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Adaptive Processing for Feature Extraction: Application of Two-Dimensional Gabor Function

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Abstract : Extracting primitives from imagery plays an important task in visual information processing since the primitives provide useful information about characteristics of the objects and patterns. The human visual system utilizes features without difficulty for image interpretation, scene analysis and object recognition. However, to extract and to analyze feature are difficult processing. The ultimate goal of digital image processing is to extract information and reconstruct objects automatically.
The objective of this study is to develop robust method to achieve the goal of the image processing. In this study, an adaptive strategy was developed by implementing Gabor filters in order to extract feature information and to segment images. The Gabor filters are conceived as hypothetical structures of the retinal receptive fields in human vision system. Therefore, to develop a method which resembles the performance of human visual perception is possible using the Gabor filters. A method to compute appropriate parameters of the Gabor filters without human visual inspection is proposed. The entire framework is based on the theory of human visual perception. Digital images were used to evaluate the performance of the proposed strategy. The results show that the proposed adaptive approach improves performance of the Gabor filters for feature extraction and segmentation.

Key Words : Adaptive Filter, 2D Gabor Function, Feature Extraction, Human Visual System.

1. Introduction

One of the ultimate goals of digital image processing is to extract information automatically. However, there is the lack of mathematical models that make automatic description and recognition of primitives from imagery (Greenspan, 1996). Primitives are qualitatively and quantitatively described by its coarseness, contrast, density, orientation, frequency, spatial patterns, regularity, etc. These elements are considered as parameters to be estimated in the visual information processing. One of the characteristics of the primitives is that it has both stochastic and deterministic properties (Tamura *et al.*, 1978; Gool *et al.*, 1985). Multi-resolution on the retinal-ganglion-cell receptive fields and functions of specialized cells correspond to the parameters of two-dimensional Gabor filters: resolution,

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orientation selectivity, and spatial frequency tuning. In this endeavor, identification and extraction of the primitives are an important step toward object recognition. It is known that the human visual system, unsurpassed in its ability to extract information, employs different visual cues to solve this difficult task. Despite progress in visual information processing research, standard paradigm has not yet emerged. The objective of this study is to develop an efficient strategy in applying Gabor filters for feature extraction and segmentation for boundary detection. An effort was made to propose an adaptive strategy that can select appropriate parameters of the Gabor filters. The motivation is to achieve automatic selection of the appropriate parameters without preliminary visual inspection and human intervention. The entire framework of the proposed strategy is based on the theory of human visual perception. The biological motivation for Gabor filters lies in their goodness of fit to receptive field profiles in human visual system. In this study, the multi-channel responses for primitive analysis are processed adaptively by using Gabor filters. One of the advantages of using Gabor filters is that they achieve optimal resolution in both space and spatial frequency. One of the main issues in the approach is determination of the appropriate parameters because using an appropriate subset of filters with optimal parameters not only increases computational efficiency but also extracts more meaningful information. The appropriate parameters are selected based on the statistical characteristics of the images. Another aspect is that the criteria suggested in this study for determining parameters have potential to develop a symbolic description of the primitives or pattern of the features.

2. Two-dimensional Gabor Filters

1) Two-Dimensional Gabor Function

Gabor functions were extended to two-dimension by Daugman (1985), called "two-dimensional visual cortical filters." A Gabor function is defined by a harmonic oscillator which is a complex sinusoidal plane wave of some frequency and orientation within a Gaussian envelope. The general form of two-dimensional Gabor functions is given by

$$G(x, y) = g(x, y) \cdot \exp[2\pi i(Ux+Vy)] \qquad (1)$$

where $i = \sqrt{-1}$, $U = F\cos\theta$, $V = F\sin\theta$, and $F = \frac{1}{T}$ (T is period), $g(x, y)$ is two-dimensional Gaussian function given by

$$g(x, y) = \frac{1}{2\pi\sigma^2}\exp\left[-\left(\frac{x^2}{2\sigma_x}+\frac{y^2}{2\sigma_y}\right)\right] \qquad (2)$$

with σ is standard deviation. From equations (1), (2), and by applying the Euler identity, equation (2) can be rewritten as:

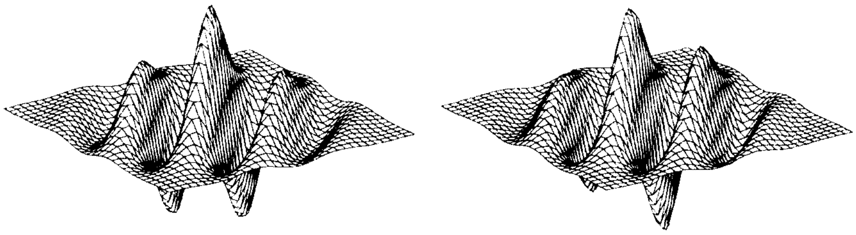
$$G(x, y) = \frac{1}{2\pi\sigma^2}\exp\left[-\left(\frac{x^2+y^2}{2\sigma^2}\right)\right] \cdot \{\cos[2\pi(Ux+Vy)]+i\sin[2\pi(Ux+Vy)]\} \qquad (3)$$

By applying the relationships $F = \sqrt{U^2+V^2}$ and $\theta = \tan^{-1}(\frac{V}{U})$, following equation is obtained (Bovik *et al.*, 1990; Dunn and Higgins, 1995):

$$G(x, y) = \frac{1}{2\pi\sigma^2}\exp\left[-\left(\frac{x^2+y^2}{2\sigma^2}\right)\right] \cdot \{\cos[2\pi(F\cos\theta x+F\sin\theta y)] + i\sin[2\pi(F\cos\theta x+F\sin\theta y)]\} \qquad (4)$$

