RESEARCH ARTICLE

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A Natural Image Compression Approach Based on Independent Component Analysis and Visual Saliency Detection

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In this paper, a natural image compression method is proposed based on independent component analysis (ICA) and visual saliency detection. The proposed compression method learns basis functions trained from data using ICA to transform the image at first; and then sets percentage of the zero coefficient number in the total transforming coefficients. After that, transforming coefficients are sparser which indicates further improving of compression ratio. Next, the compression method performance is compared with the discrete cosine transform (DCT). Evaluation through both the usual PSNR and Structural Similarity Index (SSIM) measurements showed that proposed compression method is more robust than DCT. And finally, we proposed a visual saliency detection method to detect automatically the important region of image which is not or lowly compressed while the other regions are highly compressed. Experiment shows that the method can guarantee the quality of important region effectively.

Keywords: ICA, DCT, Visual Saliency Detection, Compression.

1. INTRODUCTION

Independent component analysis (ICA) considers a class of probabilistic generative models in which an observed random vector X can be expressed as:

$$X = AS \tag{1}$$

where A is a mixing matrix and S is a vector of containing independent sources.[1] This model can be applied to the gray-scale values of images, each sample of X usually contains the pixels in an image block.

It has already been indicated that images of natural scenes are well modeled when the columns of A, which can be seen as a basis bank of wavelet-like filters, and the independent sources have heavy-tailed distributions.[1] That is to say, with high probability, only a small fraction of the elements of S have significant values; this sparse nature of S indicates the possibility of using overcomplete ICA to compression and denoising of natural images.[1] In Refs. [2, 3], the problem of using ICA for image compression is addressed. The authors of literature (Refs. [2, 3]) have presented ICA based image compression system and got a promising performance.

In this paper, we use the FastICA algorithm[1,4] to learn basis vectors from sets of training images and improve the compression ratio by enhancing the sparse nature of the independent components.[6] Besides, we proposed a visual saliency detection method which is used to detect the saliency region. And the quality of this region is guaranteed during the other regions are highly compressed.

The paper is organized as follows. Section 2 describes the proposed method based on ICA. In Section 3, we propose the framework of our saliency detection method. Experimental results are reported in Section 4, and the last section is devoted to conclusions.

2. ICA FOR NATURAL IMAGE COMPRESSION

In summary, the outline of the natural image compression approach presented in this paper is illustrated in Figure 1. It involves six steps.[5] (1) Learning ICA basis vectors from the training images by applying FastICA. (2) Calculating the inverse or pseudo inverse of bases matrix, we call the obtained matrix W. (3) Preprocessing the image which is to be compressed. First, we divide the image into small square blocks (8×8). Each block is a column of matrix X^0. Then, we subtract local mean and reduce the dimensionality by Principal Component Analysis (PCA). At last, we obtained matrix X. (4) Obtaining the independent sources S according to:

$$S = WX \tag{2}$$

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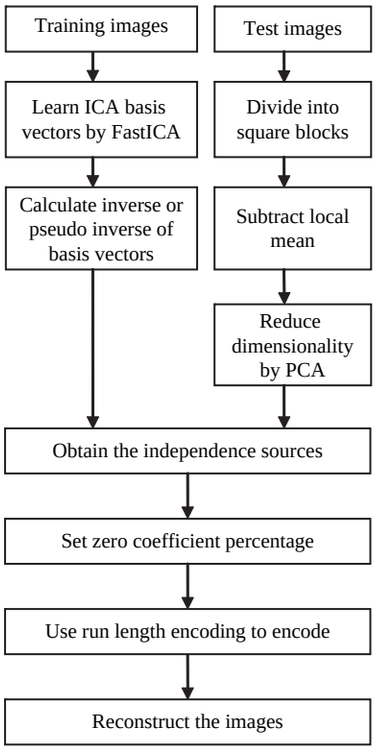


Fig. 1. The framework of the proposed approach based on ICA.

where W and X are obtained by step (2) and step (3) respectively. (5) Setting zero coefficient percentage. Only the elements with significant values are reserved while others are set to zero. After that, we get new independent sources S^*. Finally, we use Run Length Encoding method to encode S^*. (6) Reconstructing the image X^* according to:

$$X^* = AS^* + E(X^0) \tag{3}$$

3. THE SALIENCY MEASUREMENT

The saliency measurement used in our method is shown in Figure 2. There are three main steps in saliency detection: representing image patches, reducing dimensionality and

