13th Int. Conf. on Pattern Recognition, ICPR'96
Proceedings, vol. II, pp. 394–398, August 1996
IEEE Computer Society Press, Los Alamitos CA

Hidden Image Separation From Incomplete Image Mixtures by Independent Component Analysis

Włodzimierz KASPRZAK and Andrzej CICHOCKI [1]
RIKEN - Frontier Research Program
Laboratory for Artificial Brain Systems
Hirosawa 2–1, Saitama 351–01, Wako–shi, JAPAN
E-mail: {kas,cia}@zoo.riken.go.jp

Abstract

It is known that the independent component analysis (ICA) (also called blind source separation) can be applied only if the number of received signals (sensors) is at least equal to the number of mixed sources, contained in the sensor signals. In this paper an application of the ICA is proposed for hidden (secured) image transmission by communication channels. We assume that only a single image mixture is transmitted. A friendly receiver contains the remaining original sources and therefore it can separate the hidden image of lowest energy. The influence of two non–lossless signal reduction stages, compression by principal component analysis and signal quantization, onto the separation ability is tested. Constraints of the mixing process are discussed that make impossible the hidden image separation without the key images.

1. Introduction

In neural network based *independent component analysis* (ICA), called also *blind separation of sources*, one assumes that multiple signal observations are available, where each observation is a linear superposition of independent signals from different sources [6], [7]. The goal of ICA is to obtain at each output some primary source signal. Recently robust methods with global learning rules have been proposed that can handle ill–conditioned mixtures of signals [2], [3], [8], [10]. But even these methods require that the number of mixed input (sensor) sources is *at least* equal to the number of sources. This limitation of the method may be at the same time an advantage if a secured transmission of hidden images is required (e.g. for pay–television or in *cryptography* [11]).

In signal transmission over communication channels two general problems arise. An additive noise seems to be unavoidable and also one wants to perform some lossy compression of transmitted signals. These two aspects should also be considered.

In this paper we propose a new system for transmission of secured images on the basis of the ICA, performed by a neural network learning algorithm (section 2). At the sender side the mixing matrix can be randomly chosen and one mixed image should be sent only. The friendly receiver contains the predefined key images, whereas a non–friendly receiver does not posses them. The main stage performing the ICA by a neural network learning algorithm is described in section 3. For handling the communication channel problems two optional stages of signal compression and noise reduction are tested. The quality of separation in the friendly receiver case is experimentally evaluated in section 4. In section 5 we discuss cases where a non–friendly receiver may be able to separate sources from the incomplete mixture.

2. The approach

2.1. The system structure

The proposed system structure for an ICA based secured image transmission consists of the sender and receiver sides, as depicted in Fig. 1. The stages at the sender side are: source image mixing by the use of a random matrix (with some constraints), signal compression (option) and noise reduction. The compression is based on principal component analysis (PCA). For noise reduction a digital encoding (quantization) scheme is applied. At the receiver side the three stages are decoding, signal reconstruction (option), and the

[1] On leave from Warsaw University of Technology, Department of Electrical Engineering, Warsaw, Poland.

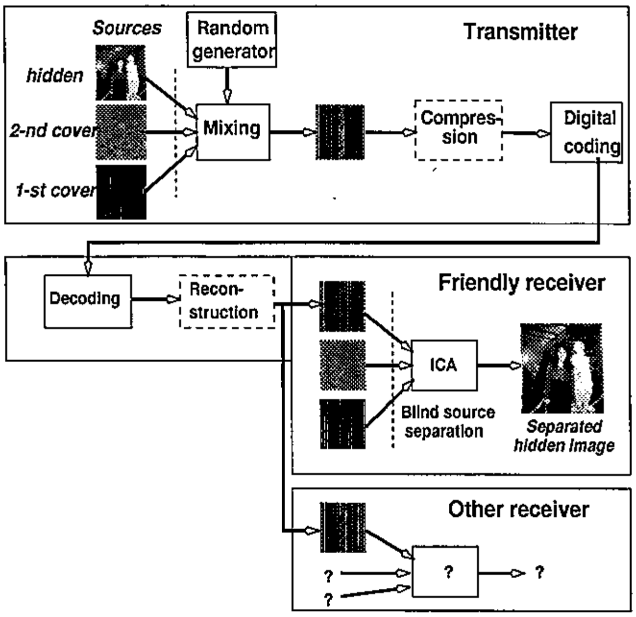


Figure 1. The system structure.

main stage of independent component analysis (ICA). One mixed image has to be sent only.

