APPLICATIONS OF INDEPENDENT COMPONENT ANALYSIS TO IMAGE CODING

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ABSTRACT

In communication systems, fast and secured transmissions have always been the ultimate goal that people want to achieve. The speed, accuracy and security of image transmissions are even more in demand for any existing communication systems. Because of the enormous demand, various image coding methods including image compression and decompression, image encryption and decryption have been introduced in the past 20 years. Among those coding or decoding techniques, Independent Component Analysis (ICA) has caught our eyes for its flexibility and diversity. In this paper, we will briefly introduce the ICA algorithm and its functions, then focus on explaining and discussing its role and impact on different image coding methods, and we conclude this paper by sharing our critical insights about applying ICA in the field of image coding.

Keywords: Independent Component Analysis (ICA), image compression, image decompression, image encryption, image decryption.

1. INTRODUCTION

Due to the evolution of digital image processing techniques, digital images now have much higher resolutions and contain more visual information than before. In exchange, the storage and transmission of digital images require more bits and more sophisticated processes. Therefore, in order to make image transmission fast and secure, research on finding effective and safe image coding methods to represent image data has become essential. In the context of image coding, there are two types of coding method, lossless and lossy. The lossless coding methods represent image data with the minimum possible number of bits, and the receiver will be able to reconstruct the original image from this received minimum bits representation without any error theoretically. The lossy image coding methods, on the other hand, allow errors to occur, however these errors are constrained within a tolerable range. Although lossy image coding methods can not reconstruct original image perfectly, it has more applications in image coding field because in many cases it can achieve a far better compression ratio than lossless image coding. Conventionally, Discrete Fourier transform (DFT) and Discrete Cosine Transform (DCT) are widely used as lossy image coding methods [1], but in this paper unconventional lossy image coding methods which are based on Independent Component Analysis (ICA) [2] are considered.

Independent Component Analysis (ICA) was originally introduced as a statistical tool to address the blind source separation (BSS) [3] problems, but recently it has gained a lot of attention due to its great potential in many other applications such as face recognition, analysis of electroencephalography (EEG) signal [4], audio signal processing, and data mining [5]. ICA models the observed data x as a linear combination of n independent sources:

$$x = As$$

Where s is a $n \times m$ matrix which each row represents a independent source and A is the mixing matrix that mixes independent sources. The goal of ICA is to retrieve the independent sources s by obtaining the unmixing matrix which is defined as $W = A^{-1}$ and perform matrix multiplication between x and W:

$$s = Wx$$

However, the recovered unmixing matrix is not always perfect because there are some ambiguities in it. For example, the permutation of original sources is ambiguous as well as the scaling of W. Fortunately, these ambiguities do not matter for most applications. However, one point worth noting is that sources s have to be non-Gaussian since Gaussian distribution is rotationally symmetric, which means there is no way to determine whether the sources were mixed with A or A^T.

2. FROM ICA TO IMAGE CODING

Independent Component Analysis (ICA) has potential in many aspects of image coding field, such as image compression and image encryption. Its ability to separate combined signal to individual independent signal sources gives researchers a tremendous amount of freedom to apply this algorithm at different stages in image coding systems. In this section, we elaborate on several aspects of image coding in which Independent Component Analysis (ICA) can make significant impact.

2.1. Image Compression and Decompression

The purpose of image compression is to find a new representation of image data using fewer bits from which original image data can be reconstructed with or without error. The result of Independent Component Analysis (ICA) can be lossy or lossless depending on the number of independent components. If all independent components are used, the reconstruction will be lossless, but without any compression at all. Thus, ICA is often used as a lossy image compression method, but it can still achieve reasonable and controllable compression ratio with very fast compression speed due to the present of FastICA algorithm [6]. To apply ICA to two dimensional data such as images, either using ICA to the whole image or using block-based ICA [7] approaches can achieve desired effect, however block-based ICA approaches are prefered since the problem of having huge matrices x and s can be avoided.