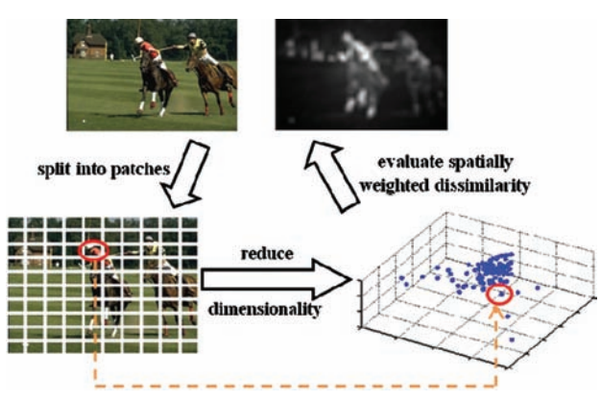


Fig. 2. The main steps of saliency measurement.[6]

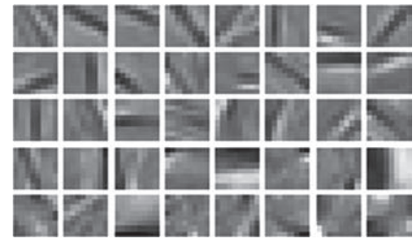


Fig. 3. Example of basis functions.

evaluating the spatially-weighted dissimilarity. Non-overlapping patches drawn from an image are represented as vectors of pixels. All patches are mapped into a reduced dimensional space. And then the saliency of each image patch is determined by aggregating the spatially-weighted dissimilarities between this patch and all the other ones in the image. In Figure 2, all patches are reduced to 3 dimensions for a better illustration; in fact, it can be arbitrary dimensions in practice. The weighting mechanism indicating central bias is used in next step. Finally, the saliency map is normalized and resized to the scale of the original image, and then is smoothed with a Gaussian filter ($\sigma = 3$). And the interested reader is encouraged to consult 6 for more details.

4. EXPERIMENTAL DETAILS

According to the proposed framework mentioned in Sections 2 and 3, our experiments including two classes. One class of experiments is based on ICA; the other is based ICA and visual saliency detection. However, there is a common step named basis functions extraction in these experiments. So we first introduce the basis functions extraction, then we compared the two class experiments. During the basis functions extraction, we choose 10 images which can be obtained from the website.[8] 50000 subwindows are extracted from these images by using 8×8 sliding window, which makes up of a 64×50000 training data set. After mean removal and whitening by principal component analysis,

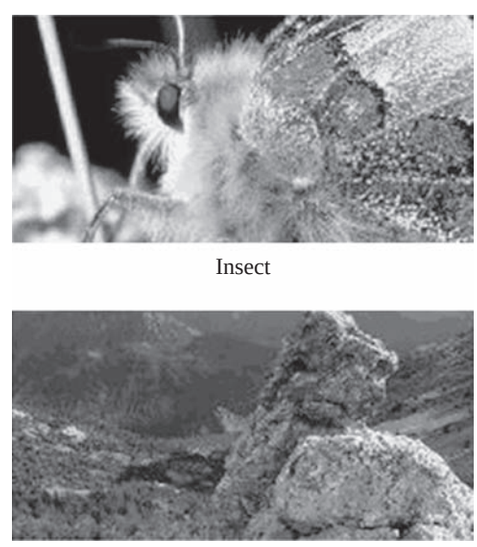
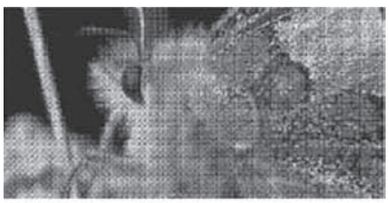


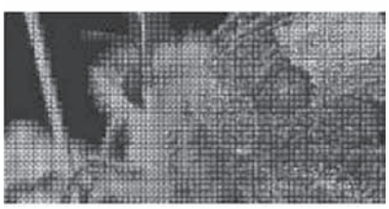
Fig. 4. Test images.

we get a 40×50000 data set X. Then we apply the FastICA algorithm to learn basis for this data set X. Figure 3 demonstrates these 40 basis functions. We can discover that ICA basis functions possess location, orientation and frequency selective properties. Then, these basis functions are used to the two class compression experiments. The details of these two class experiments are described in Sections 4.1 and 4.2 respectively.



(a) DCT 90%, PSNR=19.1042, SSIM=0.4338

(b) ICA 90%, PSNR=21.7318, SSIM=0.6341



(c) DCT 96%, PSNR=14.0427, SSIM=0.2283

(d) ICA 96%, PSNR=20.2483, SSIM=0.5300

(e) DCT 99%, PSNR=9.2889, SSIM=0.0885

(f) ICA 99%, PSNR=19.4707, SSIM=0.4441

Fig. 5. Reconstructed images for DCT and ICA. The zero coefficient percentage is set as 90%, 96% and 99%.

