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Grating cell operator features for oriented texture segmentation

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Abstract

The performance of two well-known texture operators (based on Gabor-energy and the cooccurrence matrix) is compared with the performance of a new, biologically motivated texture operator, the grating cell operator, which was proposed elsewhere by the authors. The comparison is made using a new quantitative method, based on the Fisher criterion. Together with some classification results comparison experiments the comparison shows a clear superiority of the new operator in oriented texture problems.

1. Introduction

Texture is an important part of the visual world of animals and men and their visual systems successfully detect, discriminate and segment texture. Relatively recently progress was made concerning structures in the brain which are presumably responsible for texture processing. Von der Heydt et al. [19] reported on the discovery of a new type of orientation selective neuron in areas V1 and V2 of the visual cortex of monkeys which they called *grating cell*. Grating cells respond vigorously to gratings of bars of appropriate orientation, position and periodicity. In contrast to other orientation selective cells, grating cells respond very weakly or not at all to single bars which do not make part of a grating. This behaviour of grating cells cannot be explained by linear filtering followed by half-wave rectification as in the case of simple cells, neither can it be explained by three-stage models of the type used for complex cells. Elsewhere we proposed a model of this type of cell and demonstrated the advantages of grating cells with respect to the separation of texture and form information [9, 16].

In this paper we use the output of grating cell operators as texture features and compare them with commonly used texture features as cooccurrence matrix and Gabor-energy features. For this comparison a new method is proposed which enables a quantitative evaluation of the texture discrimination properties of feature extraction operators. The method differs from the commonly used texture feature performance evaluation method which is based on the comparison of classification results [1, 3, 13, 17, 20].

The problem with the traditional comparison method is that it mixes together the performance of a classifier with the discrimination properties of the feature operator. Furthermore, it does not give an estimation of the reliability of classification: for instance, two different operators can give rise to the same number of misclassified pixels when applied to two different texture images, but this does not mean that they will perform equally in future classification tasks with other images of the same textures. Consequently, a method is needed in which the performance of a classifier can be separated from the discrimination properties of the feature operator and in which the spread in the discrimination properties can be quantified in order to estimate the reliability of classification.

2. Grating cell model

Our model of grating cells consists of two stages [16]. In the first stage, the responses of so-called *grating subunits* are computed using as input the computed responses of centre-on and centre-off simple cells with symmetrical receptive fields (for a computational model of simple cells, see [15]). The model of a grating subunit is conceived in such a way that the unit is activated by a set of three bars with appropriate periodicity, orientation and position. In the second stage, the responses of grating subunits of a given preferred orientation and periodicity are summed together within a certain area to compute the response of a grating cell. This model is next explained in more detail:

A quantity $q_{\xi,\eta,\Theta,\lambda}$, called the activity of a grating subunit with position (ξ,η), preferred orientation $\Theta(\Theta \in [0,\pi))$ and preferred grating periodicity λ, is computed as follows:

$$q_{\xi,\eta,\Theta,\lambda} = \begin{cases} 1 & if\ \forall n,\ M_{\xi,\eta,\Theta,\lambda,n} \geq \rho \mathcal{M}_{\xi,\eta,\Theta,\lambda} \\ 0 & if\ \exists n,\ M_{\xi,\eta,\Theta,\lambda,n} < \rho \mathcal{M}_{\xi,\eta,\Theta,\lambda} \end{cases} \quad (1)$$

where

$$n \in \{-3 \ldots 2\}$$

and ρ is a threshold parameter with a value smaller than but near 1 (e.g. $\rho = 0.9$) and the auxiliary quantities $M_{\xi,\eta,\Theta,\lambda,n}$ and $\mathcal{M}_{\xi,\eta,\Theta,\lambda}$ are computed as follows:

