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AN ICA BASED METHOD FOR TEXTURE RECOGNITION

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Abstract: The method proposed in this paper uses the Independent Component Analysis (ICA) for an application of unsupervised recognition of textures. The analysed texture is modelled by a weighted sum of almost statistically independent random signals that are extracted with FastICA algorithm. Each resulting signal is described by its negentropy, more precisely, by one of the approximations used by FastICA algorithm. The approximated negentropies are sorted into descending order and represented by a curve. The final step of the algorithm is the averaging of a certain number of such curves obtained from different zones of the texture. The resulting mean ”negentropy curve” displays a good discriminating power on the tested textures.

Index Terms: Independent Component Analysis, Negentropy, Pattern Recognition, Texture.

1. TEXTURE RANDOMNESS

As regular as a natural texture may look for human sight, it is nevertheless a random process. The textures’ randomness has many causes. Among others, these causes influence the size of texture’s constituents, their orientation, relative position etc. Often, in textures, the randomness' sources are statistically independent simply because they interfere in different steps of the texture’s formation or because they are related to its different constituents. We are also allowed to think that, due to the large variety of the natural textures, the statistical characteristics of these sources vary from case to case. Moreover, since the sources are rarely stationary, variations of these characteristics often appear over the same texture. Briefly, since a set of conditions is never perfectly reproducible, two natural textures, even of the same type, may never be identical from the statistical point of view. This means that the analysis of the random sources in texture images may give the possibility to discriminate among textures. And if this analysis is fine enough, it may be possible to discriminate even among patches of the same texture.

ICA (Independent Component Analysis) is a mathematical tool that can extract statistically almost independent components from an image. Originally, the ICA has been used for source separation - the so called "cocktail-party problem"-, i.e., individualization of a known number of statistically independent signals from some mixtures of them. A classical example is the separation of three simultaneous speakers recorded by some microphones held in different locations (Hyvärinen, *et al.*, 2001).

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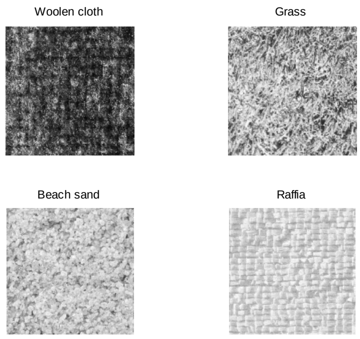

Fig.1. The analysed textures: "Wool cloth", "Grass", "Beach sand", "Raffia" (1024x1024 pixels, 8 bits/pixel).

In image processing, the ICA has already been used successfully for human faces recognition (Draper, *et al.*, 2003), (Stan, *et al.*, 2005), (Moghaddam, 2002). Such applications have two steps: first, a learning stage when a base of primitive faces is created by using a training set. Then the recognition takes place: each new face is decomposed on this base and the resulting coefficients, i.e., the independent components, are compared with those of the probe faces. The ICA has seldom been applied to textures' classification; in one of the rare occurrences that can be found in the literature (Jenssen, Eltoft, 2003), for instance, the texture segmentation method with ICA relies mainly on the similarities with the classical approach based on the Gabor transform.

In this paper, we show that, by using ICA, a texture may be reduced to a few statistically almost independent components - still called "sources", even if the original meaning is no longer the same -, specific enough to allow texture's recognition. The texture recognition method based on ICA, that we propose belongs to the unsupervised type, i.e., without any learning step.

The paper is organised as follows: in Section II, the principle of ICA is recalled and an equation approximating the negentropy from source's samples is given. Then, in Section III, we present our method and some experimental results. These results provide evidence that the sorted negentropies of the sources derived by ICA constitute a feature with a high potential in the applications of texture recognition and classification.

