COMPUTING NEGENTROPY BASED SIGNATURES FOR TEXTURE RECOGNITION

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Abstract: The proposed method aims to provide a new tool for texture recognition. For this purpose, a set of texture samples are decomposed by using the FastICA algorithm and characterized by a negentropy based signature. In order to do recognition, the texture signatures are compared by means of Minkowski distance. The recognition rates, computed for a set of 320 texture samples, show a medium recognition accuracy and the method may be further improved.

Keywords: texture recognition, Independent Component Analysis, negentropy, Minkowski distance.

1. INTRODUCTION

The natural textures, even the most regular ones, are random processes. Among the factors that determine their randomness, it worth to mention: texture’s constituents, their position and orientation, color etc.

The natural textures have different statistical characteristics, which appear also in the independent components extracted from them. Consequently, the analysis of these components may provide some discriminatory features for texture recognition and classification. This property suggested us to use the Independent Component Analysis (ICA) for developing a new method for texture recognition (Coltuc *et al.*, 2006).

ICA is a statistical tool, able to reveal sets of almost independent components that are hidden in the random signals. In the beginning, this technique was developed for source separation applications. A classical example is the “cocktail-party problem”, where several simultaneous speakers, recorded by microphones held in different locations, are separated (Hyvärinen *et al.*, 2001). Later, ICA has been successfully used also for problems like: human faces recognition (Draper *et al.*, 2003), financial time series analysis (Kiviluoto and Oja,1998), separation of interfering signals in mobile telecommunications (Ristaniemi and Joutsensalo, 1999) etc. In (Jenssen and Eltoft, 2003), the authors propose a texture segmentation method, based on ICA, which is similar to the classical approach using Gabor transform.

This paper focuses on the feature extraction stage in a texture recognition application. Thus, by using ICA, the texture is decomposed in a set of almost independent components and a texture signature is

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constituted by their negentropies (Lungu *et al.*,2007). The texture recognition is done by calculating a distance between the texture and candidates' signatures.

The paper is organized as follows: Section 2 contains a brief description of ICA, the definition of texture signature based on an approximation of the negentropy and a short description of Minkowski distances. In Section 3, the proposed method and some experimental results are presented. Section 4 concludes the paper.

2. ICA AND NEGENTROPY BASED SIGNATURES

The ICA decomposes a random signal into a weighted sum of signals whose characteristic is to be statistically independent. The resulting signals represent the independent components, also called, in a series of applications, sources of the signal.

There are different algorithms for obtaining the independent components 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 measured by the gaussianity, then the criterion is the maximization of the component nongaussianity. The 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 independent components of a signal must be more nongaussian than the signal itself. Depending on the analyzed signal, the components extracted by ICA may be completely independent or may preserve certain mutual information.

It is known that, among all the possible distributions with a given covariance matrix, Gaussian distributions have the highest entropy (Hyvärinen *et al.*, 2001). Due to this property, the entropy may be used to define a measure $J(\mathbf{s})$ of the components' nongaussianity, called negentropy. $J(\mathbf{s})$ is 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 component $\mathbf{s}$ and $H_{Gauss}(\mathbf{s})$ is the entropy of a Gaussian random variable with the same covariance matrix as $\mathbf{s}$. The definition (1) shows that the negentropy is a nonnegative quantity. It is zero only for Gaussian components. The FastICA algorithm (http://www.cis.hut.fi/projects/ica/fastica) that we use for extracting significant features for textures, 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 S (Hyvärinen *et al.*, 2001):

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

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

In deriving the independent components 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. FastICA decomposes X into a product of two matrices, A and S (Hyvärinen *et al.*, 2001):

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

where S contains the signal's independent components (each row consists of samples of the same component) and A, the weighting coefficients. 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 the mixing matrix 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 the independent components s_i (as stated in the beginning of this section). The independent components 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 component 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 the components s_i is a parameter that must be fixed by the user. For a series of applications, this number is known a priori.

In texture analysis, in order to build the matrix X, which is the starting point for FastICA, one needs more particular realizations of the analyzed texture.