$$\begin{aligned} M_{\xi,\eta,\Theta,\lambda,n} \quad = \quad & \max\{s_{\xi',\eta',\Theta,\lambda,\varphi_n} \mid \xi', \eta' : \\ & n\frac{\lambda}{2}\cos\Theta \leq (\xi' - \xi) < (n+1)\frac{\lambda}{2}\cos\Theta, \\ & n\frac{\lambda}{2}\sin\Theta \leq (\eta' - \eta) < (n+1)\frac{\lambda}{2}\sin\Theta, \\ & \varphi_n = \begin{cases} 0 & n = -3, -1, 1 \\ \pi & n = -2, 0, 2 \end{cases} \} \end{aligned} \quad (2)$$

where $s_{\xi',\eta',\Theta,\lambda,\varphi_n}$ is the output of a simple cell operator[1] of preferred orientation Θ and periodicity λ at position (ξ', η') and

$$\mathcal{M}_{\xi,\eta,\Theta,\lambda} = \max\{M_{\xi,\eta,\Theta,\lambda,n} \mid n = -3 \ldots 2\} \quad (3)$$

The quantities $M_{\xi,\eta,\Theta,\lambda,n},\ n = -3 \ldots 2$, are related to the activities of simple cells with symmetric receptive fields along a line segment of length 3λ passing through point (ξ, η) in orientation Θ. This segment is divided in intervals of length $\frac{\lambda}{2}$ and the maximum activity of one sort of simple cells, centre-on ($\varphi_n = 0$) or centre-off ($\varphi_n = \pi$), is determined in each interval. $M_{\xi,\eta,\Theta,\lambda,-3}$, for instance, is the maximum activity of centre-on simple cells in the corresponding interval of length $\frac{\lambda}{2}$; $M_{\xi,\eta,\Theta,\lambda,-2}$ is the maximum activity of centre-off simple cells in the adjacent interval, etc. Centre-on and centre-off simple cell activities are alternately used in consecutive intervals. $\mathcal{M}_{\xi,\eta,\Theta,\lambda}$ is the maximum among the above interval maxima.

Roughly speaking, the concerned grating cell subunit will be activated if centre-on and centre-off cells of the same preferred orientation Θ and spatial frequency $\frac{1}{\lambda}$ are alternately activated in intervals of length $\frac{\lambda}{2}$ along a line segment of length 3λ centred on point (ξ, η) and passing in direction Θ. This will, for instance, be the case if three parallel bars with spacing λ and orientation Θ of the normal to them are encountered (Fig.1). In contrast, the condition is not fulfilled by the simple cell activity pattern caused by a single bar or two bars, only.

In the next, second stage of the model, the response $w_{\xi,\eta,\Theta,\lambda}$ of a grating cell is computed by weighted summation of the responses of the grating subunits. At the same time the model is made symmetrical for opposite directions by taking the sum of grating subunits with orientations Θ and $\Theta + \pi$.

$$w_{\xi,\eta,\Theta,\lambda} = \int_{\Omega} e^{-\frac{(\xi-\xi')^2+(\eta-\eta')^2}{2(\beta\sigma)^2}} (q_{\xi',\eta',\Theta,\lambda} + q_{\xi',\eta',\Theta+\pi,\lambda})\, \mathrm{d}\xi' \mathrm{d}\eta', \quad \Theta \in [0, \pi) \quad (4)$$

The weighted summation is a provision made to model the spatial summation properties of grating cells with respect to the number of bars and their length as well as their unmodulated responses with respect to the exact position (phase) of a grating. The parameter β determines the size of the area over which effective summation takes place. A value of $\beta = 5$ results in a good approximation of the spatial summation properties of grating cells. For further details we refer to [16]. The grating cell operator is available on the internet [10].

[1]Halfwave rectified convolution of the image with a 2D Gabor function (see [15, 16] for further details).

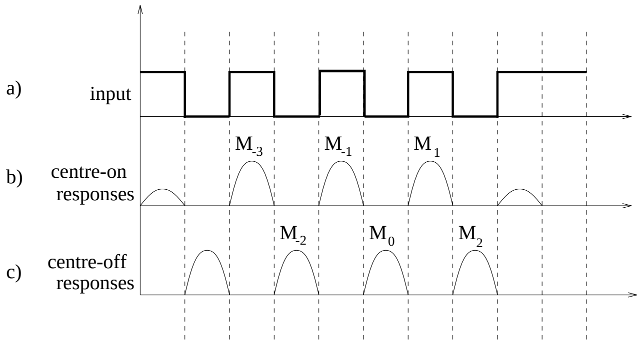

Figure 1. Luminance distribution along a normal to a set of three square bars (a), and the distribution of the computed responses of centre-on (b) and centre-off (c) simple cells along this line.

