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Dependent Component Analysis for Multi-frame Image Restoration and Enhancement

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Abstract

Independent component analysis (ICA) has been applied to the restoration of image sequences degraded by atmospheric turbulence. The original high-resolution image and turbulent sources were considered as independent sources from which the degraded image is composed of. Although the result was promising, the assumption of source independence may not be true in practice. In this paper, we propose to apply dependent component analysis (DCA), which can relax the independence assumption. The experimental result demonstrates DCA outperforms ICA under this circumstance, resulting in the flexibility in the use of adjacent image frames. In addition, the restored image can be further enhanced by employing a recently developed Gabor-filter-bank-based single-frame blind image deconvolution algorithm where DCA is also employed.

1. Introduction

Due to the space- and time-variant nature of atmospheric turbulence, we introduced the Blind Source Separation (BSS) technique to achieve the restoration of image sequences [1]. Instead of using the linear degradation model and estimating a point spread function (PSF) with the assumption of space- and time-invariance, we considered each spatial turbulence pattern as one physical source, the original high-resolution image of an image scene as another source, and the degraded low-resolution image as the combination of these sources. Then the multi-frame construction model can be represented as

$$\mathbf{G} = \mathbf{AS} \tag{1}$$

where $\mathbf{G} \in R^{N\times T}$ is a matrix of the observed or blurred images with each row representing one blurred image, $\mathbf{A} \in R^{N\times M}$ is an unknown basis or mixing matrix, and $\mathbf{S} \in R^{M\times T}$ is a matrix of the source images. Here, N represents the number of frames whereas each frame is treated as one measurement, M represents the number of source images, and T represents the overall number of pixels in each image. An image frame needs to be transformed into a row vector by either row stacking or column stacking procedure. It is also assumed that motion effects, if present, are compensated by employing some form of image registration technique.

BSS can be applied on (1) to extract the high-resolution image without the prior knowledge or estimation of PSF. The most successful solution of a BSS problem is achieved through independent component analysis (ICA). It solves a BSS problem by imposing a constraint that extracted sources are statistically independent from each other [2]. One of popular ICA algorithms, referred to as Joint Approximate Diagonalization of Eigenmatrices (JADE), is adopted due to its robustness, wherein the statistical dependence among data samples is measured by the fourth-order cross-cumulants [3].

However, it has been argued that the assumption of source independence may not be true in many situations. For instance, the atmospheric turbulence components may be correlated spatially and temporally. Thus, in this paper, we will propose the use of dependent component analysis (DCA) for image restoration, which does not require the source independency. The experimental result demonstrates that DCA outperforms ICA under this circumstance. In addition, DCA can be employed to further sharpen the restored image to achieve super-resolution.

2. Derivation of a DCA algorithm

Very few papers in the literature discuss the problem of DCA [4]. Here we adopt some previous studies conducted in [5][6]. The basic idea is to find a transform F that can improve the statistical independence between the sources but leave the basis matrix unchanged, i.e.,

$$F(\mathbf{G}) = F(\mathbf{AS}) \cong \mathbf{A}F(\mathbf{S}). \tag{2}$$

Because the sources in this new representation space are less statistically dependent, any standard ICA algorithm, such as JADE, derived for the original BSS problem can be used to learn the basis matrix **A**. Once the basis matrix **A** is estimated, the sources **S** can be recovered by applying the inverse of **A** on the multi-frame image **G** in (1).

A linear transform that possesses such a required invariance property and generates less dependent sources in the new representation is "innovation". The arguments for using innovation are that they are usually more independent

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from each other and more non-Gaussian than original processes [7]. An innovation process is referred to as the residual of linear prediction [8], which is defined as:

$$e_m(r) = s_m(r) - \sum_{i=1}^{l} b_i s_m(r-i), \quad m = 1, \cdots, M \qquad (3)$$

where $s_m(r-i)$ is the i-th sample of a source process $s_m(r)$ at location r, b's are linear prediction coefficients, and $e_m(r)$ represents the new information that $s_m(r)$ has but is not contained in the past l samples. It is proved in [7] that if $\mathbf{G}$ and $\mathbf{S}$ follow the linear mixture model (1), their innovation processes $\mathbf{E_G}$ and $\mathbf{E_S}$ (in matrix form) follow the same model as well, i.e.,

$$\mathbf{E_G} = \mathbf{A}\mathbf{E_S}. \qquad (4)$$

In other words, the transform F in Eq. (2) is the linear prediction operator as expressed in Eq. (3). Note that b's in Eq. (3) can be easily solved by a least squares approach.