2.1.1. Block-Based ICA on Color Image Overview

In block-based ICA, the color image x of size $M \times M$ is first separated into three color components R, G and B. Each color component image is further divided into m subblocks of size $N \times N$ where each subblock of the image is denoted as $x^{(i)}$. Each $x^{(i)}$ represents N linear combinations of N independent sources. These N mixed signals are N columns of the block which are denoted as $x_j^{(i)}$ where $j = 1, 2, ..., N$. $x^{(i)}$'s are then fed to ICA algorithm as training examples to compute the unmixing matrix $W^{(i)}$. From the computed unmixing matrix, a matrix of N independent sources $s^{(i)}$ can be obtained by performing matrix multiplication: $s^{(i)} = W^{(i)} x^{(i)}$. Unmixing matrix $W^{(i)}$ is then reversed to obtain the mixing matrix $A^{(i)}$. Consequently, the original image is now decomposed to two parts which are mixing matrix:

$$A = \{A^{(i)}; i = 1, 2, ..., m\}$$

and independent sources:

$$s = \{s^{(i)}; i = 1, 2, ..., m\}$$

Where $m = \frac{M^2}{N^2}$. These two parts are the results of ICA compression and the data to be transmitted over the channel. Prior to transmission, arithmetic coding will be applied to both mixing matrix and independent sources to convert them into binary format. The receiver will be able to recover the transmitted information by doing arithmetic decoding and reconstruct the original image by multiplying A and s.

2.1.2. Block-Based ICA Compression Algorithm

1. Decompose original image to RGB components.
2. Choose the size of subblock.
3. Obtain $m = \frac{M^2}{N^2}$ subblocks from each component.
4. Use subblocks as training examples for ICA.
5. Obtain mixing matrix A and independent sources s.
6. Encode the mixing matrix and independent sources.
7. Transmit the result of step 6.

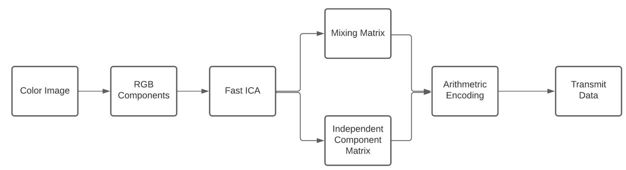

Fig. 1. Block-Based ICA Compression Flow Diagram

2.1.3. Block-Based ICA Decompression Algorithm

1. Apply arithmetic decoding to received data.
2. Obtain mixing matrix A and independent components s.
3. Recover the original data x by multiplying A and s.
4. Repeat step 3 for all color components.
5. Reconstruct the original image.

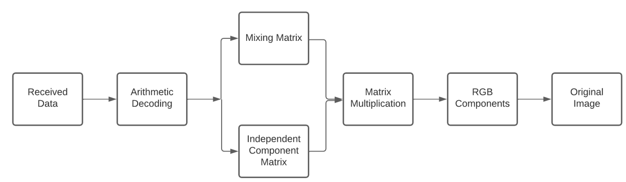

Fig. 2. Block-Based ICA Decompression Flow Diagram

2.1.4. Effect of the Number of Independent Components

The number of independent components that is sufficient to represent the original image is application-dependent. It can be chosen by comparisons between the quality of reconstructed image and original image by different quality metrics and compression ratio as shown in figure 3, or by visual comparison as shown in figure 4. Different applications may require different numbers of independent components but the trade-off between image quality and compression ratio are completely controlled by the number of independent components.