3. Texture features and the Fisher criterion

The quantities computed with the grating cell operators can be used as texture features. We next compare the following set of features:

- **Grating cell operator features:** A set of grating cell operators with eight different preferred orientations and three preferred spatial-frequencies is applied to an image, yielding a vector of 24 features in each point.
- **Gabor-energy features:** A popular set of texture features is based on the use of Gabor filters [7]. In

	T1	T2	T3	T4	T5	T6	T7	T8	T9
T1	-	4.36	9.61	9.23	4.77	8.33	9.91	13.47	13.99
T2		-	7.51	6.35	4.79	5.65	6.24	10.96	9.31
T3			-	14.62	9.60	6.24	3.84	6.72	20.40
T4				-	8.24	15.60	10.09	18.67	24.36
T5					-	7.72	9.38	13.06	11.20
T6						-	4.53	6.83	11.96
T7							-	6.14	15.33
T8								-	39.71
T9									-

Table 1. The Fisher criterion for pairs of texture images calculated on the basis of feature vectors obtained with the grating cell operator.

this case, an image is filtered with a set of Gabor filters with different orientations, spatial frequencies and phases. Using eight orientations and three preferred spatial-frequencies and combining the results of symmetric and anti-symmetric filters, this multi-channel filtering scheme yields a feature vector of 24 Gabor-energy quantities. The same preferred orientations and spatial-frequencies are used as the ones of the grating cell operators.

- **Cooccurrence matrix features:** A classic method for texture segmentation is based on the gray-level cooccurrence matrices [6]. In each point of a texture image, a set of gray-level cooccurrence matrices is calculated for different orientations and inter-pixel distances. From these matrices, a number of features is extracted which characterise the neighbourhood of the concerned pixel. In our experiments eight gray-level cooccurrence matrices were calculated in each point using a neighbourhood of size 12×12. From each of the matrices three features (energy, inertia and entropy) were extracted resulting in a vector of 24 features in each image point.

The feature vectors computed at different points of a texture using a given operator are not identical. They rather form a cluster in the multi-dimensional feature space. The larger the distance between two clusters which correspond to two different types of texture, the better the discrimination properties of the texture operator which produced the feature vectors. The distance has, of course, to be related to the size of the clusters. In order to determine the distance between two clusters of feature vectors, it is sufficient to look at the projection of the p-dimensional feature space onto a one-dimensional space, under the assumption that this projection maximises the separability of the clusters in the one-dimensional space. A linear transformation that realizes this projection was first introduced by Fisher [4] and is called Fisher's linear discriminant function. It has the following form: $y = (\vec{\mu_1} - \vec{\mu_2})^T S^{-1} \vec{x}$, where $\vec{\mu_1}$ and $\vec{\mu_2}$ are the means of the two clusters and S^{-1} is the inverse of the pooled covariance matrix. Fisher's linear discriminant function is invariant under any nonsingular linear transformation.

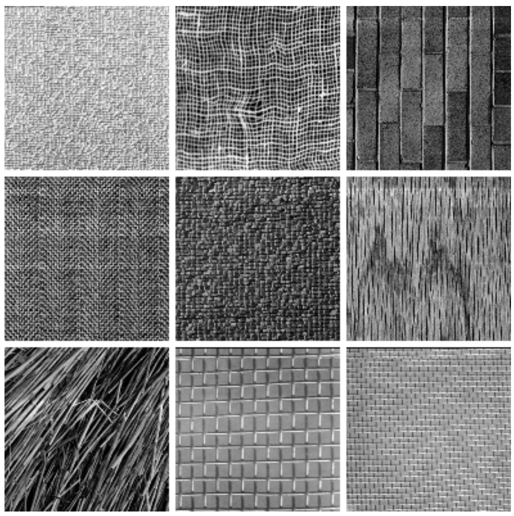

Figure 2. The nine test images of oriented textures, enumerated T1 through T9 left to right and top to bottom.

