INDEPENDENT COMPONENT ANALYSIS OF TEXTURES IN ANGIOGRAPHY IMAGES

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Abstract The technique of independent component analysis (ICA) is applied for texture feature detection. In ICA an optimal transformation (with respect to the statistical structure of the image samples set) is discovered via blind signal processing. Any texture is considered as a mixture of independent sources (basic functions of detected transformation). Experimental comparison is documented on the compactness and separability of base functions, the data-specific ICA-based and universal Gabor functions (the latter are set by default for all kinds of images).

Keywords: feature detection, texture classification, independent component analysis

Introduction

A fundamental research area in image analysis [1, 2] is the description and classification of textures [3, 4]. Typical approaches to texture analysis are: statistical features for an intensity connection matrix or for the matrix of sums and differences [5], linear transformations [6] like Fourier or Hadamard [2] or DCT transforms [6], filtering the texture by Gaussian-based kernel masks, Gabor filters [7, 8] or wavelets [2]. All these approaches provide feature detection schemas established by experience in a heuristic manner.

In this paper the technique of independent component analysis (ICA) is applied for texture feature detection. ICA allows for a statistical analysis of data samples and leads to an optimal transformation with respect to the independence of data samples representing different textures [9, 10]. Opposite to the approach of principal component analysis, that seeks for a transformation best for generalization [11], ICA establishes a best separation of samples from different classes. ICA performs a blind processing (i.e. unsupervised learning), whereas discriminate analysis searches for a feature space transformation by a supervised learning [12].

In the past one of the authors has proposed to apply ICA to image separation [13, 14] and encrypted image transmission [15]. Other authors discovered the potential of ICA as applied for feature detection [16, 17].

1. The ICA problem and solution

In Independent Component Analysis we assume that there exist m zero-mean source signals, $s_1(t), ..., s_m(t)$, that are scalar-valued and mutually (spatially) statistically independent (or as independent as possible) at each time instant or index value t. The original sources $s_j(t)$ are unknown to the observer, who has to deal with n possibly noisy but different linear mixtures, $x_1(t), ..., x_n(t)$, of the sources (usually for $n >= m$). The mixing coefficients are also unknown variables.

Denote by $x(t) = [x_1(t), ..., x_n(t)]^T$ the n-dimensional t-th data vector made up of the mixtures at discrete index value (usually time) t. The ICA mixing model is equal to:

$$\mathbf{x}(t) = \mathbf{A}\mathbf{s}(t) + \mathbf{n}(t) = \sum_{i=1}^{m} s_i(t)\mathbf{a}_i + \mathbf{n}(t), \tag{1}$$

where $\mathbf{a}_i^T$ denotes the i-th row vector of the matrix $\mathbf{A}$.

In standard neural source separation approach, an $m \times n$ separating matrix $\mathbf{W}(t)$ is updated so that the m-vector $\mathbf{y}(t) = \mathbf{W}(t)\mathbf{x}(t)$ becomes an estimate of the original independent source signals. $\mathbf{y}(t)$ is the output vector of the network and the matrix $\mathbf{W}(t)$ is the total weight matrix between the input and output layers.

Pre-processing in ICA:

- The elimination of mean value - results in an algorithm simplification. Let $\mathbf{m}$ be the mean vector of time series (observation vector) $\mathbf{x}(t)$. After estimating the sources in ICA their means can be reconstructed.
- "Whitening" - a linear transformation such that the observation vector elements will be uncorrelated and with unit variances:

  $$E\{\tilde{\mathbf{x}}\tilde{\mathbf{x}}\} = \mathbf{I}. \tag{2}$$

  Whitening allows the reduction of the ICA search problem from n^2 free matrix coefficients to only $n(n-1)/2$ elements, as the matrix must be kept orthogonal.
- Reduction of the number of outputs if some eigenvalues λ_j of the auto-correlation matrix of the input vector are comparatively small.

