. The classification done with the PCA method produces three processes. The pure spatial process retrieves the luminance distribution of a static object. The pure temporal process is directly related with the temporal noise of the system. An intermediate spatial-temporal process reveals the interaction between the compression algorithms and the spatial-frequency contents of the object. Without prior information, the PCA method is able to distinguish this interaction from the classical temporal noise. The analysis of the anomalous pixels also reveals the location in the scene where the compression algorithms work harder. An extension of this analysis identifies the origin of the anomalous behavior in terms of its spatial or temporal character. © 2004 Society of Photo-Optical Instrumentation Engineers. [DOI: 10.1117/1.1626667]

Subject terms: noise in images; web cameras; principal component analysis; image compression algorithms; bad pixels.

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1 Introduction

The amount of information distributed as video sequences by electronics means has been increasing. In the beginning, the image was acquired by analog devices, transformed as an analog video signal, and then transmitted also by analog systems. With the development of digital means of detection, storing, and distribution, it is more common to have fully digital systems. A very popular way of creating digital images for their distribution on the Internet is the use of small cameras directly connected to the computer, they are known as web cameras. The electronics associated with these cameras includes image compression algorithms to send frames through computer networks with acceptable quality and speed.1,2 These algorithms interact with the forming image and acquisition chain, producing spatial-temporal artifacts. In this paper, we use principal component analysis (PCA) to study the importance of the most relevant spatial-temporal artifacts within a fully digital image-acquisition system. We have demonstrated the application of the PCA method when characterizing noise processes in analog video sequences.3 To properly apply the PCA method to web cameras a different approach is taken. The spatial-temporal processes embedded in the data set obtained with the web cameras are revealed by using fixed targets with spatial variations adapted to the intrinsic features of the system. In addition, the analysis and interpretation of the results are related with the specific characteristics of the compression algorithms.1 The treatment of the signal in web cameras is rather different than in the analog case. However, the first step is common to both. Web cameras also have an array of detectors and readout electronics. Beyond this point, the digital systems treat those signals in a very different manner than their analog counterparts. The compression algorithms implemented in web cameras evaluate the image every certain time, producing complex interactions among the spatial features of the scene, its temporal evolution, the noise, and the compression scheme.4 In addition, the whole chain of procedures after detection is done in a fully digital environment. Although they are different, some of the features obtained in the characterization of the noise in analog devices is also found in these digital systems. They both show a spatial nonhomogeneity (purely spatial), fixed pattern noise (FPN), and a temporal noise term (purely temporal). However, the intermediate spatial-temporal processes require a special interpretation for web cameras. This is because of the dependence of the compression algorithm on the spatial structure of the object. The experimental method proposed here was specifically developed to enhance and understand these interactions between the object and the compression algorithms. However, the PCA method does not require prior knowledge of the spatial-temporal structure appearing in the data. The obtained results are also analyzed using the 3-D noise technique5 to confirm our findings and enhance the capabilities of the PCA method when applied to digital-image-acquisition systems.
To frame this paper, we present a brief description of the PCA method in Sec. 2. Section 3 contains the main contribution of the paper. We describe the specific experimental setup that we propose to analyze the spatial-temporal behavior of the data sets obtained from web cameras. We propose a metric to measure the effect of the compression algorithm on the spatial-temporal structure of the video sequence. In addition to the classification of spatial-temporal processes, the PCA method enables us to spatially map the homogeneity of the signals. This analysis classifies the spatial or temporal origin of these anomalous behaviors. All these results reveal the importance of the compression schemes in a quantitative and qualitative way. Finally, Sec. 4 summarizes the main conclusions of this paper.