The projection of the feature vectors onto the projection line maximises the so-called Fisher criterion [5] $f = \frac{\eta_1 - \eta_2}{\sigma_1 + \sigma_2}$ where σ_1 and σ_2 are the standard deviations of the distributions of the projected feature vectors of the respective clusters and η_1 and η_2 are the projections of the means μ_1 and μ_2. Since the matrix S^{-1} is positive definite, the difference $\eta_1 - \eta_2$ is always positive. The Fisher criterion expresses the distance between two clusters relative to their compactness

	T1	T2	T3	T4	T5	T6	T7	T8	T9
T1	-	4.17	4.90	5.66	3.39	4.99	4.95	4.15	6.29
T2		-	2.86	4.45	2.65	3.02	3.04	3.05	5.70
T3			-	6.38	3.64	1.80	3.19	3.25	5.96
T4				-	5.24	7.06	4.96	7.09	9.24
T5					-	3.35	3.18	3.45	5.15
T6						-	2.90	2.61	6.54
T7							-	3.31	6.46
T8								-	5.53
T9									-

Table 2. The Fisher criterion for pairs of texture images calculated on the basis of feature vectors obtained with the Gabor-energy operator.

in one single quantity.

4. Performance evaluation and comparison

The performance of the grating cell operator is evaluated according to the Fisher criterion by the separability of nine test images, each containing a single oriented texture (Fig.2). The separability is measured in the following way: a set of 24 different grating cell operators is applied to each image. In this way each image point is assigned a feature vector of 24 grating cell operator coefficients. The pooled covariance matrix is calculated for each pair of images using 1000 sample feature vectors from each image. Then the feature vectors are projected on a line using Fisher's linear discriminant function and the Fisher criterion is evaluated in the projection space.

Table 1 shows the values of the Fisher criterion for each pair of the test images. The minimum value listed is 3.8, which means that for all image pairs, the projected feature vector distributions will at most overlap for about 0.01%. Therefore all clusters of feature vectors can be separated linearly. Note that the feature vectors of each cluster are taken from an image that contains merely one texture. This means that it is *a priori* known to which cluster the feature vector samples belong to, resulting in a good estimate of the covariance matrix.

The values obtained with the Gabor-energy features (listed in Table 2) are all smaller than the ones obtained with the grating cell features. On average the Fisher criterion for the Gabor-energy features is more than two times smaller than for the grating cell features. Anyhow, the Fisher criterion is still large enough to distinguish the clusters. The Gabor-energy features are therefore suitable for the classification of a texture images as a whole, *i.e.* classification of an entire texture image based on the distribution of a large number of projected feature vectors. For the segmentation of a texture image into regions containing the same texture, *i.e.* for the classification of the individual pixels, the inter-cluster distance is not sufficiently large as can be seen from Figure 3. The quality of the cooccurrence matrix features is even worse in comparison to the Gabor-energy features. Though the inter-cluster distance is large enough for classification of texture images as a whole (Table 3), the features are inappropriate for classification of single pixels.

Figure 3 shows the results of pixel classification using K-means clustering of the generated feature vectors. It further demonstrates the superiority of grating cell operator features to Gabor-energy and cooccurrence matrix features.

In a future work, the authors will compare the grating cell operator with the operators and methods proposed by Unser [18], Laws [11] and Mitchell [12], the fractal dimension approach [14], a method based on GOP (General Operation Processor) operations [8], gray level differences, centre-symmetric covariance features, local binary patterns [17] and Markov random fields [2].

References

[1] R. Conners and C. Harlow. A theoretical comparison of texture algorithms. *IEEE Transactions on Pattern Analysis and Machine Intelligence*, 2(3):204–222, 1980.

[2] G. Cross and A. Jain. Markov random field texture models. *IEEE Transactions on Pattern Analysis and Machine Intelligence*, 5(1):25–39, 1983.