2. ICA AND SOURCE NEGENTROPY

In applications of sources separation, the ICA decomposes a random signal into a weighted sum of a certain number of signals whose characteristic is to be the less Gaussian possible. The resulting signals represent the independent components, also called sources of the signal. Nongaussianity guaranties the independence, since, according to the Central Limit Theorem, the sum of many independent, identical distributed random variables tends to be Gaussian. In other words, the sources of a signal must be more nongaussian than the signal itself.

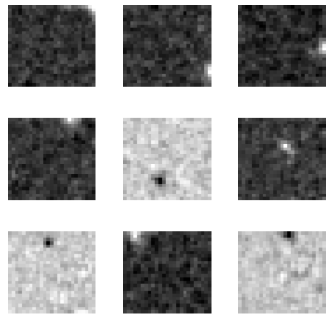

Fig.2. Nine sources of "Wool cloth" texture: s1, s5, s9, s13, s18, s23, s28, s31 and s32, in the descending order of the negentropy (from top to bottom and left to right).

Depending on the signal, the sources extracted by ICA may be completely independent or may preserve a certain mutual information.

There are different algorithms for obtaining the sources of a signal. Each one optimizes a specific criterion, depending on the way the independence condition is given. For instance, if the degree of statistical independence is expressed by source nongaussianity, then the criterion may be their negentropy, a measure whose definition is given next.

It is known that, among all possible distributions with a given covariance matrix, the Gaussian one has the highest entropy (Hyvärinen, *et al.*, 2001). Due to this property, the entropy may be used to define a measure of the nongaussianity of sources, $J(\mathbf{s})$, called negentropy and defined as follows (Hyvärinen, *et al.*, 2001):

$$(1)\quad J(\mathbf{s}) = H_{Gauss}(\mathbf{s}) - H(\mathbf{s})$$

where $H(\mathbf{s})$ is the entropy of a source $\mathbf{s}$ and $H_{Gauss}(\mathbf{s})$ is the entropy of a Gaussian source with the same covariance matrix as $\mathbf{s}$.

Definition (1) shows that negentropy is a nonnegative quantity. It is zero only for Gaussian sources. The FastICA algorithm that we use looks for independent components, by maximizing the negentropy (Hyvärinen, *et al.*, 2001). Since it is rather difficult to estimate the negentropy by using its definition (a large number of samples would be necessary for a good estimation of the conditional entropies in $H(\mathbf{s})$), the FastICA uses approximations of it, one of them being (Hyvärinen, *et al.*, 2001):

$$(2)\quad \begin{aligned} J(\mathbf{s}) = {} & k_1\left(E\left\{s \cdot \exp\left(-s^2/2\right)\right\}\right)^2 + \\ & + k_2^a\left(E\{|s|\} - \sqrt{2/\pi}\right)^2 \end{aligned}$$

where $k_1 = 36/\left(8\sqrt{3} - 9\right)$, $k_2^a = 1/\left(2 - 6/\pi\right)$ and s are samples of the source $\mathbf{s}$.

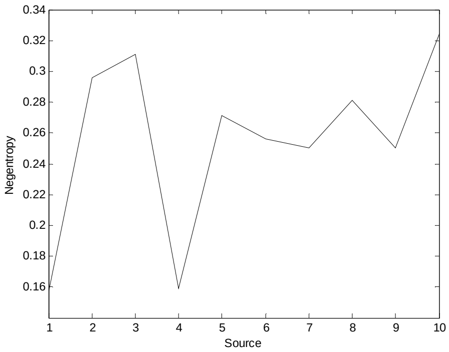

Fig.3. The negentropies of "Wool cloth" sources, represented in the same order as the sources in matrix S.

In deriving the sources of a random signal $\mathbf{x}$, FastICA starts from a set of particular realizations of $\mathbf{x}$. These realizations are collected in a matrix X, each row of X containing the samples of a particular realization. By iterations, FastICA decomposes X into a product of two matrices, A and S (Hyvärinen, *et al.*, 2001):

$$(3)\quad X = AS$$

where the rows of S contain the signals' sources, given by their samples (each row consists of samples of the same source). The factorization (3) is optimal in the sense that the rows of S have a maximum of statistical independence or, equivalently, maximum negentropies.