2 Principal Component Analysis of Noise

To properly translate the image acquisition problem in a more statistical framework we consider a sequence of frames as a stochastic process (see Fig. 1). Each frame is a random variable and each detector is an observation of the different random variables of the stochastic process. The data is a set of \( N \) frames \( F \) containing \( M \) detectors:

\[
F = \{F_1, F_2, \ldots, F_N\},
\]

where \( F_j \) are the individual frames, previously transformed to have zero mean. The covariance structure among frames is described by the covariance matrix \( S \). The PCA produces another set of variables: the principal components \( Y \) characterized by a diagonal covariance matrix. These new variables are linear combinations of the original frames and they explain the covariance of the data in decreasing order. The elements of these linear combinations are the eigenvectors of the \( S \) matrix. In this way, the principal components \( Y_\alpha \) can be seen as eigenimages:

\[
Y_\alpha = \sum_{t=1}^{N} e_{t,\alpha} F_t, \tag{2}
\]

where \( e_{t,\alpha} \) is component \( t \) of the eigenvector \( \alpha \). This equation can be inverted to produce the original frames as linear combinations of the principal components as

\[
F_t = \sum_{\alpha} e_{t,\alpha} Y_\alpha. \tag{3}
\]

Equation (3) can be used to reconstruct the original data set containing only some chosen principal components. In addition, the following parameter:

\[
\Omega_\alpha = \frac{\lambda_\alpha}{\sum_{\alpha} \lambda_\alpha}, \tag{4}
\]

represents the portion of total variance that can be reconstructed by the \( \alpha \) principal component, where \( \lambda_\alpha \) are the eigenvalues obtained in the diagonalization process.

The method produces three different kinds of objects: eigenimages, eigenvectors, and eigenvalues, that are properly associated one to each other. The eigenvalues represent the variance associated with the corresponding eigenimage, i.e., the root mean square (rms) value. The eigenimage gives the spatial distribution of the corresponding variance. Then, the method distinguishes contributions with the same amplitude but different spatial behavior. The eigenvectors are directly linked to the correlation structure of the data set. For example, an image appearing in all the frames will be interpreted as FPN. That is, an eigenimage with the same weight in each frame. This corresponds to a normalized eigenvector \( e_{\text{sp}} = 1/\sqrt{N}/1/\sqrt{N} \ldots 1/\sqrt{N} \) that defines the pure spatial direction of the set of data. Therefore, the

\[
f(Y_\beta) = \frac{1}{(2\pi)^{N/2}} \exp\left\{-\frac{1}{2} Y_\beta S_Y^{-1} Y_\beta^T\right\}
\]

Fig. 1 Left portion of this figure represents the location of the pixels when only three frames are taken into account (the maximum number of frames that can be represented in a plot). The bisectrix of this diagram corresponds to the location of pixels having the same value for the three frames, i.e., they are the FPN of the set of frames. The center of the cloud of pixels is the “mean pixel.” The eigenvectors obtained from PCA are represented as an orthogonal coordinate set rotated with respect to the coordinate set described with the frames. Parameter \( C_\beta \), the cosine of the angle between the FPN direction and the location of an individual pixel, describes the spatiality of the pixel. The right plot presents the statistical distribution of the pixels versus the Mahalanobis distance of the pixel with respect to the center of the cloud of pixels. This distribution is expressed in the equation included with the figure.
eigenvectors explain the dynamic contribution of the associated eigenimage in the original set of frames.

In any set of data, a residual variance is always associated with the acquisition procedure. If the difference in variance between two consecutive eigenvalues is less than this residual variance, it could be possible to consider them as equal. Due to the fact that they represent the same amount of variance, the associated eigenvectors and eigenimages can be substituted by a linear combination of them. This reasoning can be extended to a subset of eigenvalues obeying the previous condition for every two consecutive eigenvalues. This mathematical rearrangement can be formalized to introduce the concept of process. This classification of spatial-temporal processes can be performed automatically after giving a criteria to properly group the eigenvalues. This method produces the rms values of the processes plus the spatial distribution of it.3

In addition, the PCA method enables a rigorous definition of a bad or anomalous pixel: a pixel is considered bad if it is different from the normal ones. Then, a normal pixel is a pixel having a large probability of appearance within the set of data. Contrariwise, an anomalous pixel is a pixel whose probability of appearance is low or very low. To define the probability distribution of pixels a property derived from the PCA is used. The probability distribution of the pixels is nearly multinormal when it is expressed in terms of the principal components.9 Instead of working directly with the multinormal distribution associated with the whole population of pixels, it is more convenient to use a parameter directly related with the Mahalanobis distance defined as

\[ D^2 = Y^T S^{-1} Y, \]

where \( Y \) represents the coordinates of the pixel in the base of the principal components.9 After identifying the bad pixels, it is possible to classify them with different techniques. One technique, applied with success in analog systems, is to calculate the cosine of the angle between the direction of pixel \( \beta \) in the scatter plot of Fig. 1 and the spatial direction \( e_{sp} \). This spatiality parameter is noted as \( C_\beta \). When representing this value versus \( D^2 \) it is possible to locate all pixels in a diagram indicating their spatial or temporal character, and a value related to their probability of appearance in the image. Actually, instead of plotting the \( D^2 \) directly, it is more convenient to normalize it by using a threshold distance \( D^2_{th} \). The threshold distance is defined with respect to the expected probability of appearance of a bad pixel within the distribution.9