Two receiver types are considered: a friendly and non–friendly one. The friendly receiver contains some predefined number of mixed images. Thus it can reconstruct the mixing matrix in order to separate the secured hidden image from other transmitted sources. The non–friendly receiver can possibly break the digital encoding scheme, as well as apply the PCA decoding too. But its main problem is how to supply additional images, required by the ICA method.

2.2. Source mixing

Let us assume several stochastically independent source signals $s_j(t)$ $(j = 1, 2, \dots, n)$ are linearly and instantaneously combined via unknown mixing coefficients (parameters) $\{a_{1j}\}$ in order to form the mixture:

$$x_1(t) = \sum_{j=1}^{n} a_{1j} s_j(t). \qquad (1)$$

At least three sources should be mixed $(n \geq 3)$. The outer cover image is mixed with the highest energy. The second cover image is included with similar energy or with up to 10 times smaller energy than the first one. The secured image is hidden while mixing them with a 10-100 times weaker energy than the first one.

2.3. Optional signal compression

In order efficiently to send some signal by a transmission channel usually a lossy compression scheme is applied. The *principal component analysis* (PCA) [1], [5], [9], called also Karhunen–Loeve transformation, determines an optimal linear transformation $y = \boldsymbol{W}\boldsymbol{x}$, where $\boldsymbol{x} \in \mathcal{R}^n$ is a zero–mean input vector, $\boldsymbol{y} \in \mathcal{R}^m$ is the output vector and $\boldsymbol{W} = [\boldsymbol{w}_1, \boldsymbol{w}_2, ..., \boldsymbol{w}_m]^T \in \mathcal{R}^{m \times n}$ is a desired transformation matrix. The orthogonal vectors $\boldsymbol{w}_j = [w_{j1}, w_{j2}, ..., w_{jn}], (j = 1, 2, ..., m)$, are called *principal components.*

For image compression–reconstruction only a subset of first m components (e.g. 16) need to be estimated from the whole set of n (e.g. 64) principal components. A two–layer perceptron may be applied, where the layers perform following transformations:

$$(i)\ y_j(t) = \boldsymbol{w}_j \boldsymbol{x}(t), \quad (ii)\ \widehat{x}_j(t) = \boldsymbol{w}_j^T \boldsymbol{y}(t), \qquad (2)$$

where $\boldsymbol{w}_j \in R^n$, $\boldsymbol{x}(t) \in R^n$, $\boldsymbol{y}(t) \in R^m$, $j = 1, 2, ..., m \leq n$. The first (encoding) layer is responsible for extraction of the components and for signal compression on the basis of these components. The second layer is placed at the receiver side and it performs the signal reconstruction from transmitted image features (eigenvalues) and weights (principal components).

2.4. Signal quantization

A noise can be imposed during the transmission from emitter to receiver. One possible way to eliminate this noise from the received signal is digitally to encode the transmitted signal in such a way, that a significant distance between useful signal and noise is assured. The digitalization stage also means a lossy data compression. The main problem is here how to determine the number of quantization levels for a binary coding scheme. The hidden image must be relatively week against the covering (visible) signal in order to be invisible to the viewer. Hence in order to properly to separate the week signal at the receiver the applied a codebook should have some minimum length. But the length of this codebook should be limited in order to assure an efficient and fast transmission.

3. ICA for hidden image separation

The problem of *blind separation of sources* is equivalent to the waveform–preserving *blind estimation of multiple independent sources*, where the problem is to estimate the multiple source signals from an array of sensors without knowing the mixing parameters $\{a_{ij}\}$ from the mixing matrix $\boldsymbol{A}$. Usually following assumptions about the nature of the source signals and their mixing are made:

- The mixing process is noiseless, i.e. $\boldsymbol{x}(t) = \boldsymbol{A}\boldsymbol{s}(t)$.

- Number of sensors is equal to number of sources ($A \in R^{nxn}$).
- The mixing matrix A is nonsingular.
- Primary sources are zero–mean stochastic independent signals and at most one source has a Gaussian distribution.