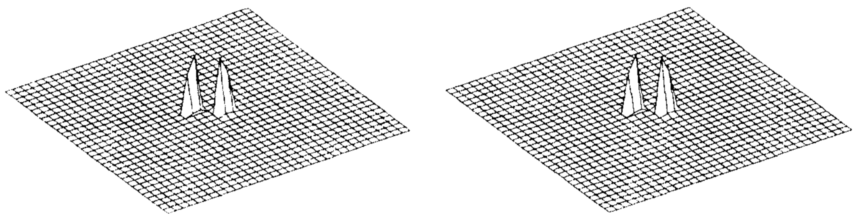
Two-dimensional Gabor functions also can be expressed with angular frequency, $\omega = 2\pi F$:

$$G(x, y) = \exp\left[-\frac{(x-x_0)^2+(y-y_0)^2}{2\sigma^2}\right] \cdot \sin\{\omega(x\cos\theta - y\sin\theta)+\varphi\} \qquad (5)$$



(a) Real component (b) Imaginary component

Fig. 1. 2D Gabor function with 16 pixel period and 45° orientation.



(a) Real compoentent (b) Imaginary component

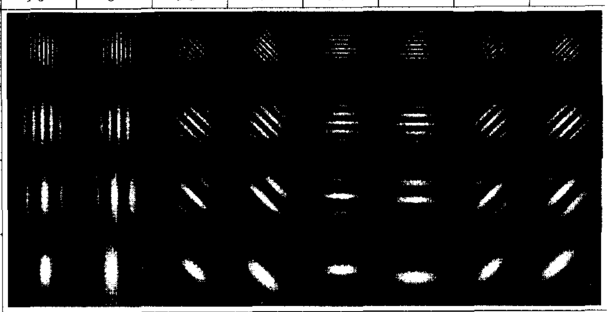
Fig. 2. Spatial frequency responses of a 2D Gabor function.

where x_0 and y_0 specify the center of the Gaussian function, and φ is the phase shift. The two-dimensional Gabor functions have real and imaginary components. The phase shift generates real components for $\varphi = 90°$ and imaginary components for $\varphi = 0°$. Fig. 1 shows a perspective view of real and imaginary components of two-dimensional Gabor functions. The spatial frequency response of the Gabor functions is obtained by the two-dimensional Fourier transform:

$$H(u, v) = \exp\{-2\pi\sigma^2[(u-U)^2+(v-V)^2]\} \qquad (6)$$

where u and v denote frequencies. Fig. 2 shows the spatial frequency responses of the Gabor functions. Fig. 3 shows a family of Gabor filter

θ	0°		45°		90°		135°	
T \ φ	90°	0°	90°	0°	90°	0°	90°	0°
4								
8								
16								
32								



Note: The filter coefficients are converted into gray values. Bright regions represent positive values and *vice versa*.

Fig. 3. Example of 2D Gabor filter bank.

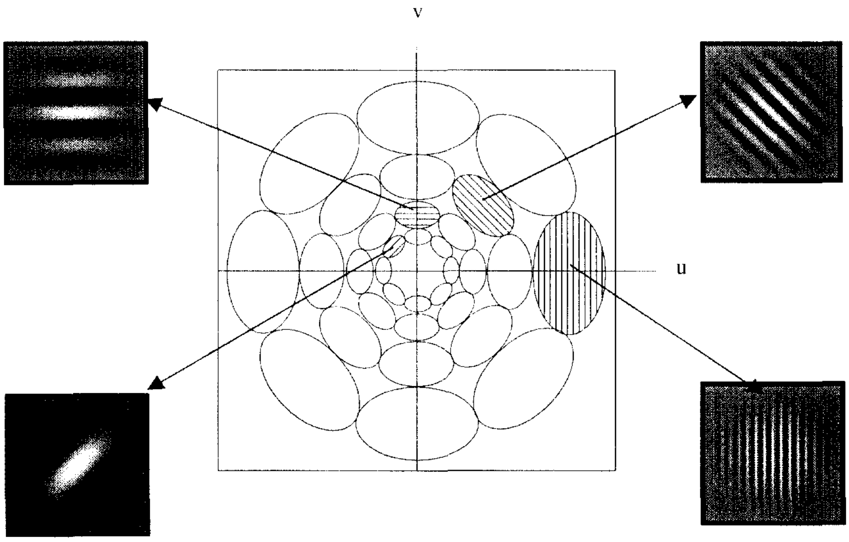


Fig. 4. 2D Gabor filter bank in the spatial-frequency domain.

bank in the spatial domain. Fig. 4 schematically illustrates the Gabor filter bank in the spatial-frequency domain.

2) Properties of the Gabor Filter

There are four parameters in two-dimensional Gabor filters: the standard deviation of the Gaussian envelope(σ), spatial frequency(ω), orientation(θ), and phase(φ). These parameters characterize certain parts of primitives of the images. Therefore, Gabor filters allow extracting pictorial information. The determination of the appropriate parameters is the most important task in applying Gabor filters for image processing. Since the parameters vary independently, optimal parameters cannot be determined uniquely (Kehrer and Meinecke, 1995). All possible combinations of the parameters result in a large set of filters.