The PCA formalism applied to web cameras required a customization of the experimental procedures and the interpretation of the results into the scope of the specific features of the digital compression algorithm included in these devices. This is described in the next section.

3 Characterization of Spatial-Temporal Artifacts in Web Cameras—Interaction Noise

Web cameras were analyzed by applying the PCA method to video sequences. We have used a commercial web-camera connected directly to the computer via a universal service bus (USB) port. The camera provides frames of 320×240 pixels at a frame rate of 15 images/s. The analyzed video sequence is a central portion of 100×100 pixels. Note that the values of the pixels in the analyzed set of frames are not exactly the values of the output from the actual pixels in the FPA of the web camera. The analyzed pixels already include the artifacts added by the compression algorithms and readout electronics.

The compression algorithms used to create the data set operate with intrinsic spatial and temporal frequencies. One of the goals of this paper was to prove the capability of the PCA method to identify and classify the spatial-temporal artifacts embedded in the image and produced by the compression scheme.2 To do that, the object is a fixed computer-generated quasinousoidal pattern presented to the camera by using a CRT monitor. The web camera stares at the monitor and a movie is recorded using the software provided with the camera. Each sequence contains 50 frames. This movie, stored as an audio video interleave (AVI) file, is sectioned in frames and analyzed with the PCA method. The spatial frequency of the pattern varies slightly from the top to the bottom of the frame to include a narrow variation of the spatial frequency when moving along the vertical direction. This was done to preclude aliasing artifacts along the whole image. We chose three sets of frames to show how the PCA works with these digital images. These frequencies are labeled as low, medium, and high frequencies. The period, given as a number of pixels, for each set of frames ranges from 33 (bottom) to 28.6 (top) for the low-frequency data set, from 11 to 10 for the medium-frequency one, and from 5 to 4.7 for the high-frequency sequence. Figure 2 shows the type of images that were taken and analyzed. For the high-frequency image, it is possible to distinguish the effect of the compression algorithm on the image. The appearance of clusters distorted by this compression algorithm are also revealed when the noise processes are analyzed. One of the most relevant effects of the compression algorithm reveals a square blocking structure. The blocking structure comprises squares of 8×8 pixels. When the compression algorithm interacts with the object, the blocking structure is more or less relevant, depending on the spatial frequency of the object and its location with respect to the squared grid structure. Note that the PCA method was applied blindly to the data set, without prior knowledge of the possible artifact embedded in the video sequence.

![Fig. 2 Original sets of frames for noise processes classification are 50 frames at three different spatial frequencies labeled as low, medium, and high frequencies. The first frame of each sequence is shown here. The actual frame used with the PCA is a central portion of 100×100 pixels of these original data sets. For the high-frequency case it is possible to see the artifacts introduced by the compression algorithm.](Image 303x644 to 537x729)
3.1 Process Classification

As noted Sec. 1, the PCA method applied to analog video sequences sectioned several contributions of noise. This classification is also obtained for the video sequences produced by the web cameras. In the analog case, the analysis was made by using uniform illuminated objects and the results were directly interpreted as noise contributions. However, in the web camera case, the dependence of the compression algorithm on the spatial frequency of the object suggested the use of fixed quasisinusoidal patterns with different spatial frequencies. The spatial-temporal structures were classified as follows:

1. FPN: This corresponds to the actual irradiance distribution of the object. Although it can not be directly related to the spatial noise of the system, we maintained the same name because the corresponding eigenimage appears in all the frames with identical amplitude. It carries most of the variance of the data set. This process is described with a single eigenimage corresponding to the largest eigenvalue.