If we denote by s_j, the rows of S, by $a_{i,j}$ the elements of A and by x_i, the rows of X, the equation (3) may be re-written in the following way:

$$(4)\quad x_i = \sum_j a_{i,j} s_j$$

expressing each particular realization of X as a linear combination of sources s_i (as stated in the beginning of this section).

The sources s_i are all of unit variance and have an undetermined sign; their order in matrix S is also irrelevant. The number of samples of each source is the same as that of a particular realization in X (a natural constraint for having compatible dimensions in matrix product (3)). On the contrary, the number of sources s_i is a parameter that must be fixed by the user. For a series of applications, this number is known a priori. When it is not known, it may be estimated from the covariance matrix of X. In such cases, the source number is taken equal to the number of eigenvalues accounting for more than 90% of the signal energy.

3. TEXTURE ANALYSIS BY ICA

The reasoning made in Section I has encouraged us to consider that a texture is a mixture of many random signals, with a rather high degree of statistical independence.

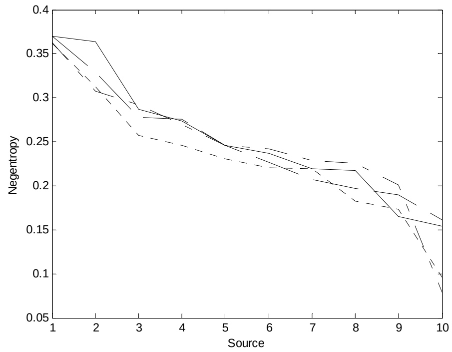

Fig.4. The negentropy curve: first zone (dotted line), second zone (dashed line), mean curve (continuous line).

As we have seen in Section II, some of these signals may be extracted by applying an ICA.

In order to build matrix X, which is the starting point for ICA, one needs more particular realizations of the analysed texture.

In our experiments, the particular realizations come from 64 adjacent patches of 25x25 pixels with zero mean. The patches, once serialized, constitute the rows of X. In a first stage, 10 sources were extracted. As initial guess for A, we took a matrix with all elements equal to the unity. Thus, neither a source, nor a mixture was privileged.
The tests have been done on the four textures in Fig. 1 representing, respectively, wool cloth, grass, sand and raffia trellis. These texture images -taken from SIPI database (http://sipi.usc.edu/database)-, are scanned prints from Brodatz album. The sources extracted by ICA are given by their samples (in our case, 625 samples for each source). By reshaping each source's samples in a 25x25 pixels image, one gets the 10 "sources" of the considered zone. For "Wool cloth", nine sources are shown in Fig. 2.

Statistically, a source may be described in many ways: by samples, histogram, moments etc. Among all possible representations, we have chosen to describe the sources by their negentropy. The reasons were the compactness - the negentropy is a simple numerical value - and, moreover, the fact that it represents the measure optimized by the FastICA algorithm. In order to compute our 10 negentropies, we did not use the definition in (1), but the approximation given in (2), also used by FastICA. The reason of this choice has been given in Sec. 2.

The raw sequence of negentropies (as found in matrix S), is plotted in Fig. 3 for "Wool cloth" texture. Such a curve, without any obvious trend, is difficult to interpret. However, since ICA does not extract the sources in a specific order, the negentropies can be sorted in a decreasing order. With this new representation (Fig. 4, solid line), we can see that five sources have a negentropy higher then 0.25, while the last ones are rather close to the Gaussian distribution.

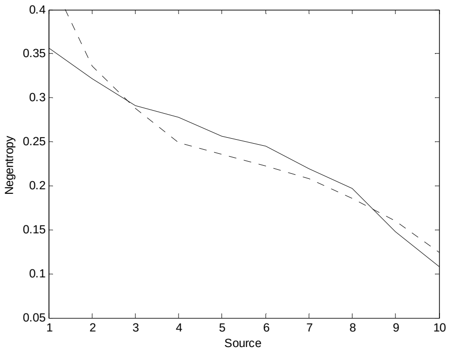

Fig.5. Two mean negentropy curves corresponding to the upper and lower halves of “ Wool cloth” texture.