• **Standard Deviation**: The standard deviation of the Gaussian envelope controls the spatial extent as well as the band width of the filters. Physiological evidence suggests a tendency toward decreasing spatial extent with increasing frequency preference (Kulikowski and Bishop, 1981; Turner, 1986). However, increasing the length of the filters along the axis parallel to the plane wave tends to improve the sensitivity of the filter to such local features (Turner, 1986). With increasing filter size, larger overlapping neighborhoods at a center pixel result. Determination of the standard deviation is a tradeoff between output variation and boundary localization (Dunn and Higgins, 1995).

• **Spatial Frequency**: The number of cycles per period is the spatial frequency. The period is related to the size of the primitives. It controls the resolution that is related to the amount of information. Various resolutions are obtained as different generations of wavelets are created by varying dilation factors.

• **Orientation**: The orientation angle varies from 0° to less than 180°. Proper selection of the orientation can detect the directionality or dominant orientation of the primitives or patterns. According to Voorhees (1987), there is evidence that the human visual system has a special sensitivity for vertical and horizontal orientations, and requires around 20° or more to preattentively perceive orientation differences. Orientation preference is a particularly important feature of simple cells in the visual cortex. Their maximum response occurs where edges are oriented at a particular angle to the visual axis. The preference is quite distinctive; rotating the stimulus by more than 20° from the preferred direction greatly reduces the cell's firing rate (Bruce and Green, 1992). Therefore, a certain level of discretization is reasonable, not only for computational simplicity but also from psychological evidence.

• **Phase**: Two-dimensional Gabor functions are composed of two components, real and imaginary components with a 90° phase shift between them. The phase can solve the ambiguity problem. It cannot be decided unequivocally which parameter variation is responsible for the activity of the filter change.

3. Adaptive Processing for Extracting Information

This section describes the proposed adaptive strategy for extracting information with Gabor filters. The motivation of an adaptive approach lies in the fact that meaningful information could not be extracted from imagery with one kind of operator only since extracting information involves with variety of parameters. According to Dunn and Higgins (1995), "*Distinctive discontinuities are detectable only if the Gabor filter parameters are suitably chosen.*" The strategy of using multiple filter sizes has been proven successful in other applications. For example, if a fixed size operator is selected then unacceptable loss of information may occur in some parts while noise was removed in the other parts of the image. The optimal filter size depends on the image contents which are characterized by statistical properties. In this study, progressive subdividing scheme is suggested for the initial segmentation. The similar schemes are applied in sampling for digital elevation models (DEMs) and split-and-merge algorithm (Makarovic, 1973; Gonzalez and Wintz, 1987; Pavlidis, 1982). A scheme for determining appropriate parameters of two-dimensional Gabor filters is proposed in this study. The size of the Gabor filter for each region was determined based on the statistical properties of the image.

The theory of human visual processing was applied to the entire framework. Blobs were detected by using the Laplacian of the Gaussian (LoG) operator. The dominant orientation and spatial frequency were computed with blobs for each region which was defined by the progressive subdividing scheme. Each region of the image then was adaptively processed with pairs of two-dimensional Gabor filters (0° and 90° phase). The adaptive processing is considered as attentive (or focal attention) visual perception. Unsupervised classification technique for segmentation of the images was performed.

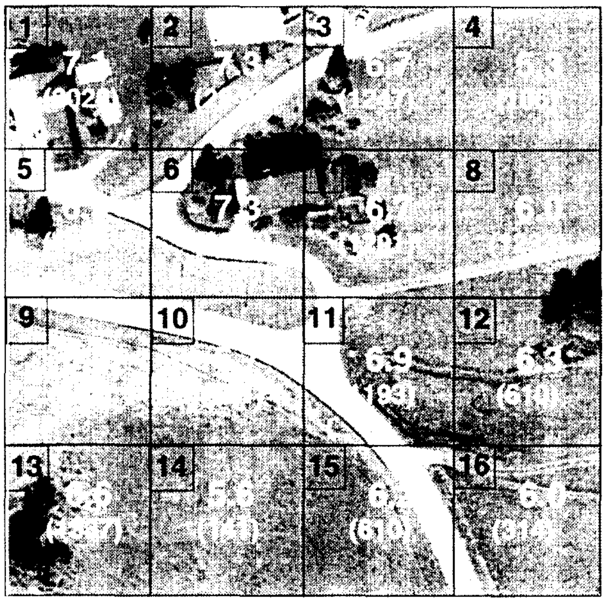
1) Statistical Characteristics of an Image

Mean, variance, and entropy are fundamental statistical values to characterize images. The mean measures the overall brightness of an image, and the variance expresses the contrast. Entropy and variance can be used as indicators for representing complexity and randomness of an image (Gonzalez and Wintz, 1987). Entropy is defined as

$$H = -\sum_{i=0}^{n} p(i)\log_2 p(i) \qquad (7)$$

where n is number of variables with probabilities, $p(i)$, and i indicates a certain gray value. Areas with lower entropy are homogeneous ande *vice vrsa*. Fig. 5 shows the entropy and variance for each block of a natural image.

