New Statistics for Texture Classification Based on Gabor Filters

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Abstract. *The paper introduces a new method of texture segmentation efficiency evaluation. One of the well known texture segmentation methods is based on Gabor filters because of their orientation and spatial frequency character. Several statistics are used to extract more information from results obtained by Gabor filtering. Big amount of input parameters causes a wide set of results which need to be evaluated. The evaluation method is based on the normal distributions Gaussian curves intersection assessment and provides a new point of view to the segmentation method selection.*

Keywords

Texture segmentation, image segmentation, Gabor filters, efficiency evaluation.

1. Introduction

An image segmentation process is an operation with a basic aim – to detect different kinds of regions, i.e. forest, urban zone, rivers, etc. The scene is a set of pixels with their grayscale values. Most methods use homogeneity criteria based on grayscale similarity to determine the regions in the nature image. More satisfactory interpretation of scenes should contain a textural aspect of regions.

Several methods for a texture description have been developed, i.e. co-occurrence matrix, local binary pattern, methods based on Markov Random Field, Gabor filters [2][3].

In this paper we present a technique which is capable to evaluate efficiency of those methods. The technique provides information of the texture separation in the texture feature space.

Let us take into consideration that the texture segmentation process can be divided into few steps: preprocessing (a manipulation with an image to achieve a higher efficiency of segmentation), dividing image into small areas, feature extraction, segmentation and boundary refinement [1]. These steps are separable thus we can focus on each of them without an interaction with the others.

The mentioned evaluation process analyzes the output of the feature extraction part of the process and gives information about its efficiency.

As a set of features Gabor filters have been chosen. Gabor filters have got a considerable attention because of certain cells in the visual cortex of some mammals can be approximated by them. Moreover these filters have been shown to posses optimal localization properties in both spatial and frequency domain and thus they are well suited for texture segmentation problems.

2. Feature Extraction

2.1 Gabor Filters

Gabor filter is an often used operator for texture properties description [4], [5], [7]. This filter has a sense of directionality and spatial frequency which belong to the basic texture properties.

Gabor filter's characteristics (Fig. 1) is a Gaussian signal (also called an envelope) modulated by a cosine signal (also called a carrier).

$$g_{\lambda,\Theta,\varphi}(x,y) = e^{-\frac{(x'^2+\gamma^2 y'^2)}{2\sigma^2}} \cos(2\pi \frac{x'}{\lambda} + \varphi)\,, \qquad (1)$$

$$x' = x\cos\Theta + y\sin\Theta\,,$$

$$y' = -x\sin\Theta + y\sin\Theta\,.$$

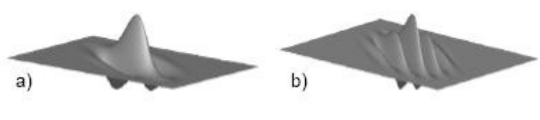


Fig. 1. Two Gabor signals with different frequencies.

The standard deviation σ determines the effective size of the Gaussian signal. The eccentricity of the Gaussian and herewith the eccentricity of the convolution kernel g is determined by the parameter γ called the spatial aspect ratio. λ determines the frequency (wavelength) of the cosine. Θ determines the direction of the cosine function and finally, φ is the phase offset.

An input image $I(x,y)$, $x,y \in \Omega$ (Ω - the set of image points), is convolved with a two-dimensional Gabor function (1) $g(x,y)$, $x,y \in \Omega$ to obtain a Gabor feature image as follows:

$$r(x,y) = \iint_{\Omega} I(\xi,\eta) g(x-\xi, y-\eta) d\xi d\eta \cdot \tag{2}$$

2.2 Gabor Family

We use a Gabor family of filters. There are two positions of angle and two frequencies in the family. It means each image can be convolved by 4 Gabor filters in this case (Fig 2).

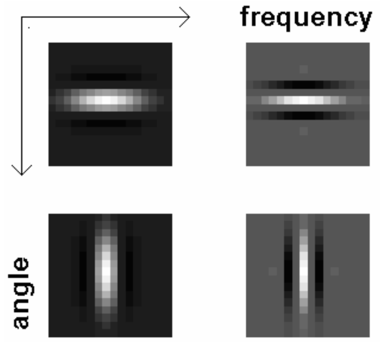


Fig. 2. Gabor family containing 2 frequencies F1=1, F2=2 and 2 angles A1=0°, A2=90°.

The texture image (or a part of the image, because the segmentation process often divides the whole image into small squares first) is convolved (2) with each filter of the Gabor family (Fig 3).