Applying the natural gradient approach we may derive the learning rule for on-line ICA as [10]:

$$\Delta\mathbf{W}(k) = \theta(k)[\mathbf{I} - f(\mathbf{y}(k))g(\mathbf{y})^T(k)]\mathbf{W}(k), \tag{3}$$

where $f(.), g(.)$ is a pair of suitable activation functions (see [13, 14, 15]) and θ is the learning coefficient.

An efficient "batch" approach is the method "FastICA" of Hyvarinen et al. [9]. The batch processing allows a preliminary "whitening" step for the zero-mean mixture signals, which improves the convergence speed of the ICA procedure. Both "on-line" and "batch" methods should converge to the same solutions if the input mixtures satisfy the source independence conditions.

2. Texture analysis by ICA

Image blocks (of size $k \times l = N$) are assumed to be decomposable, i.e. to be a weighted sum of m independent components (Fig. 1). In the ICA de-mixing process we should extract the independent components (unknown sources) from image data samples. The set of observed image blocks is scanned into input vectors $\mathbf{x}_i(t), (i = 1, ..., n; t = 1, ..., N)$.

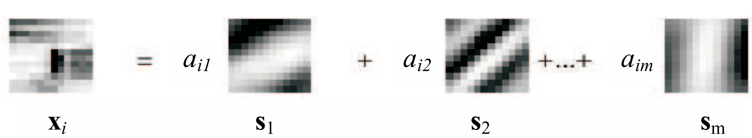


Figure 1. The idea of image decomposition into an additive set of base blocks (independent components).

Hence $\mathbf{x}(t)$ represents the vector of n mixtures. The $\mathbf{a}_i$-s $(i = 1, ..., n)$ are n weight vectors of size m (representing features of given block in the space that we search for) and they constitute rows of the mixing matrix $\mathbf{A}$. The $\mathbf{s}_i$-s are unknown N-element vectors (in total m sources).

In the ICA process we estimate both the source vector $\mathbf{y}(t)$ and the de-mixing matrix $\mathbf{W}(t)$. After convergence of the weights, $\mathbf{W}$ gets "frozen" and we compute the final source vector $\mathbf{y}$. The weight matrix itself is not of interest in this step.

In the feature extraction step the equation $x(t) = \mathbf{a}^T\mathbf{s}(t)$ is still valid, but now both the observable single mixture $x(t)$ (i.e. current image block for which we want to compute its features) and the source vector $\mathbf{y}(t)$ are available, whereas only the coefficient vector $\mathbf{a}$ is unknown. This constitutes a standard linear equation problem, which can be solved by a least square method.

3. Tests

The experimental verification of our approach is illustrated in two ways: (a) by the examination of detected base vectors (ICA components) and (b) by measuring the compactness and separability of point clusters for different textures in ICA-based space. A comparison is made against Gabor-based features, induced by a constant set of filter masks (Fig. 2).

Gabor filters are the same if applied to Brodatz textures (Fig. 3) or to angiography images (Fig. 4), whereas these two sets of images exhibit quite different statistical nature.

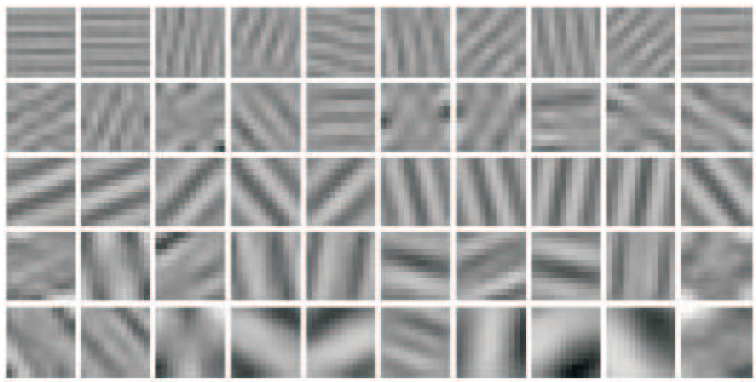


Figure 2. A set of 50 base functions in Gabor filtering (represented as blocks of size 12×12 - kernel masks for image filtering).