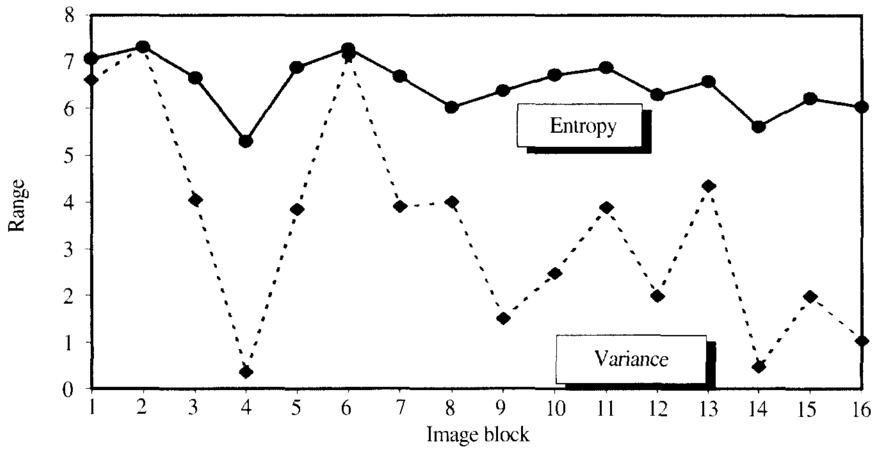
Fig. 6 shows the relationship between entropy and variance of the image shown in Fig. 5. Therefore, the overall behavior of entropy and variance are similar over each image block. To use entropy may provide an advantage over



Overall entropy = 6.8, Overall variance = 1198

Note: Numbers in squares are block numbers. Numbers in the parentheses represent variance.

Fig. 5. Entropy and variance of each block of the natural image.



Note: Variances are normalized to entropy range for comparison with the entropy.

Fig. 6. Relationship between entropy and variance.

variance, since we know the range of entropy, *i.e.* $H = 0 \sim 8$ for 8bit images. In this study, initial segmentation of the image for an adaptive approach is based on entropy.

2) Human Visual Perception

Julesz and Bergen (1983) introduced the notion of textons which are basic features such as blobs or line segments with associated orientation, dimension, color, and their terminators and crossings. There are two modes in the human visual system: preattentive vision and attentive vision (or scrutiny vision). Texton extraction is a preattentive process and corresponds to the primal sketch in Marr's vision theory (Marr, 1976). Textons form a part of other elements of the primal sketch including edges with their geometrical distribution and organization such as orientation, contrast, and dimensions. According to Julesz and Bergen's experiments (1983), there is evidence that preattentive discrimination of primitives in *"the human visual system can instantaneously (160 milliseconds or less) detect differences in a few local conspicuous features, regardless of where they occur."* Preattentive primitive feature discrimination can serve as a model with which to distinguish the role of local primitive or feature element detection from global computation in visual perception (Julesz, 1981).

The issue is how to extract primitives from images. Voorhees (1987) proposes to use the LoG operator for detecting blobs in images. The LoG is given by

$$\nabla^2 G(x,y) = \frac{1}{2\pi\sigma^4}\left[\left(\frac{x^2+y^2}{\sigma^2}\right)-2\right] \cdot \exp\left(\frac{x^2+y^2}{2\sigma^2}\right) \quad (8)$$

The relationship between the size of the LoG operator and the standard deviation of a Gaussian is

$$w = 3 \cdot (2\sqrt{2}\sigma) \quad (9)$$

where w denotes the size of the LoG operator. The LoG operator was devised by Marr and Hildreth (1980) to construct the primal sketch. The primal sketch is a symbolic representation of the image with primitives such as zero-crossings, blobs, terminators and discontinuities, edge segments, virtual lines, groups, curvilinear organization, and boundaries. As mentioned earlier, these tokens of the primal sketch correspond to textons, therefore LoG is considered an appropriate operator for detecting blobs as primitives. It has been shown that the receptive fields in the retina are the biological equivalents to the LoG operator. The convolution of an image, $f(x, y)$, with an LoG, provides zero-crossings which represent intensity edges of the image. Blobs are regarded as duals of edges, i.e., positive for dark blobs and negative for light blobs (Voorhees,1987). After convolving the image with LoG the positive regions were assigned to represent blobs.

Selection of the standard deviation (σ) of the LoG, which controls scale, is an important issue. Voorhees (1987) suggests using different scales over different parts of the image. However, to use a single scale is reasonable since primitive extraction is a preattentive process. The human visual system is not able to utilize different resolution channels during the extremely short preattentive time (*e.g.*, 160 milliseconds or less). Fig. 4. 3 shows a natural image and detected blobs. In this study, noises in the images are considered as part of the primitives. Both LoG operators and Gabor filters have the capability of removing a certain level of noise, therefore any further additional noise removing process is not necessary in this study.

3) Progressive Segmentation to Determine Image Block

An Image is segmented with progressive fashion based on its statistical characteristics. First, the image is divided into blocks. Then, entropy is computed for each image block. Blocks with an entropy exceeding a predetermined threshold (one reasonable value is an overall entropy of the image), are further subdivided into four quadrants, and the recursive process is repeated. It might be reasonable if the subdivided regions are not smaller than the smallest filter size. Adaptive filtering with Gabor filters is performed by combining the results from progressive segmentation and appropriate parameter selection. Fig. 7 illustrates the procedure of the progressive segmentation.

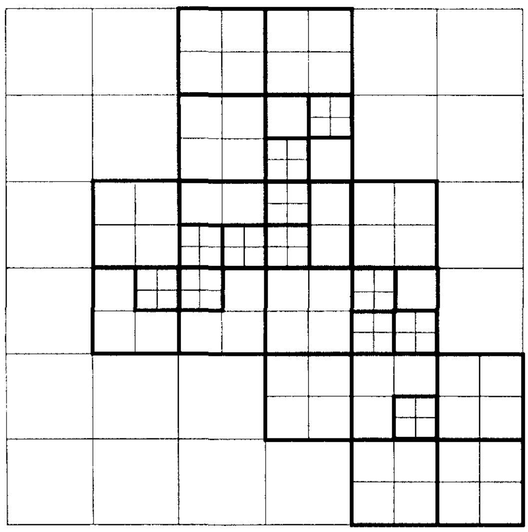
Each segmented region is now processed with Gabor filters whose parameters were chosen by a proposed strategy. Consequently, homogeneous areas are processed with larger size filters and larger spatial frequency of the Gabor filters, and *vice versa*. The advantages of the proposed strategy are to imitate human visual perception and to increase computational efficiency. There is a trade-off between uniqueness and accuracy in determining block size, and it depends on the characteristics of the image such as scale, resolution and contents. The scale of the image and the area of the image (*e.g.*, agricultural, built-up, or residential area) may provide some information to decide the initial starting block size.