2.2. Image Encryption and Decryption

Besides efficient compression during transmission, information security is another important factor to be considered. In order to achieve secure information transmission, image encryption and decryption become increasingly important. As a

Number of Independent Components	Mean Square Error (MSE)	Signal to Noise Ratio (SNR)	Peak Signal to Noise Ratio (PSNR)	Compression Ratio
1	288.9443	18.189	23.0682	88.5284
2	182.3956	20.189	25.0662	47.2906
3	140.9408	21.3068	26.1859	32.9019
5	85.5514	23.4749	28.354	20.4505

Fig. 3. Comparison between reconstructed image and original image using different quality metrics (data from [7])

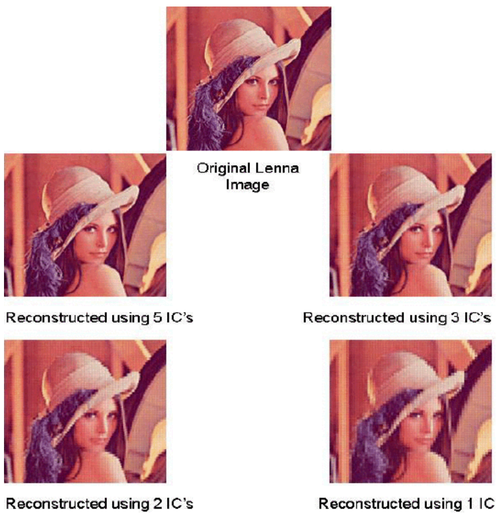

Fig. 4. Block-based ICA compression with different independent components (image from [7])

statistical method that recovers independent sources from several mixed sources using statistic independent principle [8], Independent Component Analysis (ICA) provides a possible way to encrypt and decrypt the image. In this section, a new ICA-based image encryption and compression method is examined [9].

2.2.1. ICA-Based Image Encryption and Decryption Overview

The general purpose of the new ICA-based image encryption and decryption method is to separate the independent components from the mixtures. The mixtures are designed and generated from original images in encryption, and the original images can be reconstructed by the ICA algorithm in decryption.

2.2.2. ICA-Based Image Encryption Method

In the encryption stage, the new method divides the original images into several small subblocks, and each of which is applied to two-dimensional Discrete Cosine Transform (DCT). DCT has an excellent energy-compaction property, concentrating the majority of signal energy(information) in the top-left corner of the energy spectrum [10]. For natural images, energy concentrates at low frequencies. Thus, using lowpass filters to throw high frequencies away can reduce the amount of information without losing too much image quality.

Because ICA will be used to retrieve DCT components in receiver, all DCT components should be independent to each other before transmission. For natural images, there are high dependence between two neighboring pixels, and thus between two subblocks. To eliminate such high dependency as possible, the rotation operation that randomly rotates each DCT subblock will be used. Meanwhile, rotation information (such as rotation degree) will be stored into the rotation key, which will also be sent to receiver during transmission.

The last step of encryption stage is to make a mixed image. Random images are merged with DCT components, so that the original images can be hidden under random images, and they are unrecognizable for non-authorized people without ICA algorithms and the rotation key.

2.2.3. ICA-Based Image Decryption Method

In the decryption stage, the authorized receiver will receive the mixture and the rotation key. The receiver will use ICA algorithm (i.e., FastICA) to demix the mixtures. The results of demixing are DCT components separated from other random images. The rotation key will then be used to rotate these DCT components back to the original positions, in which low frequencies are retained in the top-left corner of each subblock. Finally, Inverse Discrete Cosine Transform (IDCT) will be applied onto the DCT components to reconstruct the original images from the encrypted mixtures.

2.2.4. ICA-Based Image Encryption Algorithm

For the rigor and simplicity of the paper, we only consider grayscale images in the algorithm, but color images can also be applied in the same way.

1. Choose the size of subblocks.
2. Divide the original image into different subblocks based on the subblock size.
3. Use DCT to obtain DCT components of each block.
4. Apply lowpass filter to extract low-frequency components.
5. Rotate each DCT component randomly to eliminate dependency of each subblock.
6. Mix DCT components with some random images.
7. Apply arithmetic encoding to the image mixture and rotation key.
8. Transmit the data to receivers.