3. DCA for single-image enhancement

After a high-resolution frame is reconstructed, it can be further improved using a sharpening approach in a post-processing step. In general, it is difficult to conduct image sharpening just based on a single-frame image due to the lack of additional information. It is easier if more observations are available about the scene, and image details can be extracted from these observations.

Here, we investigate a single-frame multi-channel image enhancement approach [9]. A 2D Gabor filter bank can be employed to realize multi-channel filtering, considered as multiple observations for ICA or DCA [9]. After the multi-channel versions of the original image are generated, an ICA or DCA algorithm can be applied to them to extract an enhanced image. Here, the multi-channel linear mixture model of an observed image, in the form of (1), is used by assuming that source signals are the high-resolution source image and its higher order spatial derivatives. Note that this special class of sources is mutually statistically dependent and a DCA algorithm is a better choice than an ICA algorithm to fulfill image enhancement.

4. Experiments

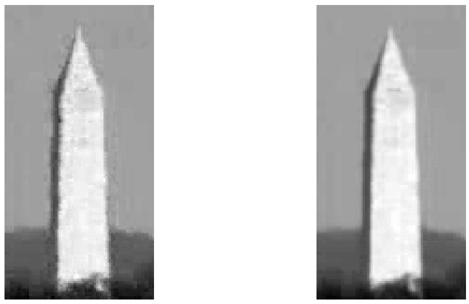
4.1 Multi-frame image restoration

An image sequence of the Washington Monument was used in the experiment, which is the same as in [1]. Note that the frames with 10-frames spacing were used in [1]. In Figs. 1-6, we compared the performance of the ICA algorithm (i.e., JADE) and the DCA algorithm (i.e., innovation followed by JADE, as described in Sec. 2) when frame selection was changed.

In order to objectively evaluate the image quality after restoration, the Laplacian operator can be applied, which is an approximation to the second derivative of image brightness. It actually is a spatial high-pass filter. It yields a larger response to a point than to a line. An image with turbulence is typically comprised of points varying in brightness, and the Laplacian operator will emphasize the points. A "no-reference" image quality metric I_4 in [10] based on Laplacian operator was adopted which takes the average of second-order derivatives of pixels in an entire image. An image with better quality should have a smaller value of I_4.

<u>Case 1</u>: using 10 consecutive frames (Fig. 1)

In this case, the observations were strongly dependent. So the ICA algorithm yielded a poor result. The DCA algorithm provided better performance.

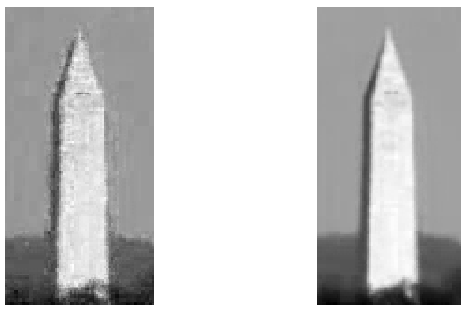


ICA (I_4 = 2.3736) DCA (I_4=1.5236)

Fig. 1. The comparison on ICA and DCA algorithms when using 10 consecutive frames.

<u>Case 2</u>: using 50 consecutive frames (Fig. 2)

The performance of the ICA algorithm became even worse, and the performance of the DCA algorithm became better with the number of frames (i.e., observations) being increased.