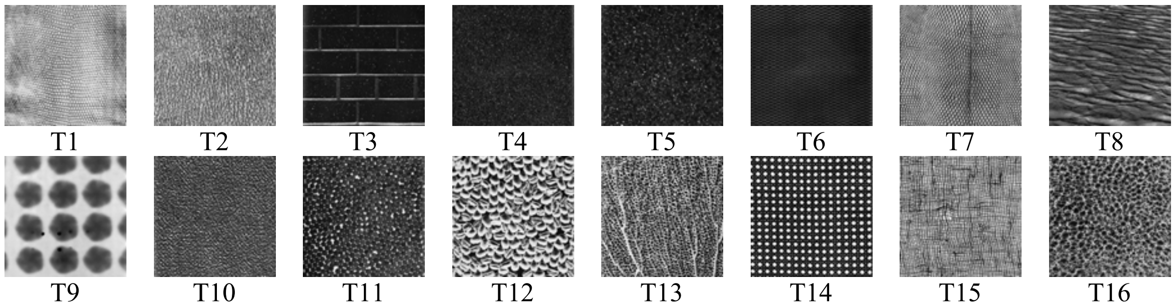

Fig. 1. The sixteen textures used for the experiments (640x640 pixels, 8 bits/pixel).

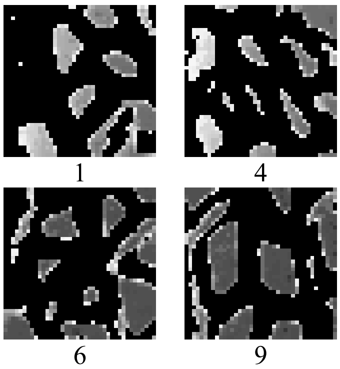

Fig. 2 Four patches of texture T13 (40x40 pixels, 8 bits/pixel).

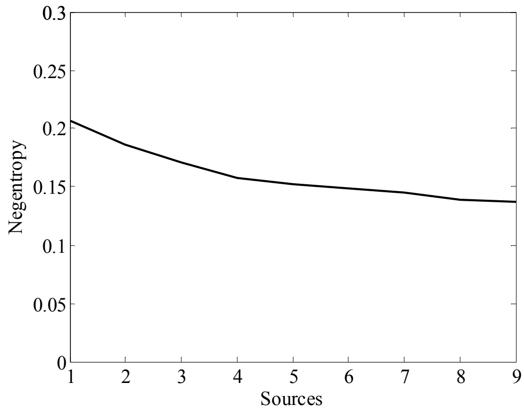

Fig. 3. The signature of a zone of texture T13, represented as a negentropy curve.

In our approach, as only one image of the texture is usually available, serialized texture patches are used for obtaining X. Then, in order to have maximum accuracy, FastICA is asked to extract a number of independent components equal to that of the particular realizations.

Statistically, an independent component may be described in many ways: by samples, histogram, moments etc. Among all possible representations, we have chosen the negentropy. The reasons were the compactness - the negentropy is a simple numerical value - and the fact that it represents the independence measure optimized by FastICA. In our approach, estimates of the components' negentropies are calculated by using equation (2). Then, the obtained negentropies are sorted in descending order and assembled into a vector that constitutes the texture signature.

One important step in any recognition method is represented by the proper selection of a distance measure. From the wide variety of distances proposed in literature (Rubner et al., 2003), we have chosen for our approach, the Minkowski distance defined by :

$$(5)\quad d_r(\mathbf{u},\mathbf{v}) = \left(\sum_{i=1}^{n} \left|u_i - v_i\right|^r\right)^{1/r}$$

where u_i and v_i are the elements of two vectors $\mathbf{u}$ and $\mathbf{v}$ of the same length n and r is a parameter. For $r = 1$, the Minkowski distance becomes equal to:

$$(6)\quad d(\mathbf{u},\mathbf{v}) = \sum_{i=1}^{n} \left|u_i - v_i\right|$$

which is known as City Block distance. For $r = 2$, the well known Euclidean distance is obtained:

$$(7)\quad d_2(\mathbf{u},\mathbf{v}) = \left(\sum_{i=1}^{n} (u_i - v_j)^2\right)^{1/2}$$