4) Determination of the Gabor Filter Size

The appropriate filter size depends on the characteristic of the image in terms of its statistical properties, scale, and resolution. The standard deviation (σ) of the Gaussian function controls the size of a Gabor filter. The Gaussian function is symmetric with respect to zero, and the function value cannot be zero. Eq. (10) is used to determine the relationship between σ and filter size.

$$\exp(-x^2/\sigma^2) = 10^{-N} \tag{10}$$

Therefore, the filter size is determined by



Note: Thicker squares represent regions with higher entropy where subdivisions are performed.

Fig. 7. Progressive segmentation scheme.

$$w = (2\sqrt{2N\ln 10})\sigma \tag{11}$$

It is known that there are several different sizes of the retinal-ganglion-cell receptive fields (*i.e.*, resolution channels) in the human visual system. In this study, different standard deviations of 3, 6, 9, and 12 are selected which corresponds to 15×15, 31×31, 47×47, and 65×65 of the Gabor filter, respectively. The purpose of using different standard deviations is to perform processing with multi-resolution in a image. Entropy was chosen to represent homogeneousness in an image. Therefore, a larger σ was chosen for the region with small entropy and *vice versa*:

Entropy(H)	Standard deviation(σ)	Filter Size(w)
$H \geq 6.5$	3	15×15
$6.0 \leq H < 6.5$	6	31×31
$5.5 \leq H < 6.0$	9	47×47
$H < 5.5$	12	65×65

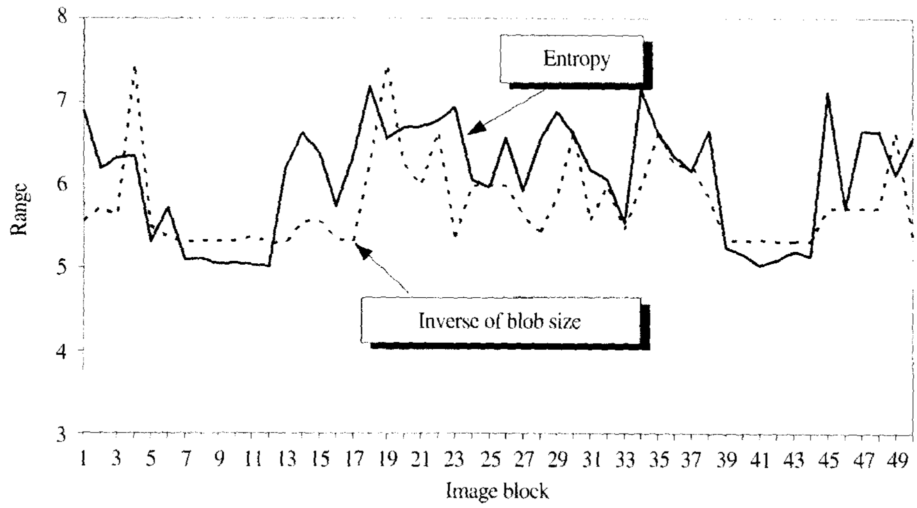
To select an optimal value is subjective because it is scale dependent. It is suggested to use 65w65 for the largest filter size based on our experiments and agreement with other authors' experiments including Turner(1986), Fogel and Sagi(1989). Fig. 8 shows the relationship between entropy and size of the blob.

5) Determination of Dominant Local Orientation

Rao (1990) developed a scheme for estimating the orientation of a primitive field by modifying Kass and Witkin's (1987) algorithm. In this study, Rao's scheme of "inverse arctangent method" is applied to compute the dominant local orientation of the blobs for each image block. Fig. 9 illustrates the method to compute dominant local orientation of a set of blobs in a window. In order to compute the orientation at the (i, j) pixel location, gradient vectors using finite differences are computed as

$$G_r(i,j) = \begin{bmatrix} G_x(i,j) \\ G_y(i,j) \end{bmatrix} = \begin{bmatrix} \dfrac{\partial f(i,j)}{\partial x} \\ \dfrac{\partial f(i,j)}{\partial y} \end{bmatrix} \tag{12}$$

where $f(i, j)$ represents gray values, $G_x(i, j)$ and $G_y(i, j)$ are x- and y-component of the gradient vector at (i, j) pixel, respectively, and computed by



Note: The blob sizes are normalized to entropy range for comparison purpose and part of the natural image is plotted.