Let us consider a feed–forward neural network described as

$$y_j(t) = \sum_{p=1}^{n} w_{jp}(t) x_p(t), \text{ or : } \boldsymbol{y}(t) = \boldsymbol{W}(t)\boldsymbol{x}(t). \quad (3)$$

At the receiver side it is required to estimate the synaptic weights w_{ij} of a single–layer feed–forward neural network, in order to combine observations in each layer and to form optimal estimates of the sources. The optimal weights correspond to the statistical independence of the output signals and they simultaneously ensure self–normalization of these signals. The source separation is achieved as soon as the composite matrix $\boldsymbol{P}(t) = \boldsymbol{W}(t)\boldsymbol{A}$ has exactly only one non–zero element in each row and each column [7].

For ill–conditioned problems a robust learning algorithm with nonlinear activation functions $\boldsymbol{f}, \boldsymbol{g}$ is applied ([2]):

$$\Delta \boldsymbol{W}(t) = \bar{\eta}(t)\,[\boldsymbol{I} - \boldsymbol{f}[y(t)]g^T[y(t)]]\,\boldsymbol{W}(t) \quad (4)$$

where $\bar{\eta}(t)$ is the learning rate. In scalar form these learning algorithm can be written as

$$\delta w_{ji}(t) = \bar{\eta}(t)\left[w_{ji}(t) - f[y_j(t)]\sum_{p=1}^{n} w_{pi}(t) g[y_p(t)]\right] \quad (5)$$

Examples of activation function pairs are:

$$f[y(t)] = y; \qquad g[y(t)] = tanh(10y(t)) \quad (6)$$

$$f[y(t)] = y^3; \qquad g[y(t)] = y(t) \quad (7)$$

4. Friendly receiver

In our experiments grey scale images with resolution 512×512 were divided into 4096 blocks of 8×8 pixels each and converted into vector samples of 64 elements. One single mixture of three images has been transmitted, as shown in Fig. 2. At the friendly receiver side the second and third image are already known (these are the keys). They can be mixed together giving two more mixed images (Fig. 3). The separation problem is well determined, as there are three mixtures of three images.

4.1. The influence of digitalization

In Fig. 4 the results of hidden image separation are shown if there is no intermediate compression/reconstruction stage of the transmitted mixed image. Only a digital encoding with different number of quantization levels may be performed before sending. The associated quantitative results are provided in Fig. 5. For this kind of mixture already a 12-bit quantization leads to good separation quality and with a 15-bit quantization the influence of the quantization onto the separation stage is no longer observable. Already by using a 7-bit coding scheme the receiver was still able to separate the hidden image.

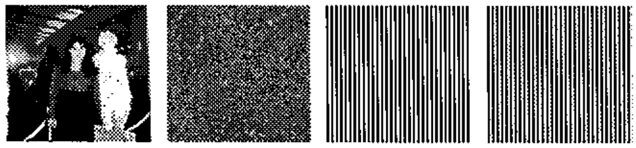
SNR means the signal to noise ratio of the separated image signal and PI is an error index defined as:

$$PI = \sum_{j=1}^{m}\left(\sum_{i=1}^{n}\frac{|p_{ij}|^2}{max_i|p_{ij}|^2} - 1\right). \quad (8)$$

The p_{ij}-s are entries of matrix $\boldsymbol{P}(t) \in R^{n \times m}$, where every row of $\boldsymbol{P}$ was normalized by $\sum_{j=1}^{m}|p_{ij}| = 1, \forall i$.

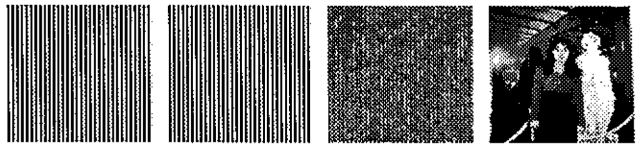
4.2. The influence of compression

We test the use of a neural PCA technique for lossy compression of transmitted image mixture. In a recent



Secured image Inner cover Outer cover Transmitted

Figure 2. The secured image is mixed with two cover images. The transmitted mixture looks nearly similar to the outer cover image.



Received image First key Second key Separated

Figure 3. Besides the received mixture two known key images are used for separation. The hidden image is very well separated.

No quantization 10 bits 8 bits 7 bits

Figure 4. The results of secured image separation for different quantization resolution but without the PCA based encoding/decoding.