3. METHOD DESCRIPTION AND EXPERIMENTAL RESULTS

In this section, a novel recognition method, based on the ICA algorithm, is presented and tested. By considering that a texture is a weighted sum of almost statistically independent random signals, a signature consisting of its independent components'

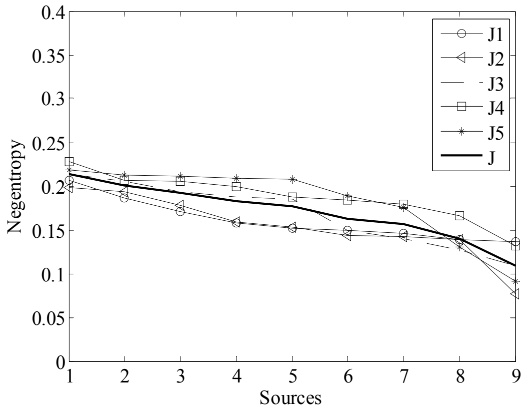

Fig. 4. The fascicle of negentropy curves obtained for the training set and T13 signature (thick line).

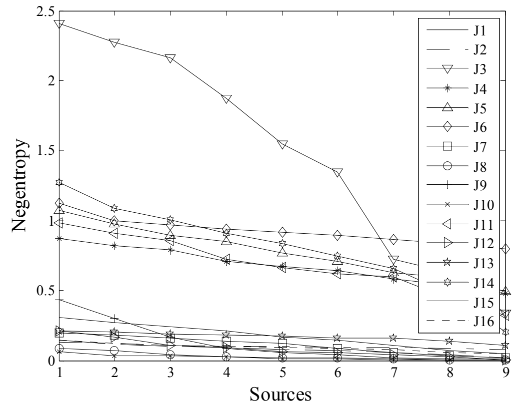

Fig. 5. The signatures of the 16 textures used in the experiments.

negentropies is associated to the texture. In order to discriminate among the textures, their signatures are compared by means of Minkowski distance.

For the experiments, 16 textures (Fig. 1) from Brodatz album (http:// sipi.usc.edu/database) were used. These scans represent natural or hand made materials. Each texture image has a resolution of 640x640 pixels with 256 gray tones (color depth of 8 bits/pixel).

In order to extract a signature, the texture is divided into 25 zones of 120x120 pixels. In the next step, each zone is further divided into 9 square patches of 40x40 pixels. Fig. 2 shows, for example, 4 patches of such a zone in texture T13. The patches are serialized and constitute the rows of matrix X, the input matrix of the FastICA algorithm. As initial guess for the mixing matrix A, it is considered a diagonal matrix with all the elements of the main diagonal set to one. With this structure of matrix X, FastICA can extract, at maximum, 9 independent components. In this case, the analyzed zone is characterized by a 9 negentropy

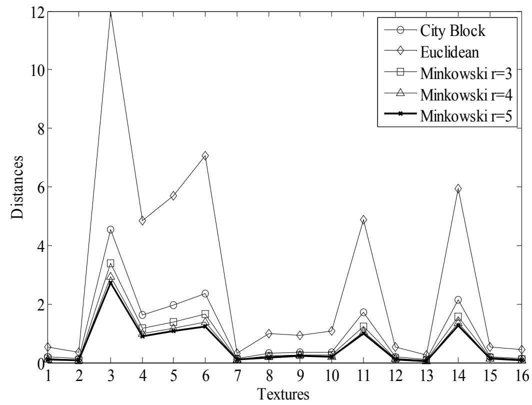

Fig. 6. Recognition benchmarks for one T13 zone.

values vector. These negentropy values are sorted in descending order and constitute the texture zone signature. Fig. 3 shows, for example, the signature of a zone from texture T13, represented as a curve in 2D plot. It is interesting to note that only the first four negentropy values are greater then 0.15. This means that other 5 components have, in this case, an almost Gaussian distribution. As the low negentropies values do not contribute to the signatures' distance in a significant way, these almost Gaussian components are not essential for texture recognition, in this approach.

For each texture, the signatures extracted from the first 5 adjacent training zones (the image top stripe) constitute a cluster, represented by a fascicle of curves in Fig. 4. The center of the cluster, computed as the average of the five negentropy signatures, is considered the texture signature and is represented by a thick line in Fig. 4. In Fig. 5, one may see the texture signatures of all the 16 textures used in the experiments. The remaining 20 adjacent zones of each texture were used for evaluating the recognition rate.