In contrast to Gabor filtering the base functions (ICA components), found for Brodatz textures and angiography images are much different one from the other (Fig.5). For every Brodatz texture a block of size 40×40 pixels was selected to be a single input mixture signal. Hence the input vector consisted of 20 mixtures with 1600 samples each.

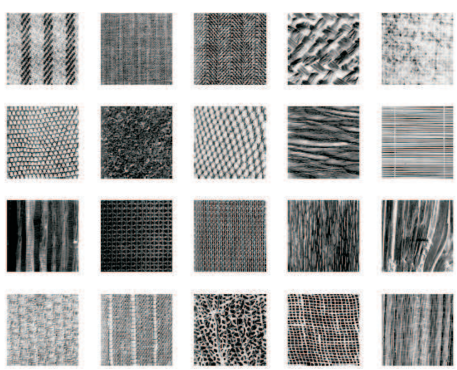


Figure 3. 20 Brodatz textures supplied to the ICA procedure.

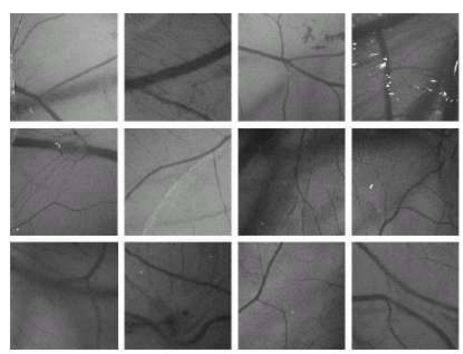
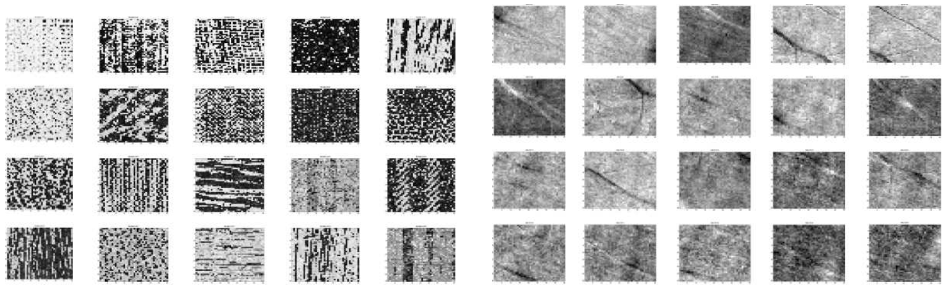


Figure 4. 16 angiography images that were subject to the ICA analysis - blocks of size 40×40 were taken as inputs of the ICA procedure.



(a) (b)

Figure 5. 20 base vectors (converted into image blocks) found by ICA for (a) Brodatz textures or (b) angiography images.

The independence of base vectors was examined by checking if they are pair-wise un-correlated - it appeared that in all cases the correlation values were below 1 % (this is in practice a good result).

In order to compare the compactness and separability of class clusters in the spaces determined by ICA and Gabor functions we have computed a distance merit as a simplification of the Fisher information. For the test set of textures, classified "by hand" into 5 classes for angiography images and 20 classes for Brodatz images, we have computed the class centers. Then the relation between average ”in-class” variance to the average ”between-classes” variance was computed. It appeared that for Brodatz textures the merit for ICA results was slightly better than Gabor filtering (lower by 4%) but it was much better for the angiography images (by 13 %).

4. Summary

We presented an ICA-based texture feature detection method, in which the base functions matches the statistical structure of images. The optimal transformation (with respect to the image samples set) is discovered by blind signal processing. We have compared the compactness and separability of base function, retrieved by ICA, with Gabor functions, that are set by default for all kinds of images. The results are promising. The research work will be continued by considering various classifiers of image features and making comparisons of classification results for texture features, obtained by ICA and Gabor filtering.

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