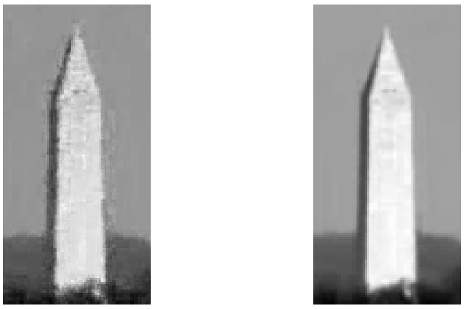


ICA (I_4 = 3.4932) DCA (I_4 = 1.3756)

Fig. 2. The comparison on ICA and DCA algorithms when using 50 consecutive frames.

<u>Case 3</u>: using 25 frames with 2-frames spacing (Fig. 3)

In this case, the observations became less dependent. But the performance of the DCA algorithm was still better than that of the ICA algorithm.

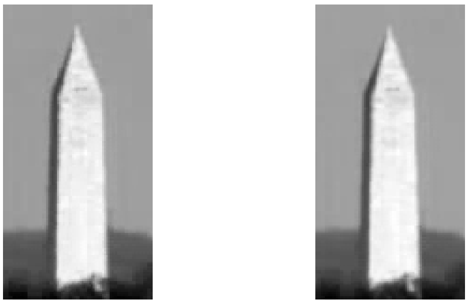


ICA (I_4 = 2.8660) DCA (I_4 = 1.3600)

Fig. 3. The comparison on ICA and DCA algorithms when using 25 frames with 2-frame spacing.

Case 4: using 10 frames with 5-frames spacing (Fig. 4)

In this case, the observations became more independent. The performance of the ICA algorithm became much better, and the DCA performance remained unchanged.

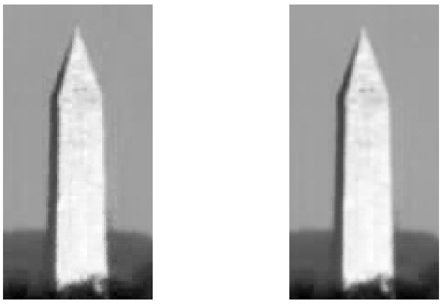


ICA (I_4 = 1.5192) DCA (I_4 = 1.3880)

Fig. 4. The comparison on ICA and DCA algorithms when using 10 frames with 5-frame spacing.

Case 5: using 10 frames with 10-frames spacing (Fig. 5)

In this case, the observations became quite independent. The performance of the ICA algorithm was slightly degraded; the performance of DCA remained unchanged.

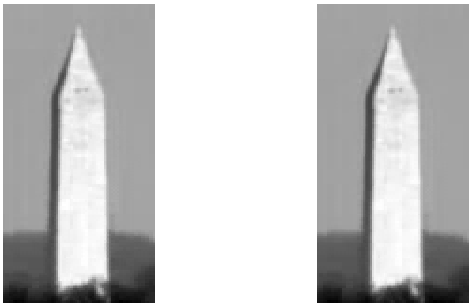


ICA (I_4 = 1.6712) DCA (I_4 = 1.3828)

Fig. 5. The comparison on ICA and DCA algorithms when using 10 frames with 10-frame spacing.

Case 6: using 5 frames with 20-frames spacing (Fig. 6)

In this case, the observations became very independent. So the performance of the ICA algorithm was improved; the performance of the DCA algorithm remained unchanged.



ICA (I_4 = 1.4856) DCA (I_4 = 1.4248)

Fig. 6. The comparison on ICA and DCA algorithms when using 25 frames with 2-frame spacing.

The observations can be summarized as: 1) when the ICA algorithm is applied, using consecutive frames causes the difficulty in source separation; it has to use the frames with spacing; increasing the number of frames even worsens the situation; 2) the DCA algorithm can relax the constraints on frame selection, greatly simplifying future hardware design; 3) the DCA algorithm may yield slightly better results than the ICA even when the ICA performs well.