Once the training stage completed, the recognition may start. For this stage, a test database was constituted, by getting together the remaining zones (not used for training) of the 16 textures. Thus, a database of 320 texture samples was obtained. The corresponding 320 signatures were matched to the 16 texture signatures, by using the Minkowski distance and the texture corresponding to the lowest distance was declared as the matching one for the tested zone.

Five versions of Minkowski distance have been tested: City Block ($r=1$), Euclidean ($r=2$) and Minkowski distance with $r=3$, $r=4$ and $r=5$. Fig. 6 shows, for example, the recognition benchmarks for a zone of texture T13. In this case, all of the considered distances gave a correct classification. The minimum distance between the zone signature and texture T13 signature is obtained in the case of Minkowski distance with $r = 5$. This is explained by the subunitary negentropies of this texture (r is the negentropy power in equation (5)).

Table 1. The recognition rates (%) for five versions of Minkowski distance.

Textures	r=1	r=2	r=3	r=4	r=5
1	20	20	20	25	25
2	80	80	90	90	95
3	90	70	75	75	75
4	90	90	90	90	90
5	5	15	15	10	10
6	90	90	90	90	90
7	30	30	30	30	30
8	80	80	80	80	80
9	55	70	75	70	70
10	80	75	75	80	80
11	80	70	75	70	70
12	30	25	25	25	25
13	**95**	**95**	**95**	**95**	**95**
14	75	75	70	70	70
15	**90**	**90**	**90**	**95**	**95**
16	5	5	5	5	5
Total	**60,93**	**61,25**	**62,50**	**62,50**	**62,81**

The recognition rates are given in Table 1. They were calculated as the percentage of the correctly recognized zones from the 20 available ones of each texture. The highest recognition rates were obtained for textures T13 and T15 (90%, 95% for all five distances). The highest negentropies in the signatures of these textures are 2.18 (texture T13) and 0.32 (texture T15), as shown in Figure 5. They are medium and low values comparing with the other texture maximum negentropies, which shows that the recognition is not dependent on the level of the components' negentropy.

The visual inspection of the textures with low recognition rates shows either a strong non-uniformity of the analyzed sample, as in the case of T1 and T7, or a higher periodicity comparing to the patch size, like for T12 and T16. This suggests that the patch size should be adapted to the texture type, in order to obtain better results. Another improvement might be obtained if a sliding window would be used for selecting the patches instead of using adjacent patches. Such approach would reduce the influence of the texture sample non-uniformity.

Concerning the distance versions, in order to see which one is more appropriate, a global recognition rate has also been estimated (last line in Table 1). It was calculated as the percentage of the total number of correct recognized zones from the 320 available ones. The highest global recognition rates was obtained for the Minkowski (r = 5) distance (62.81%) and the lowest one for r = 1 (60.93%).

4. CONCLUSIONS

The method for texture recognition, proposed in this paper, relies on the assumption that a natural texture is the result of various random processes, some of them being statistically independent. With this hypothesis, by using ICA, the textures samples are reduced to negentropy based signatures that are compared by means of Minkowski distance, in order to be classified and recognized.

The experiments have shown a strong dependency of recognition rate on the texture type, the obtained values varying in the range of 5% to 95%. Another conclusion regards the distance used for comparing the texture signatures: from the five Minkowski distance versions that were tested, the best one proved to be Minkowski (r = 5) distance.

Although, for some textures, the recognition rates were very high, the global results show a medium accuracy of the proposed method. One of the reasons must be the errors in negentropy estimation. The method attempted to improve this estimation by using larger patches of texture (40x40 pixels instead of 25x25 pixels) and another model for the mixing matrix A (Lungu *et al.*,2007). By comparison with the results obtained by (Lungu *et al.*,2007) one can easy observe a general improvement of the global recognition rate. The next step will regard the description of the independent components extracted by ICA. As the negentropy gives a very poor description, other possibilities, like histograms for instance, will be investigated. Other types of distances will be also tested, in order to have meaningful and efficient classification.

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