[3] J. Du Buf, M. Kardan, and M. Spann. Texture feature performance for image segmentation. *Pattern Recognition*, 23:291–309, 1990.

[4] A. Fisher. *The mathematical theory of probabilities*, volume 1. Macmilan, New York, 1923.

[5] K. Fukunaga. *Introduction to statistical pattern recognition.* Academic Press, 1990.

[6] R. Haralick, K. Shanmugam, and I. Dinstein. Textural features for image classification. *IEEE Transactions on Systems, Man and Cybernetics*, 3(6):610–621, 1973.

	T1	T2	T3	T4	T5	T6	T7	T8	T9
T1	-	3.72	3.74	3.57	3.24	3.54	3.41	3.85	3.98
T2		-	2.92	3.49	2.62	3.88	3.38	3.47	3.38
T3			-	3.76	2.62	2.80	3.00	3.32	3.77
T4				-	3.61	4.26	3.56	4.19	4.25
T5					-	3.41	2.85	3.41	3.55
T6						-	2.97	3.66	4.45
T7							-	3.32	4.03
T8								-	2.41
T9									-

Table 3. The Fisher criterion for pairs of texture images calculated on the basis of feature vectors obtained with the cooccurrence matrix operator.

Figure 3. Results of segmentation experiments using the K-means clustering algorithm. The left-most image shows an input image containing nine different textures. The exact segmentation of the input image is shown in the second image from the left. The three right-most images show the segmentation results based on the grating cell operator features (middle column), the Gabor-energy features (second column from the right) and the cooccurence matrix features (right-most column).

[7] A. Jain and F. Farrokhnia. Unsupervised texture segmentation using gabor filters. *Pattern Recognition*, 24(12):1167–1186, 1991.

[8] H. Knutsson and G. Granlund. Texture analysis using two-dimensional quadrature filters. In *IEEE Workshop CAPAIDM*, Pasadena, CA, 1983.

[9] P. Kruizinga and N. Petkov. A computational model of periodic-pattern-selective cells. In J. Mira and F. Sandoval, editors, *Proc. IWANN '95*, Lecture Notes in Computer Science, vol.930, pages 90–99. Springer-Verlag, 1995.

[10] P. Kruizinga, N. Petkov, and U. Hettema. The grating cell operator interactive software implementation. http://www.cs.rug.nl/˜imaging/grcop.html.

[11] K. Laws. Textured image segmentation. Technical Report USCIPI 940, Image Processing Institute, University of Southern California, 1980.

[12] O. Mitchell, C. Myers, and W. Boyne. A max-min measure for image texture analysis. *IEEE Transactions on Computing*, C-2:408–414, 1977.

[13] P. Ohanian and R. Dubes. Performance evaluation for four classes of textural features. *Pattern Recognition*, 25(8):819–833, 1992.

[14] S. Peleg, J. Naor, R. Hartley, and D. Avnir. Multiple resolution texture analysis and classification. *IEEE Transactions on Pattern Analysis and Machine Intelligence*, 6:514–523, 1984.

[15] N. Petkov. Biologically motivated computationally intensive approaches to image pattern recognition. *Future Generation Computer Systems*, 11:451–465, 1995.

[16] N. Petkov and P. Kruizinga. Computational models of visual neurons specialised in the detection of periodic and aperiodic oriented visual stimuli: bar and grating cells. *Biological Cybernetics*, 76(2):83–96, 1997.

[17] O. Pichler, A. Teuner, and B. Hosticka. A comparison of texture feature extraction using adaptive gabor filtering, pyramidal and tree structured wavelet transforms. *Pattern Recognition*, 29(5):733–742, 1996.

[18] M. Unser. Local linear transforms for texture measurements. *Signal Processing*, 11:61–79, 1986.

[19] R. von der Heydt, E. Peterhans, and M. Dürsteler. Periodic-pattern-selective cells in monkey visual cortex. *Journal of Neuroscience*, 12:1416–1434, 1992.

[20] Z. Wang, A. Guerriero, and M. Desario. Comparison of several approaches for the segmentation of texture images. *Pattern Recognition Letters*, 17(5):509–521, 1996.