2. Interaction noise (IN): This process depends on the spatial frequency of the object. It is revealed at those locations in the image where the signal varies most. This spatial-temporal process represents the interaction of the image-compression algorithm with the spatial structure of the object. Due to the dependence on the spatial frequency of the object, the number of eigenimages grouped inside this process varies.

3. Temporal noise (TN): This process is undistinguishable from a pure temporal noise and it is the most clearly related to an actual noise contribution. Although some blocking spatial structure still appears in those eigenimages associated with this process, the amplitude of this blocking can not be distinguished from random noise. Typically, this TN groups the largest number of eigenimages. This process is independent of the object scene.

Before describing the behavior of these processes we analyze them by using the already well established 3-D noise model. To perform this analysis we filtered the original sequences using the eigenvectors grouped with each one of the processes. After filtering we obtain three sets of frames. The set corresponding to FPN is not analyzed because its temporal behavior is trivial. Instead, we focus our attention on the IN and TN. In Fig. 3 the 3-D analysis shows that TN is always larger than IN, and it is more or less constant for the three spatial frequencies. Contrariwise, the total noise for IN depends on the spatial-frequency content of the object. This different behavior is also presented in Table 1, where we represent the total 3-D noise in rms values for the frames reconstructed for both processes along with its ratio. From the data we can conclude that the IN is less noticeable when the spatial frequency of the object is closer to the spatial frequency of the blocking structure (the medium-frequency case). Note that the 3-D analysis performed here would not be possible before applying the PCA method. In addition, the 3-D analysis shown in Fig. 3 does not provide a clear understanding of the difference between the IN and TN noise processes. It is very important to give not only rms values but also the spatial structure.

3.2 IN Metric

The importance of these three spatial-temporal structures for the three spatial frequencies is shown in Table 2 as the percentage of the total variance calculated using Eq. (4). We can see that the FPN carries more than 99% of the variance of the data. The IN process explains less variance than the TN process. This means that the IN process would not be revealed in a classical analysis of noise because its

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### Table 1: Values of the rms for the IN and TN processes in arbitrary units.

<table>
<thead>
<tr>
<th>Frequency</th>
<th>Low Frequency</th>
<th>Medium Frequency</th>
<th>High Frequency</th>
</tr>
</thead>
<tbody>
<tr>
<td>rms (IN)</td>
<td>1.48</td>
<td>1</td>
<td>1.46</td>
</tr>
<tr>
<td>rms (TN)</td>
<td>1.91</td>
<td>2.00</td>
<td>2.15</td>
</tr>
<tr>
<td>rms (IN)/rms (TN)</td>
<td>0.78</td>
<td>0.50</td>
<td>0.68</td>
</tr>
</tbody>
</table>

### Table 2: Percentage of the total variance explained by each one of the noise processes.

<table>
<thead>
<tr>
<th>Frequency</th>
<th>Low Frequency</th>
<th>Medium Frequency</th>
<th>High Frequency</th>
</tr>
</thead>
<tbody>
<tr>
<td>FPN (%)</td>
<td>99.91</td>
<td>99.78</td>
<td>99.67</td>
</tr>
<tr>
<td>IN (%)</td>
<td>0.02</td>
<td>0.02</td>
<td>0.08</td>
</tr>
<tr>
<td>TN (%)</td>
<td>0.07</td>
<td>0.18</td>
<td>0.24</td>
</tr>
</tbody>
</table>
contribution to the total variance of the data is lower than the variance due to the pure TN. This fact demonstrates the advantages of the PCA method to show spatial-temporal processes that are well concealed within the original data. This is possible because the PCA focuses on the covariance structure of the data and not only on the rms values.

The values presented in Table 2 for the interaction noise measure the relative importance of it. Therefore, we define them as a metric of this spatial-temporal artifact. This metric is given by

\[
\text{IN}_i = \frac{\sum_{k=L_\text{IN}} \lambda_k}{\sum_{j=1}^N \lambda_j}.
\]

where \(L_{\text{IN}}\) comprises the eigenvalues of the principal component associated to the interaction between compression algorithm and scene. Another metric of interest is the ratio between the IN and random TN. This measures the concealment of the interaction noise within the temporal noise structure. As can be seen in the last row of Table 1, these ratios are less than 1. Then, the spatial structure of the IN noise is usually embedded within the TN. This could be of interest in other fields in which the masking of spatial-temporal structures in digital systems such as watermarking \(^{10}\).