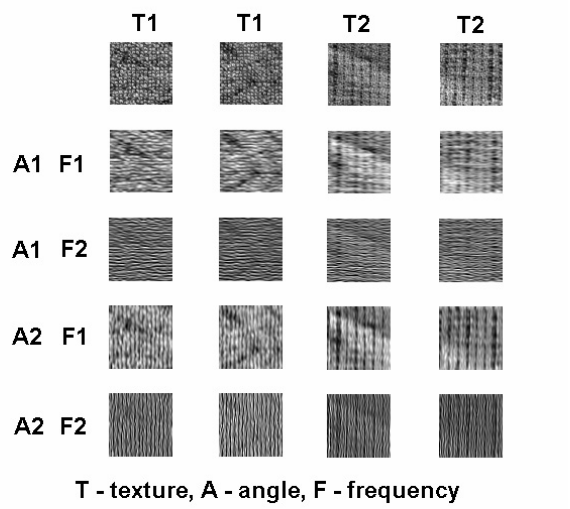


Fig. 3. The first line – the texture images of 2 kinds. 2nd – 5th line – the results after texture images convolution with Gabor filters. Each line represents one filter of the Gabor family (A1=0°, A2=90°, F1=1, F2=2).

2.3 First-Level Description

Several statistical approaches are applied to the convolution result. In our case we have used: mean, variance, energy (3), 25% percentile, median, 75% percentil, skewness, kurtosis, entropy and finally max probability. Definitions of most mentioned statistics are well known; in our case energy is defined as a sum of all values powered by 2.

$$ENERGY = \sum C_i^2 \tag{3}$$

C_i are values in convolution result.

These statistical values are considered as descriptive and discriminative parameters of different texture areas. Comparison and evaluation of these parameters are the aims of this article.

2.4 Outex Database

For our tests a large texture image database named Outex [6] has been used. The database contains a set of texture images assigned into groups. Each group contains 20 images of the same texture. This base of texture images is often used for texture segmentation development and testing.

2.5 Feature Data

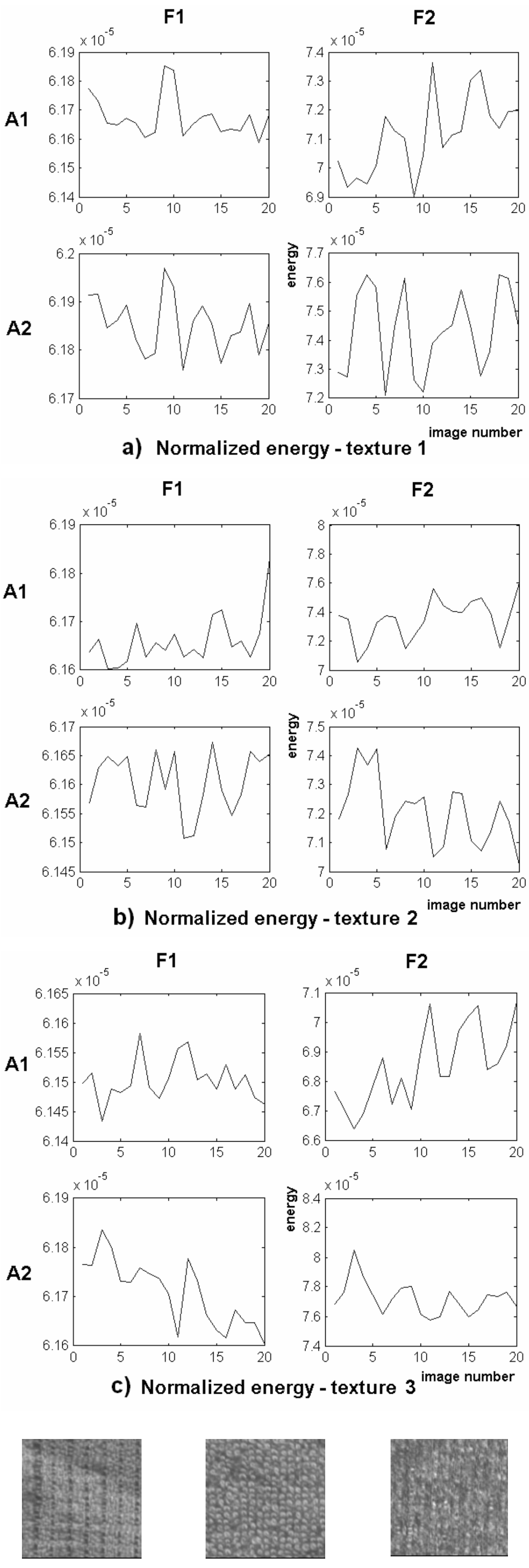
In Fig. 4 you can see statistical parameters (first-level statistics) of the convolution results of the texture images of 3 kinds. In the a) part of Fig. 4 on the coordinates A1 F1 there is a graph of the first-level statistic – energy (3) for each of 20 texture images of one kind. This graph contains the data related to the images convolved by Gabor filter with frequency F1 and angle (orientation) A1. You can see that the data are deterministic in this graph, thus they appear between the values 6.16 and 6.19 in this particular case. The a) part of Fig. 4 contains results also for other Gabor frequencies and orientations (combinations of F1, F2 and A1, A2). The parts b) and c) of Fig. 4 contain the data of the same kind but for other texture types.