Fig. 8. Relationship between entropy and blob size.

$$G_x(i,j) = f(i+1, j-1)+2f(i+1, j)+f(i+1, j+1) - [f(i-1, j-1)+2f(i-1, j)+f(i-1, j+1)] \quad (13a)$$

$$G_y(i, j) = f(i-1, j+1)+2f(i, j+1)+f(i+1, j+1) - [f(i-1, j-1)+2f(i, j-1)+f(i+1, j-1)] \quad (13b)$$

The orientation angle at the (i, j) pixel location is computed by

$$\theta_{ij} = \tan^{-1}\left[\frac{G_y(i, j)}{G_x(i, j)}\right] \quad (14)$$

The dominant local orientation is computed by weighted average of the orientations of blobs in each block. Therefore, the estimated orientation is computed by:

$$\hat{\theta} = \frac{1}{\sum_{i=0}^{m-1}\sum_{j=0}^{n-1} l_{ij}} \sum_{i=0}^{m-1}\sum_{j=0}^{n-1} \theta_{ij} l_{ij} + \frac{\pi}{2} \quad (15)$$

where $l_{ij} = [G_x^2(i,j) + G_y^2(i,j)]^{1/2}$, m and n determine the window size. If the gradient vectors are smaller than a certain threshold value or the standard deviation exceeds a certain threshold value, there is not a dominant local orientation. Finally, the orientations were discretized by 45°. The discretization of the orientation, which is based on psychological experiments, was discussed in the previous section. Fig. 10(a) shows a test image, and Fig. 10(b) represents computed dominant local orientations.

6) Computation of Spatial Frequency

The local spatial frequency is defined as $\omega = 2\pi/T$, where T is the wavelength that is considered an average local dimension of blobs within a segmented block. Fig. 11 illustrates the computation of the blob size.

In order to compute the blob size for each window, it is suggested to compute the dominant local orientation before hand because the spatial frequency depends on the orientation. For 0° orientation, the summation of black pixels (*i.e.*, $f(x,y)=0$), which are occupied by blobs, is computed for vertical direction (*i.e.*, column-wise). This sum is divided by the number of blobs:

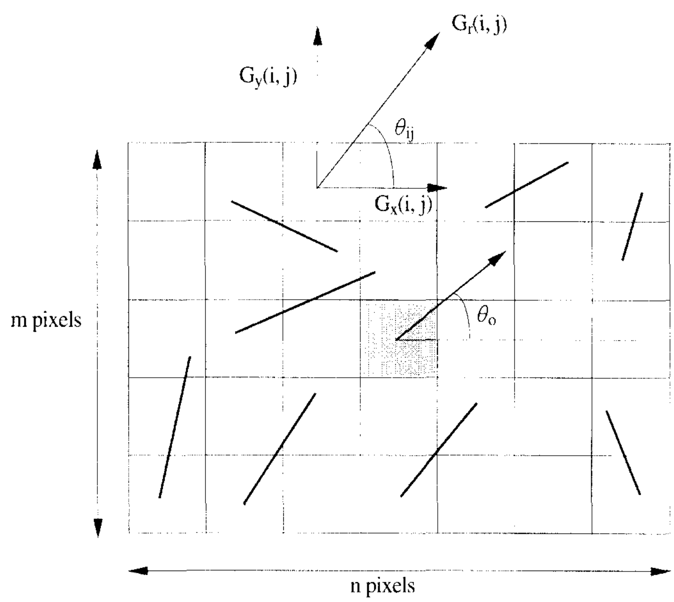
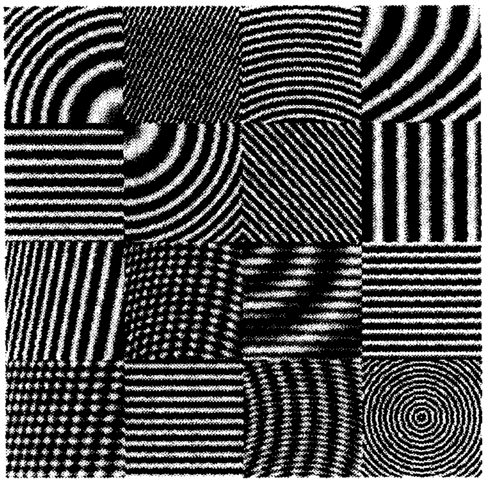


Fig. 9. Computation of the local dominant orientation ($\theta°$) in a group of blobs.(Adapted from Rao (1990) with permission of the publishers.)

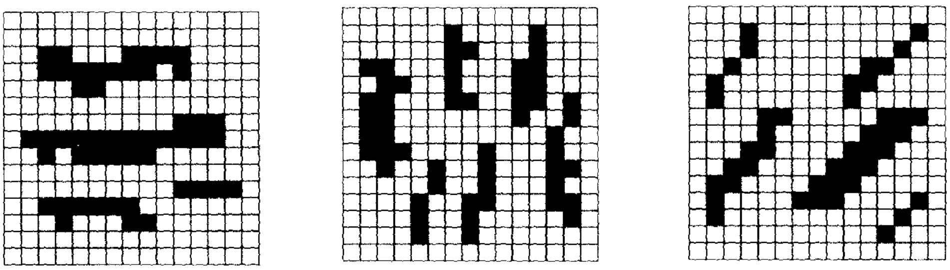


41 (45)	69 (90)	33* (45)	41 (45)
3 (0)	41 (45)	131 (135)	85 (90)
68 (90)	ND	20* (0)	1 (0)
64 (90)	1 (0)	46* (45)	ND

(a) Test image (b) Dominant orientation of each block (in degree)

Note: Numbers in parenthesis are discretized orientation.ND denotes no dominant orientation, and * indicates wrong results.

Fig. 10. Computation of the dominant orientation.



(a) orientation = 0° (b) orientation = 90° (c) orientation = θ.