### 3.3 Importance of the Spatial Structure

One of the major advantages of the PCA method is that it provides us with images. It also enables filtering the original set of data taking into account only those principal components comprising the spatial-temporal structures of interest. Figure 4 shows the application of the PCA to the set of frames under study. The images were obtained after filtering the original set with those eigenvectors and eigenimages grouped at each one of the three noise processes. The left column corresponds to the FPN. Note that those effects related to the blocking structure and appearing at the original frames were already filtered out in this column. The central column is related to the IN process and it still contains information concerning the spatial distribution of the object. This process reveals where in the image the compression algorithm works harder to reconstruct the original object. Finally, the column on the right corresponds to the TN. Here, the information about the spatial distribution of the object has disappeared. Then, by using the PCA method, it is clear that the difference between the IN and TN is their spatial noise distribution. This behavior also appears when analyzing the covariance of the reconstructed frames associated with IN and TN. Figures 5 and 6 represent the covariance of the frames corresponding to these IN and TN processes, respectively as 3-D plots. When we compare these plots, it is clear that the covariance structure of the TN process is almost diagonal for the three spatial frequencies analyzed here, and it shows almost constant amplitude. This is the behavior expected for a pure TN, which does not depend on the spatial frequency structure of the object.

However, the structure of the covariance of the IN filtered set is strongly dependent on the spatial frequency. This structure is better revealed when plotting the correlation function as an image (see right column of Fig. 5). The periodic structure of the correlation, with a period of about 15 frames, shows the temporal interaction of the compression algorithm with the structure of the image. For the medium-frequency case, the spatial frequency of the object is better adjusted with the inner period of the compression algorithm, which shows blocking cells of 8 \(\times\) 8 pixels. Then, the compression algorithm works better and the IN produces a simpler correlation structure. To better understand the link between the spatial frequencies of the object and the filtered frames we calculated the power spectrum of each frame for the three filtered sets of frames, and for the three spatial frequencies, and we represent the mean power spectrum by averaging all the frames reconstructed with a given process at a given spatial frequency. The results are shown in Fig. 7. The left column contains the power spectrum of the FPN for the three frequencies and it follows the expected behavior. The column in the center corresponds with the IN and it clearly shows a spectral distribution also related with the object. Finally, the right column is the spectrum of the TN and shows a maximum at the frequency related to the pixel size. The shape of the spectra shown in this right column is quite independent of the spatial frequency of the object.

### 3.4 Bad Pixel Analysis and Blocking Size Extraction

One of the principal artifacts in digital compression systems is the so-called “blocking.” It appears as square cells containing a fixed number of pixels. The compression algorithm works inside these units, producing a characteristic shape of the images.\(^{1,2}\) Two adjacent pixels belonging to different blocks will show clearly different spatial-temporal behavior because the compression algorithm will work differently in each of the square blocks. This difference is revealed when analyzing the statistical distance of pixels within the data set. This is done by a bad pixel analysis, which we performed using a uniform background presented to the web camera. Figure 8 plots the left column the map of the ratio \(D^2/D^2_{\text{th}}\), where \(D^2\) is related to the Mahalanobis distance for each pixel, and \(D^2_{\text{th}}\) is the threshold value of \(D^2\) above which the pixel is considered a bad pixel. In this case, the threshold is chosen in such a way that the probability of classifying a good pixel as being bad...
The method based on the PCA not only classifies good and bad pixels, but also takes into account the spatial structure of distance $D^2$. This structure is produced mainly by the blocking effect of the compression algorithm. Note that this analysis can be applied without prior knowledge of the existence of any compression algorithm or its characteristics. In this sense, it can be used as a characterization tool. In our case, the blocking structure was revealed as having a size of $8 \times 8$ pixels, as expected.

The spatiality of the pixels is also shown in the plots in the right column, where we plotted the location of the pixels in a graph where the $C_B$ parameter indicates the spatiality of the pixel. This parameter is also represented in Fig. 1 as the angle between the FPN location and the vector determining the location of the pixel. When the pixel is located along the FPN direction, $C_B = \pm 1$. The top row represents the pixels for the original set of frames taken.