In other words, Fig. 4a) is related to 20 images of the type on the figure 4d). Each of the four graphs is related to one combination of the angle and frequency of the Gabor filter. 20 images of the same kind of texture are convolved by this filter and the statistical result (energy) is shown in the graph. Fig. 4b) and 4c) represent the results for textures in Fig. 4e) and 4f).

2.6 Second Level Description

As we have mentioned before, the values in each graph (the results of the first level description) are somehow grouped. This data can be approximated by normal distribution - 2nd level description. Parameters of this distribution are to be compared in the next step. The 2nd level parameters (mean, variance) taken from 4a) A1 F1, 4b) A1 F1 and 4c) A1 F1 are compared. These parameters show the separability of textures in the feature space.

The mean values of the distributions should differ significantly in the meaning of good separation. Variances are the smaller the better. If the data are separated enough, we will consider the method as successful.



d) e) f)

Fig. 4. Energy as statistical feature used for 3 kinds of texture - results a) related to texture d), b)-e), c)-f) and 4 filters

2.7 Error Rate Evaluation

On the normal distributions (each for one kind of texture) we use the Error rate (ER) (4) criterion for evaluation purpose. In Fig. 5a) you can see 2 normal distributions representing 2 kinds of texture. In this example classification threshold will be 2.5 in order to decide between 2 textures. Overlapping areas represent cases of misclassification. Let us define the ER as a ratio between the area of overlapping sections and the sum of all normal distributions areas.

$$ER = \frac{A(os)}{\sum_i A(PDF_i)} = \frac{A(os)}{i} \qquad (4)$$

os – overlapping sections, *PDF* – the probability density function, *i* – the number of texture types (distributions).

In the example in Fig. 5a) the value i=2 is used related to the equation (4). In the meaning of classification ER is the average percentage of faulty texture affiliation. The ER value is the final information which we consider to be an evaluation parameter.

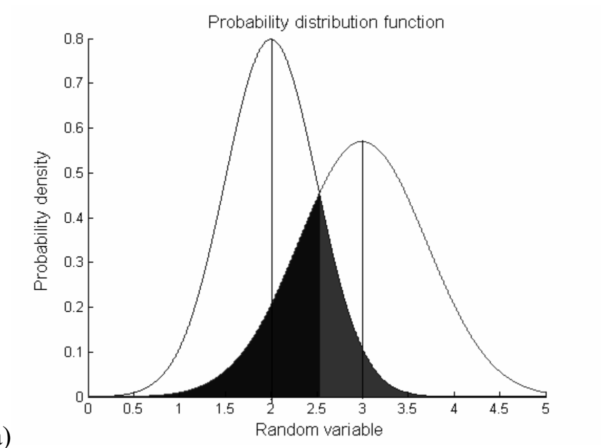
If we used the data from the example in Fig. 3a, b, c), we would become 4 graphs (4 combinations – A1F1 A1F2 A2F1 A2F2) and 3 distributions in each of them. You can see similar results in Fig. 5b). There are 10 distributions in each graph, because in real testing we have used 10 kinds of textures. Finally the average value of all 4 filters from Gabor family will be counted to get one result for one statistical approach (in examples case – energy).

This comparison can be done also for other mentioned first level descriptors (mean, variance, energy, 25% percentile, median, etc.). Proceeding this test we get a wide set of information about efficiency of texture classification based on statistics in feature space.

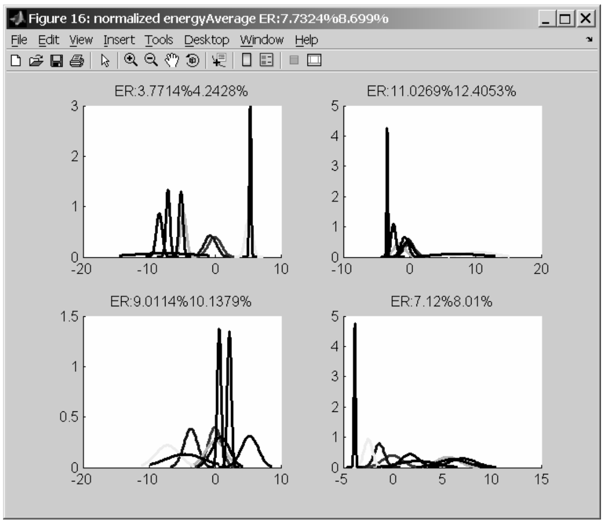
In Tab. 1 you can see the ER and Relative error rate (RER) (5) results. RER makes ER invariant to amount of distributions (and so to amount of texture types). I.e. a) if we have 2 exact same distributions the ER will be 50%, which is the biggest theoretical value. b) if we have 3 distributions, ER will be 66.66%. RER projects this theoretical value to 100%.