4.1. Experiments Based on ICA

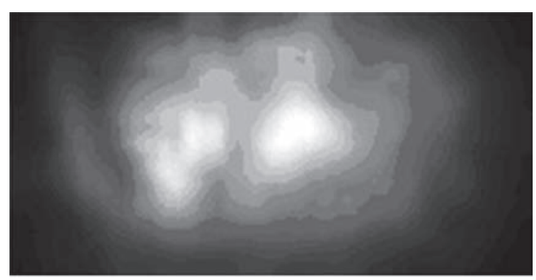
To evaluate the performance of proposed framework mentioned in Section 2, we have compressed two images (not used in the learning set) for ICA and DCT. Then, the compressed images were compared using Peak Signal-Noise-Ratio (PSNR) and Structural Similarity Index (SSIM) measurements respectively. PSNR is an objective measurement based on mean squared error (MSE) which has a visual metric as discussed in Ref. [7]. To overcome the drawback of PSNR, SSIM is adopted. It takes into account the retention of the original structure when evaluating a distorted version.[7]

Table I. Values of PSNR for reconstructed images.

Zero coefficient percentage (%)	PSNR			
	Insect image		Mountain image	
	DCT	ICA	DCT	ICA
70	29.3636	27.3743	30.5651	30.5606
80	24.9162	24.5154	26.4796	28.2839
90	19.1042	21.7318	21.4979	25.7784
99	9.2889	19.4707	11.8607	22.7453

Table II. Values of SSIM for reconstructed images.

Zero coefficient percentage (%)	SSIM			
	Insect image		Mountain image	
	DCT	ICA	DCT	ICA
70	0.8341	0.8373	0.8119	0.8558
80	0.6857	0.7536	0.6519	0.7840
90	0.4338	0.6341	0.3884	0.6750
99	0.0885	0.4441	0.0495	0.4922



(a) Saliency map

(b) Binary image

Fig. 6. Saliency Detection results on the insect image. (a) is obtained by our saliency detection method[6] and (b) is got by converting image (a) to binary image.

(a) ICA 90%, PSNR=23.7361 SSIM=0.7977

(b) ICA 96%, PSNR=22.1870 SSIM=0.7363

(c) ICA 99%, PSNR=21.3431 SSIM=0.6804

Fig. 7. Insect image reconstructed results based on ICA and visual saliency detection. The important regions are not compressed while the zero coefficient percentages of unimportant regions are kept at 90%, 96% and 99% respectively.

Figure 4 presents two test images in our experiment. Figure 5 shows the reconstructed images of insect image along with the respective values of PSNR and SSIM.

Figure 5 shows that PSNR and SSIM values of reconstructed images for DCT and ICA method when the zero coefficient percentage is set as 90%, 96% and 99% respectively. Under the same compress ratio, the PSNR and SSIM values of ICA method are larger than that of DCT method in Figure 5. As we know, when the PSNR and SSIM values are larger, the quality of the reconstructed image is better. Therefore, we can say that better quality reconstructed image can get when using ICA compression method. In order to validate the robustness of ICA compression method, we do more experiments. And the detailed experiments results are shown in Tables I and II. From these results, we can find that when the zero coefficient percentage is small ($\leq 80\%$), the performances of DCT and ICA are similar. But the performance of ICA is more promising than that of DCT in the case of zero coefficient percentage is high. Consequently, the proposed method based on ICA is more robust to distortions than DCT in the case of high compression ratio.

4.2. Experiments Based on ICA and Visual Saliency Detection

In Section 4.1, every region of test image is compressed with the same ratio. Actually, some regions of an image are important while other regions are not. It is not reasonable if the same compression ratio is used to these different regions. So the compression ratios of the important regions should be low and other regions should be highly compressed. It not only can improve the compression ratio but also can guarantee the quality of important regions. However, to solve this problem, the most important thing is to judge automatically whether a region is important. We introduce a visual saliency detection measurement which is depicted in Section 3 to detect the important region of image automatically. Figure 6 shows the saliency detection results on insect image. We can find that the proposed method can successfully detect the important region (the head of the insect). And Figure 7 demonstrates the reconstructed results after using saliency detection method. The zero coefficient percentage of regions which are unimportant are kept at 90%, 96% and 99% respectively while the important regions are not compressed. Compared (a), (b) and (c) in Figure 7 with (b), (d) and (f) in Figure 5, we can find that the quality of the three images in Figure 7 is better than that of three images in Figure 5 obviously. And the important regions of images in Figure 7 are still clear though the unimportant regions are blurred. So, it can be claimed that the presented method can guarantee the quality of important region effectively.

5. CONCLUSIONS

We have proposed a natural image compression method based on the ICA and visual saliency detection. The sparse nature of the independent components was successfully used to compress images. This method was compared with DCT through PSNR and SSIM measurements. The results showed our method is more robust to distortions than DCT. The saliency detection method can successfully detect the important region and when it was used to the compression, the quality of important region was guaranteed effectively.

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