![Fig. 5 Interaction process showing the dependence on the spatial frequency of the object. This can be seen in the representation of the covariance of the frames filtered with the IN process on the left and on the right, plots of the correlation function, showing an inner correlation time of about 15 frames.](image)

![Fig. 6 Covariance of the TN process for the three spatial frequencies. The covariance is almost diagonal, as expected for a pure TN.](image)
from a uniform object. The central row corresponds with the frames rectified with the FPN (responsible for the non-uniformity). We can see that the pixels are purely spatial, and the parameter $C_b = \pm 1$. Finally, the bottom row represents the signals of the pixels obtained after subtracting the FPN. Now the location of the pixels are around $C_b = 0$, showing their temporal character. As a consequence of the analysis, we can see that the spatial distribution of the distance shown in the original data, as a square grid, is explained by the temporal portion, disappearing in the filtered FPN. This reinforces the interpretation of the action of compression algorithm as an interaction with the image producing temporal artifacts. Figure 9 shows a new alternative way of representing the previously mentioned classification of pixels. Here the bad pixels are located outside a square obtained when the statistical distance is larger than the threshold distance. This representation helps identify the temporal or spatial character of the pixel. It distinguishes whether the pixel is anomalous because it has a bad temporal behavior or a bad spatial behavior.

### 4 Conclusions

We applied the PCA method for the characterization of artifacts in fully digital image-acquisition systems. The practical application was performed using video sequences taken with USB cameras. The PCA method provided three different sets of spatial-temporal structures. Due to the resemblance of these results to those obtained in the characterization of noise of focal plane arrays, we followed a similar analysis and we called these three processes FPN (purely spatial), IN, and TN (purely temporal). However, the classification of these three processes and their relation to the image-treatment processes required an experimental setup specifically developed for these systems. Then, instead of using a uniform scene, a series of quasisinusoidal patterns with different spatial frequencies were presented to the camera. Within this approach, the FPN is related with the static pattern, and only the TN is interpreted as a pure TN. The adaptation of the compression algorithm to the scene is clearly revealed within the IN process. Only by using the experimental setup proposed in this paper could we notice and quantify the importance and origin of these spatial-temporal structures and their relation to the spatial-frequency content of the object. This enabled us to define a metric characterizing the importance of the interaction noise. The study of the correlation of the IN frames revealed temporal periods close to 15 frames related to the compression algorithm.

Moreover, the blocking pattern was also revealed when the PCA method was applied to identify and classify the anomalous behavior of the pixels in the image. The results obtained here made it possible to locate those regions in the digital image where the blocking artifacts affect more the homogeneity of the spatial-temporal characteristics of the

![Table and Diagram](image-url)
A dedicated analysis of the map of the statistic distance defined to identify anomalous pixels distinguished the origin of the abnormality in terms of its spatial or temporal character and enabled us to quantify the blocking size.

Although the PCA method was applied without prior knowledge of the intrinsic features of the sequence of frames, the results obtained revealed the presence of the artifacts related to the compression algorithm. The spatial structure of the map of statistical distances and the temporal behavior of the IN contains the inner spatial structure of the blocking, which consisted of $8 \times 8$ pixels. In addition, the variation of the correlation between frames showed an inner temporal period of 15 frames.

The advantages of the application of this method are based on the fact that the PCA gives not only rms values of noise, but also images revealing the spatial structure of the noise and the spatial-temporal artifacts, even when the associated rms values are below the temporal noise. The filtering capabilities of PCA were demonstrated. Therefore,

**Fig. 8** Left: map of the ratio $D^2/D_{\text{in}}^2$. A value greater than 1 indicates a bad pixel. Right: pixels in a 2-D diagram, where coordinates are the previously defined ratio and the spatiality parameter $C_{\beta}$. The first row corresponds to the original set of frames, the central row to the data filtered using only the FPN component, and the bottom row to the results for the temporal portion of the frames.

**Fig. 9** Location of the pixels in a 2-D plot. The horizontal axis is the relative distance for the pixels of the frames filtered with the FPN process. The vertical axis is the relative distance for the pixels of the frames filtered with the temporal process. The pixels lying inside the dotted area are good pixels.
the PCA method becomes a fast tool to asses the artifacts affecting digital image-acquisition systems.

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References

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