Fig. 11. Computation of the local blob size.

$$T_{(\theta=0^\circ)} = \frac{\sum_{i=0}^{m}[run\ length\ for\ f(i,j)=0]}{N} \quad (16)$$

where m is number of rows in the window, and N is the number of the blobs. For 90° orientation, the same process is repeated, except for the horizontal direction (*i.e.*, row-wise). In this case, the blob size is computed by

$$T_{(\theta=90^\circ)} = \frac{\sum_{j=0}^{m}[run\ length\ for\ f(i,j)=0]}{N} \quad (17)$$

where n is the number of columns in the window. For 45° and 135° orientations, the vertical and horizontal blob sizes are computed and then combined by

$$T_{(\theta=45^\circ\ or\ \theta=135^\circ)} = \left\{[T_{(\theta=0^\circ)}]^2 + [T_{(\theta=90^\circ)}]^2\right\}^{1/2} \quad (18)$$

If there is no dominant orientation in a window, the blob widths for all directions are computed. Voorhees (1987) performed various psychophysical experiments to determine minimum perceivable ratio of the blobs. The experiments show that the ratio is about 1.3. In this study, a ratio of 2 is chosen since the image pixel size is integer value then discretization of the blob size was performed as:

IF (T ≤ 4) T = 4
IF (4 < T ≤ 8) T = 8
IF (8 < T ≤ 16) T = 16
IF (T > 16) T = 32

7) Feature Extraction

If there is a dominant orientation for a certain region of the image, the region is processed with a pair of Gabor filters with corresponding orientation. If there is no dominant orientation, pairs of the Gabor filters with all orientations (*i.e.*, $\theta = 0°, 45°, 90°$, and $135°$) are used. The results of the multi-channel response are integrated as follows

$$f_n(i,j) = \Big[\big(\sum_{k=1}^{m} [f_n(i,j)*G(x,y\,|\,\sigma,\omega,\theta_k,\varphi=0°)]\big)^2 + \big(\sum_{k=1}^{m} [f_n(i,j)*G(x,y\,|\,\sigma,\omega,\theta_k,\varphi=90°)]\big)^2\Big]^{1/2}$$

$$m = \begin{cases} 1 & \textit{for regions with a dominant local orientation.} \\ 4 & \textit{for regions without dominant local orientation.} \end{cases} \qquad (19)$$

where $f_n(i,j)$ is a region of the image, and *denotes convolution operator. Actually, no dominant local orientation exists in many regions of the natural images. The convolution process is performed region by region adaptively, *i.e.*, each region of the image is processed with a different set of parameters selected by the proposed scheme in this study. There is biological evidence that human observers pay more attention to regions with abrupt luminance changes than homogeneous regions of an image or natural scene (Hubel, 1988). During this process, human visual system analyzes features or primitives adaptively by varying visual channels such as resolution, orientation, and spatial frequency.

8) Image Segmentation

The purpose of image segmentation is to form meaningful regions by grouping features that have common characteristics and properties distinct from their neighboring regions. Each region should be uniform and homogeneous with respect to some attributes including tone, color, or texture (Low, 1991; Schalkoff, 1989). Image segmentation involves the procedure of classification and pattern recognition. Unsupervised classification is considered a suitable technique for automatic processing, since it requires less prior information than supervised classification. Segmentation with unsupervised classification can be performed without an operator's intervention. In this study, *ISODATA* is applied for segmenting the images after adaptive processing with the Gabor filters. *ISODATA* is one of the iterative optimization methods for unsupervised pattern classification based on minimum distance decision. *ISODATA* is similar to K-means clustering since the cluster centers are iteratively determined sample means in both methods (Gnanadesikan, 1977; Tou and Gonzalez, 1974).

9) Procedure of the Adaptive Scheme

The procedure for the implementation is summarized as follows:

1. Computing overall entropy.
2. Performing progressive segmentation to define the image blocks.
3. Detecting primitives by the modified LoG operator.
4. Determining size of the Gabor filters for each block.
5. Computing dominant local orientation for each block.
6. Computing spatial frequency for each block.
7. Performing adaptive processing with Gabor filters using the parameters selected in steps 4, 5 and 6.
8. Performing segmentation by unsupervised classification.

9. Detecting segmented boundary by the LoG operator.

4. Results

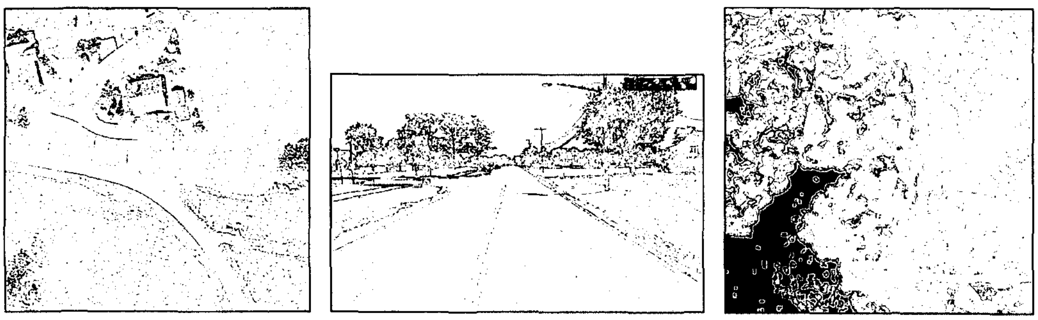
This section presents experimental results obtained from the adaptive strategy for extracting information from imagery. Test images include an aerial image, an image captured by mobile mapping system (GPSVan, Center for Mapping, The Ohio State University), and a halftone image. Results are analyzed and the performance of the proposed strategy is evaluated.