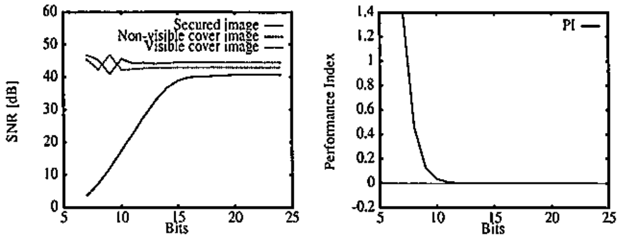
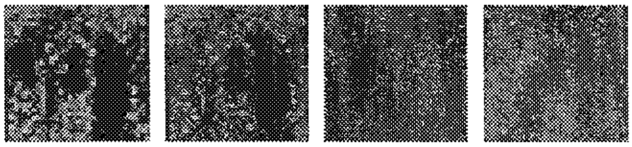


Figure 5. SNR and PI of separation in dependence on quantization for different quantization levels but without the PCA based encoding/decoding.



With 60 PC's With 48 PC's With 24 PC's With 8 PC's

Figure 6. The results of hidden image separation with an intermediate PCA stage. Even if nearly all components are applied the information about the small energy image is lost.

paper [4] an efficient neural algorithm for hierarchical extraction of principal components by a cascade neural network, called CRLS PCA, was developed. By applying this method we are able to perform this task very fast (for the first several components this may be done in one iteration) and still we approximate the optimum solution with very high accuracy.

In Fig. 6 the results of secured image separation are shown if there is an intermediate PCA encoding and decoding. Either no digitalization stage is applied or a binary 12-bit coding scheme is used. For week energy secured signal (approximately 100 times weaker than the cover image) this compression stage is eliminating the secured image nearly completely from the mixture. Even by the use of nearly all components for compression–reconstruction of the transmitted image mixture the secured image can not be properly separated.

5. Non–friendly receiver

Atlhough the separation problem is under–determined if one mixture is available only, but if no restrictions are posed onto the transmitted mixture, then sometimes the non–friendly receiver will be able to extract the hidden image.

5.1. The possible non–secured situation

Let us assume, that only the outer cover image is visible in the transmitted mixture and the inner cover is suppressed, e.g the second cover is at least 10 times weaker mixed than the first one. Let us pass the mixture image through a digitalization step that eliminates the small energies of the remaining images. In this way the outer cover is already extracted.

Now let us assume further that the remaining two images are of different nature – one is a synthetic image and the other one is a natural image. Let us take some random natural image to be the second original image (Fig. 7). With two known and two unknown sources let us now solve a four source–four sensor–problem (Fig. 8). The separation results in Fig. 9 clearly show that the second covered image *Noise* has been separated with well accuracy.

In this way two of the three original sources are available to the non–friendly. Hence another separation stage can be performed with three sensor images (the transmitted mixture and the two cover source approximations). If only little cross–talking exists between the approximated cover images, the secured image can be separated from the mixture.

Transmitted image Extracted cover Added random image

Figure 7. Three images used for separation at the non–friendly receiver: from the transmitted mixture the clear cover image is extracted manually and some random natural image is added.

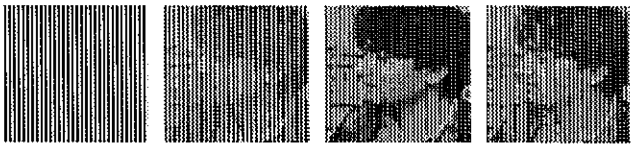
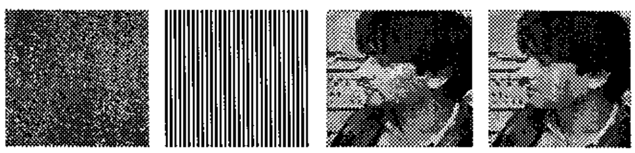


Figure 8. Additionally to the received mixed image (left image), that contains a three–image mixture, three mixed images containing only the two new source images are added.



SNR = 17.7 dB 39.8 dB 22.8 dB 22.7 dB

Figure 9. The results of separating four mixed images (one received mixture and three additional mixtures of two added images) by the non–friendly receiver.

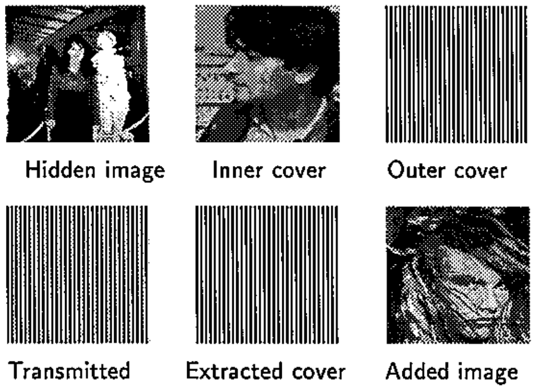


Figure 10. The secured case with natural second cover image (top row) and possible input images for separation in the non-friendly receiver.