2.2.5. ICA-Based Image Decryption Algorithm

1. Apply arithmetic decoding to the data from transmitter.
2. Use FastICA to demix the mixtures.
3. Rotate DCT components back with received rotation key.
4. Use IDCT to restore the original images.

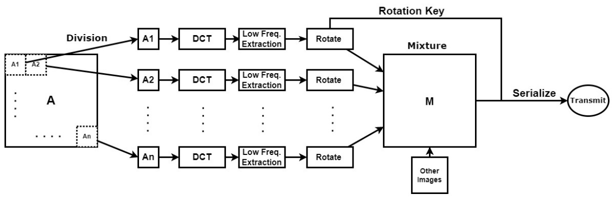

Fig. 5. ICA-based Image Encryption Flow Diagram

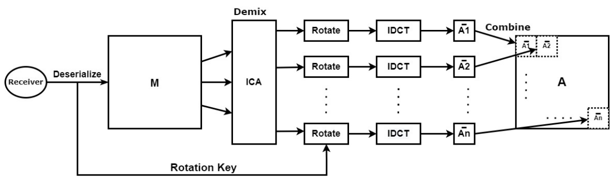

Fig. 6. ICA-based Image Decryption Flow Diagram

2.2.6. *Simulation Result*

As shown in figure 7, ”Lena” and ”Baboon” images are simulated in the new encryption and decryption method [9]. In the first row, images of ”Lena”, ”Baboon” and a random image are used as original source ((a)-(c)). These images will be processed in the encryption stage and be transmitted into the receiver. The encrypted images are shown in the second row ((d)-(f)). Authorized people can demix received images with rotation key to reconstruct images in the decryption stage, shown in the third row ((g)-(i)). It is noticeable that these reconstructed images are very close to the original images, which demonstrates that the ICA algorithm provides a possible and effective way in image encryption and decryption.

Fig. 7. 1st row: Original images; 2nd row: IDCT of mixed DCT components; 3rd row: Restored images (image from [9])

3. CRITICAL THINKING

The major advantage of ICA-based image coding methods is flexibility. The degree of compression and the quality of reconstructed image are completely controlled by the number of independent components. If the quality is the main concern, compression with more independent components will result in more accurate reconstruction, but the compression ratio may be reduced. On the other hand, if we need to minimize the number of bits representing the image, using less independent components leads to higher compression ratio but less accurate reconstruction. In addition, the presence of block-based ICA method and FastICA algorithm has ensured the fast convergence of ICA for two-dimensional data, which can dramatically decrease the image encoding and decoding time. Furthermore, ICA-based methods have demonstrated diversity. Their applications are not limited to only one phase of the coding system, they can show promising results in other phases as well, such as in encryption and decryption phases. ICA-based image coding methods are often compared with another statistical methods called Principal Component Analysis (PCA) [11]. The block-based ICA methods outperform PCA-based methods on both compression ratio and quality [7], and the speed advantage of ICA-based methods stands out for short transmission time.

Since the whole idea of ICA is established on the assumption that components are being independent and non-Gaussian, the drawbacks of ICA-based image coding methods are their poor adaptability to mutually dependent and Gaussian distributed data, in which case the unmixing matrix W can not be recovered due to the rotationally symmetry property of Gaussian distribution. To further improve ICA-based image coding method, preprocessing techniques such as decorrelation transformation (i.e., sphering and whitening) can be performed to normalize and decorrelate data.

4. CONCLUSION

In this paper, we have examined the applications of ICA in the field of image coding by describing different ICA-based image coding algorithms and showing their simulation results. We have seen the great potential of this algorithm as well as its subtleties. Its flexibility and diversity allow people to use this algorithm in various applications without worry too much about the compression and quality trade-off, and its speed advantage also allows fast convergence and potentially faster image coding speed. However, future research on how to overcome the constraint of having non-Gaussian distributed image source are still necessary.

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