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Noise Separation from Multiple Copy Images Using the FastICA Algorithm

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Abstract. This paper proposes an effective method to separate noise from multiple copy images (MCIs). Suppose that noise and original image are mutually independent in mixed signals, the mixed signals are thus decomposed to an original image independent component and a noise component by using fast independent component analysis (FastICA). The original image independent component is selected to reconstruct the resulting image according to the standard deviation of its time course. By modeling the noise as Gaussian, experimental results show that zero-mean and nonzero-mean Gaussian noises can be separated effectively from multiple copy images by the proposed method, which is effective in the case of stable and unstable noise intensity.

Keywords: multiple copy images, noise separation, the fast independent component analysis (FastICA)

1. Introduction

The rapid development of image acquisition technology has made it possible to acquire multiple copy images (MCIs) in real time. For a degraded video sequence, suppose that a few consecutive frames in which motion is not significant are chosen, and that the registration problem has already been taken into account, the frames can be viewed as multiple noisy copies of the same image. When an unsatisfactory electronic form of the image is obtained by scanning a picture, one can scan the picture repeatedly to get multiple copies, and then remove the noise from the copies employing a denoising algorithm of MCIs to acquire a noise-free image. An increasing number of applications can be found for denoising methods for MCIs [1-5].

The standard method for combining multiple copies is to compute their weighted average. Since the wavelet transform filter is shown to effectively denoise a single noisy image, some researchers applied wavelet transform into noise separation from MCIs. FENG et al. [6] presented a color correction algorithm based on wavelet transform for noisy multiview images to eliminate noise effect to the fullest extent. QIAO et al. [7] introduced a multi-channel wavelet filter bank to recover palm print images with serious deformation. CHANG et al. [8, 9] presented a method that combined two operations for MCI denoising, namely, averaging operation and wavelet thresholding, and discussed the problems of near-optimal thresholds for each ordering of the two operations. In the methods based on wavelet transform, the threshold operation was performed on the coefficients of the detail subbands while thresholding is a nonlinear technique, thus the denoising effect was limited.

In MCIs, the original image signal is still, while the noise signal varies in each image. The source of the original image signal is different from that of the noise signal. Therefore, the noise and the original image can be viewed as mutually independent components, and independent component analysis (ICA) can be used to separate noise from MCIs. In algorithms for ICA, the fast independent component analysis (FastICA) [10] has the advantage of fast convergence. The problem of noise separation in MCIs by FastICA algorithm was studied in this paper. The mixed signals were decomposed using FastICA. Then, the original image independent component (OIIC) was selected to reconstruct the resulting image according to the standard deviation of its time course. By modeling noise as a zero-mean or nonzero-mean *Gaussian* noise in the case of stable and unstable noise intensity, experimental results were presented to show the effectiveness of the proposed method.

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2. Principle of FastICA

The FastICA algorithm is based on fixed-point algorithm that shares most benefits of neural leaning rules. The main advantage of the fixed-point algorithm is that its convergence is very fast. The ICA problem is formulated as the search for a linear transformation that minimizes the mutual information of the resulting components. This is roughly equivalent to finding directions in which negentropy is maximized; the latter can likewise be considered as projection pursuit directions [10].

In the simplest case, an approximation of negentropy is of the form

$$J(y_i) \approx c[E\{G(y_i)\} - E\{G(v)\}]^2 \tag{1}$$

where $G(\cdot)$ is practically any nonquadratic function, c is an irrelevant constant, and v is a *Gaussian* variable of zero-mean and unit-variance. $E(\cdot)$ is a mathematical expectation. To find an independent component, or a projection pursuit direction as $y_i = w^T x$, the function $J_{G(W)}$ is maximized. The $J_{G(W)}$ is given by

$$J_{G(w)} = [E\{G(w^T x)\} - E\{G(v)\}]^2 \tag{2}$$

where w is an m-dimensional (weight) vector constrained so that $E\{(w^T x)^2\} = 1$. Thus, the problem of ICA can be deduced to the optimization problem

$$\text{maximize} \quad \sum_{i=1}^{n} J_{G(w_i)}, wrt.w_i, i = 1,\ldots,n \tag{3}$$

$$\text{under constraint} \quad E\{(w_k^T x)(w_j^T x)\} = \delta_{jk} \tag{4}$$

where at the maximum, every vector $w_i, i = 1,\ldots,n$ gives one of the rows of the weighted matrix W. The ICA transformation is then given by $Y = WX$, and the signal can be reconstructed by $X = W^{-1}Y$, where X is the synthetical matrix of mixed signals and Y is the synthetical matrix of the ICs.

3. Scheme of noise separation

3.1. FastICA decomposition

In image processing, the ICA method is classified as Temporal ICA (TICA) and Spatial ICA (SICA) according to the formation of the mixed matrix used for decomposition [11,12]. In the SICA method, standard deviation of time course can be used to identify the noise component. The computation time of SICA is less than that of the TICA due to the different formation of the mixed matrix to be decomposed. Therefore, SICA was employed to construct the mixed matrix in the algorithm.

In SICA, every image is reshaped to a row vector, with all row vectors combining into a mixed matrix $X_{n\times(MN)}$, where n is the number of images and M and N are the height and the width of the image, respectively. The matrix X is then decomposed to $Y = WX$ using the FastICA algorithm. All rows in matrix Y are ICs in space. Every column of W^{-1} is the time course of the corresponding ICs.

To validate the ICA approach, an underlying assumption is that, at most, one source in the mixture model can be allowed to be a *Gaussian* source. This is because a linear mixture of *Gaussian* sources is still a *Gaussian* source [13]. Thereby, only two ICs can be obtained from mixed signals because of the *Gaussian* noise. One of the ICs represents the static original image, and another the variable noise.

3.2. Selection of original image IC

Suppose MCIs are degraded by Gaussian noise. Then, based on FastICA, MCIs are decomposed into the two ICs previously mentioned, as shown in Fig. 1.

It is easy to find that there exists an obvious difference between the time courses of the two ICs. For OIIC, the time course varies slightly, which implies that the signal from OIIC is static. Thus, the signal determined by OIIC is the original image. For the noise IC (NIC), the time course varies significantly, which implies that the signal from NIC is variable. Consequently, the signal determined by NIC is the noise. The standard deviation can be used to describe different properties of a stochastic variable. The standard