As a Gaussian source may hide other sources (according to the Central Limit Theorem), for the purpose of texture recognition, one has to look mainly at high negentropy sources. The negentropy curves, obtained for another zones (Fig. 4), show some variations compared with the first one. Two possible explanations for these variations are the differences existing between the considered zones due to the texture unstationarity and the estimation error (the sources have been estimated from 64 patches and the negentropy from 625 samples).

In order to reduce this effect, we have averaged eight negentropy curves from eight not superposed zones. The mean curve characterizes an area of 8x64x25x25 pixels, which is equivalent to a squared patch of texture of about 550x550 pixels. The mean curves for the upper and the lower halves of the “Wool cloth” texture are shown in Fig. 5. Although slightly less important, the differences still exist. This time, we explain them mainly by the texture unstationarity. We shall use further the mean negentropy curve to characterize a texture.

As already mentioned in Section II, the number of sources is imposed by the application, not by the algorithm. Since the textures are signals with a high degree of complexity, theoretically, one may extract a very large number of sources. However, by considering that only the most nongaussian sources are significant for the texture identity and, besides, that noise is present in any image of natural texture, an upper limit for the number of sources should be imposed. In the case of our textures, we have limited the extracted sources to ten, a number equal to the number of eigenvalues responsible for more than 55% of the patches’ energy. In order to assess the discrimination capability of the negentropy curve among different textures, we have derived it for “Beach sand”, “Grass” and “Raffia” (Fig. 6).

Like for the “Wool cloth”, 64 patches of 25x25 pixels were used to extract ten sources. Eight negentropy curves were averaged in each case. One may observe important differences all along the curves, especially in the domain of high negentropies.

The results shown on Fig. 6 confirm that the negentropy’s mean curve is a feature with a rather high discriminatory potential for textures.

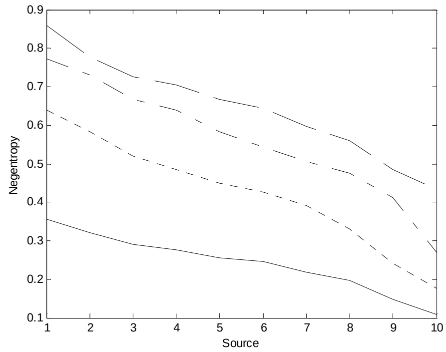

Fig.6. The negentropy mean curves for “Wool cloth” (continuous line), “Raffia” (dashed line), “Sand” (dotted line) and “Grass” (dashed-dotted line).

This feature can be used in applications like recognition or classification, but it is less appropriate for textures' segmentation because its precise estimation requires a large zone. For instance, in our tests, we used a zone of 8x64x25x25 pixels which is equivalent to a squared area of about 550x550 pixels.

4. CONCLUSIONS AND FURTHER DEVELOPMENTS

The method proposed in this paper is based on the assumption that a texture may be modelled as a linear combination of many random signals, with a rather high degree of statistical independence. Under this hypothesis, a number of components is extracted by ICA from each analyzed texture. In order to have a significant and compact description of these components, their negentropies are estimated from samples. The obtained values are ordered and represented by a descending curve that is designated by “negentropy curve”. The tests have shown that this curve is specific to each texture and, therefore, that it can be used as a discriminatory feature in applications like recognition and classification.

Our conclusions are based only on a visual evaluation of the negentropy curves. In order to have a complete recognition method, one has to provide also a well-adapted distance.

Even if the results obtained so far are promising, adjusting parameters like patches’ size, number and placement should reduce the standard deviation of the negentropy curve. Besides, some other ways should be considered for the description of the texture independent components.

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