$$RER = ER\left(1 - \frac{1}{i}\right). \qquad (5)$$

The testing has been done on 10 texture types with 5 different Gabor filter sizes, 4 different Gabor filters taken from the Gabor family and 10 different statistics. You can see all the results in Tab. 1. Regarding the results we can see, that Gabor filters of size 8x8 give in average the best results. Of course the result depends on the scale of the texture in the image. This measurement has been done on the images taken from the Outex texture image database. We can see, that from the used statistical methods the variance, energy, 25%, 75% percentile give better results than the others. Therefore we can assume that they are more suitable for next use in segmentation process.



a)



b)

Fig 5. The probability distributions of texture features. a) Two distributions with overlapping area which represents the Error rate. b) 4 graphs represent 4 Gabor filters of the Gabor family and there are 10 distributions (texture types) in each of them.

Gabor size		MEAN	VAR IANCE	ENE RGY	0,25 PER CENTIL	MEDIAN
4X4	ER	37,27	14,1	34,8	**9,48**	10,2
	RER	41,68	15,61	38,9	**10,42**	11,47
8X8	ER	35,81	11,05	24,9	11,95	**7,9**
	RER	40,28	12,43	28	13,45	**8,64**
16X16	ER	31,1	**10,92**	**24**	14,85	13,09
	RER	34,99	**12,28**	**27**	16,71	14,72
32X32	ER	**20,52**	13,32	25,4	16,64	26,46
	RER	**34,33**	14,98	28,6	18,72	29,76
64X64	ER	31,72	21,08	31,9	31,59	31,72
	RER	35,68	23,72	35,8	35,54	35,68

Gabor size		0,75 PER CENTIL	SKEW NESS	KURT OSIS	ENT ROPY	MAX PRO BABILITY
4X4	ER	**7,1**	8,5	**6,55**	11,39	**8,67**
	RER	**7,79**	9,31	**7,12**	12,81	**9,5**
8X8	ER	8,48	**5,77**	6,96	**9,8**	10,1
	RER	9,54	**6,5**	7,83	**10,77**	11,36
16X16	ER	13,79	6,49	10,4	13,36	12,7
	RER	15,51	7,31	11,7	15,03	14,28
32X32	ER	20,03	17,67	20,3	22,72	20,44
	RER	22,53	19,88	22,8	25,56	22
64X64	ER	31,79	30,47	34,1	32	33,55
	RER	35,76	34,28	38,4	36	37,74

Tab. 1. Error rate (%) of methods using several sizes of filters and 10 statistics.

The feature extraction and segmentation are isolated operations. ER provides information how the feature distinguishes different textures (how it separates them).

3. Conclusion

Evaluation process of the texture feature extraction has been presented in this paper. For a texture feature extraction we used Gabor filters of different sizes with several frequencies and orientations. The results gave us information about the texture separability in the feature space. The results have shown that variance, energy and percentiles are useful first level descriptors.

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References

[1] CONG, L., SHA, Y., HOU, B., JIAO, L. Unsupervised image segmentation based on the anisotropic texture information. In *The 3rd Int. Conf. on Image and Graphics (ICIG '04)*. 2004. pp. 124-127.

[2] LUCCHESE, L., MITRA, S. K. Color image segmentation: a state-of-the-art survey. In *Image Processing, Vision, and Pattern Recognition. Proc. of the Indian National Science Academy (INSA-A)*. New Delhi, India, vol. 67 A, no. 2, Mar. 2001, pp. 207-221.

[3] Digital image processing: Image analysis and understanding : Texture, [Iowa, USA], 1997. Available on http://www.icaen.uiowa.edu/~dip/LECTURE/Texture.html. [cited on May 19, 2007].

[4] YIMING, J. Efficient edge detection and object segmentation using Gabor filters. In *Proceedings of the 42nd annual Southeast Regional Conference*. Huntsville (Alabama), 2004, pp. 254-259.

[5] IDRISSA, M., ACHEROY, M. Texture classification using Gabor filters. *Pattern Recognition Letters*, 2002, vol. 23. no. 9. pp. 1095-1102.

[6] OJALA, T. et al. Outex – New framework for empirical evaluation of texture analysis algorithms. *Pattern Recognition*, 2002, vol. 1, pp. 701-706.

[7] GRIGORESCU, S. E., PETKOV, N., KRUIZINGA, P. Comparison of texture features based on Gabor filters. *IEEE Transactions on Image Processing*, 2002, vol. 11, no. 10, pp. 1160–1167.

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