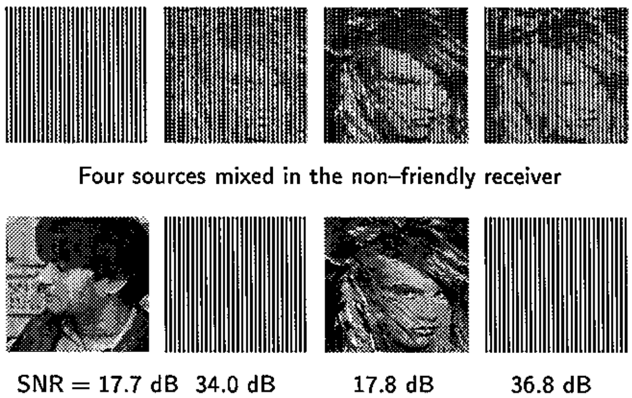


Figure 11. In the secured case the hidden image can not be separated by the non–friendly receiver.

5.2. Secured case

At first view similar results can be obtained if the inner cover image is a natural image (of the same nature as the secured image) instead of being a synthetic one (Fig. 10). If the outer cover is clearly extracted by conventional techniques this natural image can also be separated from the mixture, similarly to *Noise* in previous case. But there remains some cross–talking effect between the two natural images. As both these images and the week secured image belong to the same class, the non–friendly receiver is not able to separate the hidden image in the next separation stage. Instead of expected hidden image a double copy of either the inner cover image or the randomly added natural image occurs at the output (Fig. 11).

6. Conclusion

In this paper we proposed a secured image transmission approach on the basis of independent component analysis. At the transmitter the image is mixed with other covering images, where the mixing parameters are unknown to all participants and can randomly be chosen (within some restrictions). The secured image can be clearly separated by a friendly receiver, which contains the cover images (keys), by a neural network learning process.

In case of transmitting very week signals a lossy compression stage will not be allowed but an appropriate quantization scheme may be used. In our experiments a 12–bit coding scheme for 8–bit grey scale images already gave nearly best separation ability.

Computer simulations have shown that if a non-friendly receiver can extract clearly the outer cover, it can separate the inner cover by adding a random natural image. But even in this case it will not be able to separate the hidden image due to small energy of this image and its class similarity with the cover image.

References

[1] S. Amari. Neural theory of association and concept formation. *Biological Cybernetics*, 26:175–185, 1977.

[2] S.-I. Amari, A. Cichocki, and H. Yang. A new learing algorithm for blind signal separation. In *NIPS'95*, vol. 8, Cambridge, Mass., 1996. MIT Press. (in print).

[3] J. Cardoso, A. Belouchrani, and B. Laheld. A new composite criterion for adaptive and iterative blind source separation. In *Proceedings ICASSP-94*, volume 4, pages 273–276, 1994.

[4] A. Cichocki, W. Kasprzak, and W. Skarbek. Adaptive learning algorithm for PCA with partial data. In *Cybernetics and Systems '96.*, vol. 2, pages 1014–1019. Austrian Soc. for Cybernetic Studies, Vienna, 1996.

[5] A. Cichocki and R. Unbehauen. *Neural Networks for Optimization and Signal Processing.* John Wiley & Sons, New York, 1994.

[6] P. Comon, C. Jutten, and J. Herault. Blind separation of sources, part ii: Problems statement. *Signal Processing*, 24(1):11–20, 1991.

[7] C. Jutten and J. Herault. Blind separation of sources, part i: An adaptive algorithm based on neuromimetic architecture. *Signal Processing*, 24(1):1–10, 1991.

[8] E. Moreau and O. Macchi. A complex self–adaptive algorithm for source separation based on high order contrasts. In *Proceedings EUSIPCO-94*, pages 1157–1160, Lausanne, 1994. EUSIP Ass.

[9] E. Oja. Principal components, minor components and linear neural networks. *Neural Networks*, 5:927–935, 1992.

[10] E. Oja and J. Karhunen. Signal separation by nonlinear hebbian learning. In *Computational Intelligence*, pages 83–96. IEEE Press, 1995.

[11] M. Rhee. *Cryptography and Secure Communications.* McGraw–Hill, New York, 1994.