1) Test Images

- **Aerial Image**: The image shows a rural area around Marchetsreut near Passau in Germany (see Fig. 5.1). The scale of the image is 1:15,000 and digitized with a pixel size of 15 m, yielding a ground resolution of 0.23m. The overall entropy of the image is 6.8.
- **GPSVan Image**: The image shown in Fig. 12(a) was taken with a Pulnix CCD camera installed on the GPSVan from the Center for Mapping of The Ohio State University. The number of pixels are 760 (H) × 480 (V) with a pixel size of 11.6μm (H) × 8.0μm (V). The nominal focal length is 8 mm. The overall entropy is 6.2.
- **Halftone Image**: The image shown in Fig. 12(b) is a part of the cover page of the journal Photogrammetric Engineering and Remote Sensing (Vol. 63, No.9, 1997). The image was scanned with an HP ScanJet 4c color scanner at a

(a) Aerial image (b) GPSVan image (c) Halftone image

Fig. 12. Test images.



(a) Aerial image (b) GPSVan image (c) Halftone image

Fig. 13. Blobs of the test images.

resolution of 600 dpi in black and white (*i.e.*, gray tone) mode. The image size is 512×512 pixels and the overall entropy is 4.7.

2) Primitives of Images with Detected Blobs

Detected blobs shown in Fig. 13 are detected using the modified LoG operator described in previous section. After several experiments with different σ values it was found that σ = 0.55 provides best results. This value was applied to all test images to obtain primitives.

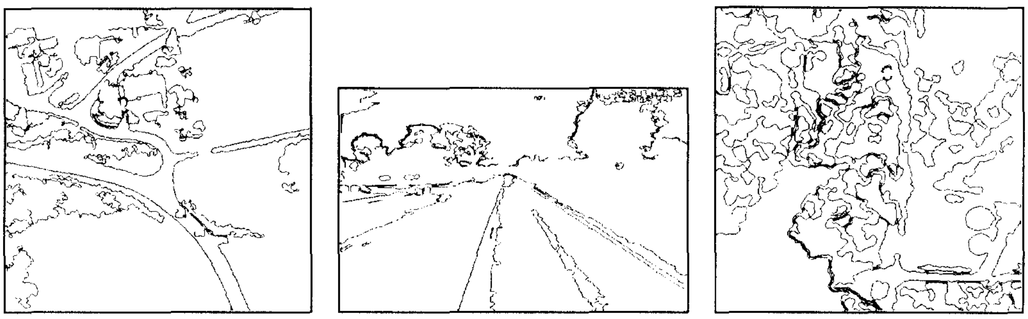
3) Parameters of the Gabor filters and boundary detection

Appropriate parameters are determined for each image block. This procedure includes determination of the filter size, orientation, and spatial frequency of the Gabor filters. A certain part of the results from a test image is listed in Table 1.

After segmenting images using *ISODATA* classification, boundaries were detected by edge detection operator. In this case any edge detection operator provides the same results since the images are already segmented. Detected

Table 1. Parameters of the Gabor filters of the aerial image.

Starting coordinates		Ending Coordinates		Entropy	σ	Filter size	Orientation	Blob size
row	col	row	Col			(pixel)	(deg)	(pixel)
96	256	127	287	6.88	3	15	90	9
96	256	111	271	6.19	6	31	90	7
96	272	111	287	6.32	6	31	45	8
112	256	127	271	6.34	6	31	90	2
112	272	127	287	5.31	12	65	45	10
96	288	127	319	5.71	9	47	ND	14
96	320	127	351	5.10	12	65	ND	17
96	352	127	383	5.11	12	65	ND	16
96	384	127	415	5.04	12	65	ND	16
96	416	127	447	5.06	12	65	ND	16
96	448	127	479	5.04	12	65	ND	14
96	480	127	511	5.02	12	65	45	17
128	0	159	31	6.19	6	31	ND	18
128	32	159	63	6.62	3	15	ND	9
128	64	159	95	6.38	6	31	ND	9



(a) Aerial image (b) GPSVan image (c) Halftone image

Fig. 14. Detected boundaries of the test images.

boundaries of the images are shown in Fig. 14.

5. Conclusions

Human successfully extract information and use it for image understanding and scene analysis without difficulty. Therefore, it is natural to be attracted by methods which resemble the performance of human visual perception. An adaptive strategy for extracting feature from images was developed and the performance was evaluated. The properties of the Gabor filters, which are conceived as hypothetical structures of retinal receptive fields in the human visual system, were identified and the advantages of using the Gabor filters were discussed.

Information from primitive identification and segmentation can be utilized in remote sensing and geographic information system (GIS) such as image matching, object recognition, classification of the terrain, and boundary detection. Experiments with various test images of natural scenes were carried out to examine and demonstrate the feasibility of the proposed adaptive method, and the following conclusions are drawn:

1. Two-dimensional Gabor filters should be used with appropriate parameters in order to extract information accurately.
2. Improvement of the texture segmentation can be achieved after processing the image with the Gabor filters region by region which are progressively determined based on the characteristics of the image.
3. The entire framework is to integrate multi-channel filter responses which is accompanied by multi-resolution processing in an image.
4. Adaptive processing for automatic determination of the parameters reduces human intervention for visual examination and the prior knowledge of the image.
5. The optimal block size depends on the image contents. Therefore, the starting block size influences the quality of the final result,
6. Meaningful object boundaries can be obtained from the proposed approach.
7. Identification of the parameters (*e.g.*, orientation and spatial frequency) provides possibility to develop the symbolic description of the feature which could be a gateway to high-level image processing such as image understanding and patter recognition.

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