Note that increasing the frame spacing results in more independent observations. Consequently, the mixing matrix **A** is better conditioned. This certainly improves the performance of the ICA algorithm. However, the performance of the DCA algorithm is not influenced much by this strategy due to its capability of handling dependent sources. However, if spacing is increased too much, then the slow quasi-periodic variation of the turbulence can make the measurements more linearly dependent, which will degrade the ICA performance again. Hence, DCA can significantly relax the constraints on the selection of frames and the number of frames to be used for restoration.

4.2 Single-frame image enhancement

Fig. 7 shows the image obtained after multi-frame restoration with the DCA. To further enhance it, the approach described in Sec. 3 was applied. Fig. 8 shows the 16 versions obtained after Gabor filtering with two spatial frequencies and four orientations. Then 17 channels (including the original in Fig. 7) were processed by the DCA. An extracted source was the final sharpened image as shown in Fig. 9 where windows and edges were highlighted.

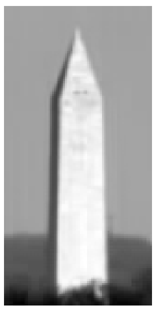


Fig. 7. A reconstructed frame.

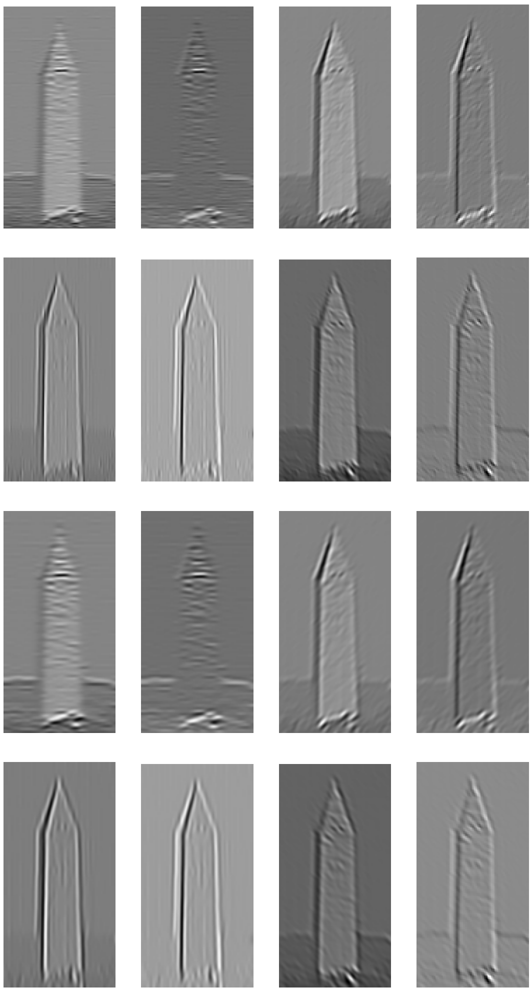


Fig. 8. Multi-channel version of the original image in Fig. 7 produced by the 2D Gabor filter bank with two spatial frequencies and four orientations.

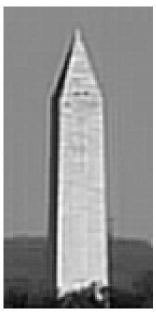


Fig. 9. Image enhancement for Fig. 7 using single-frame multi-channel filtering and DCA.

5. Conclusions

In our previous research, we applied ICA for the restoration of image sequences degraded by atmospheric turbulence. The degraded image was assumed to be composed of the original high-resolution image and turbulent sources that exist at the same space-time location. The assumption made on the high-resolution image and turbulent sources is that they are mutually statistically independent although they are emitted from the same space-time location. Although the result was promising, the assumption of source independence may not be true in practice. To make the ICA result acceptable, we need to select frames with certain spacing. This leads to problems in real-time or near real-time implementation. In this paper, we propose to apply DCA, which can relax this requirement. The experimental results demonstrate that the DCA with innovation can significantly improve the restoration performance, without imposing any requirement on the selection of frames to be used in the restoration process.

In addition, the restored image can be further sharpened through a post-processing step with a single-frame multi-channel blind deconvolution method based on Gabor-filter bank and DCA. It is noteworthy that DCA performs similarly to ICA when the assumption of source independence is satisfied.

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