Texture Segmentation.Gabor Filter Bank Optimization Using Genetic Algorithms

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***Abstract*—we are presenting a method of optimizing Gabor Filter Banks using an evolutionary approach. Texture segmentation has multiple usages from medical imaging to satellite terrain mapping. Gabor filters are the most widely used texture feature extractors. Multi-channel approach to texture segmentation using Gabor filters is subject to optimization. Genetic algorithms are used to generate an optimal filter bank for the source image.**

***Keywords*—texture segmentation, Gabor filter, genetic algorithm**

I. Introduction

In the classical approach images are seen as collections of pixels in the spatial domain or as sums of sinusoidal components in the frequency domain. Daugman's [11] research demonstrates that Gabor filters are optimal for offering maximum resolution in both the spatial and frequency domain. From neurobiology 2D Gabor filters are a good approximation of the receptive cells in the striate cortex (Macelja [13]).

In texture-image segmentation 2D Gabor filters are widely used as extractors of local texture information. Basically a Gabor filter acts as a band-pass filter for the local spatial frequency distribution in the texture. In order to completely segment a texture image, a number of different Gabor filters are used in what is called the multi-channel image filtering. Selecting the filter bands for efficient discrimination of all the textures in an image is one of the major issues in texture segmentation based on Gabor filters. Bovik et al.[1] have used one filter per texture class each tuned to the peak frequency. This approach offers optimum results if the textures are stable (the peak frequencies do not have fluctuations).

The classical approach to texture segmentation using Gabor [12] filters is to create a filter bank that when seen in frequency domain will resemble the shape of a rosette.

In this paper we approach the concept of using a filter bank that is generated using evolutionary methods.

A. Gabor filter

Gabor filters are of Gaussian nature, having a center frequency one orientation and two parameters of spatial expansion. By varying these parameters the filter can be tuned to filter any elliptical area in the frequency domain.

In the spatial domain the filter is defined as follows:

$$g(x,y) = s(x,y)w(x,y) \tag{1}$$

where $s(x,y)$ is a complex sinusoid known under the name of the *carrier*.

$$s(x,y) = \exp(-j(2\pi(u_0 x + v_0 y))) \tag{2}$$

where u_0 and v_0 define the spatial frequency of the sinusoid in Cartesian coordinates.

Function $w(x,y)$ is a 2D Gaussian known also under the name of *envelope*.

$$w(x,y) = K\exp(-\pi(a^2(x-x_0)_r^2 + b^2(y-y_0)_r^2)) \tag{3}$$

As mention before based on biological studies Gabor filters are good approximations of the receptive cells that are found in the striate cortex of cats and macaques. Based on Daugman's observations the simplified version of the Gabor filter can be used:

$$G_{\lambda,\theta,\varphi,\sigma,\gamma} = \exp(-\frac{x'^2 + \gamma y'^2}{2\sigma^2})\cos(2\pi\frac{x'}{\lambda} + \varphi) \tag{4}$$

$$x' = x\cos\theta + y\sin\theta \tag{5}$$

$$y' = -x\sin\theta + y\cos\theta \tag{6}$$

where x and y specify the position of a luminous stimulus (light pulse) in the visual field, and σ is the standard deviation of the Gaussian term. The ellipsoid is given by γ called *spatial aspect ratio*. Through biological observations it has been determined that it varies in the 0.23 – 0.92 range. This parameter is not controllable directly but by varying λ and b.

The λ parameter represents the wavelength or the spatial frequency ($1/\lambda$). The term σ/λ determine the bandwidth of the filter. The relationship between b, λ and σ is as follows:

$$b = \log_2 \frac{\frac{\sigma}{\lambda}\pi + \sqrt{\frac{\ln 2}{2}}}{\frac{\sigma}{\lambda}\pi - \sqrt{\frac{\ln 2}{2}}} \tag{7}$$

$$\frac{\sigma}{\lambda} = \frac{1}{\pi}\sqrt{\frac{\ln 2}{2}}\frac{2^b + 1}{2^b - 1} \tag{8}$$

neurophysiologic research has shown that the bandwidth of the filters vary in the 0.5 – 2.5 octave range for cats and 0.4 – 2.6 range for macaques. Event thought the domain is considerably larger most of the receptive cells are grouped in the 1.0 – 1.8 octaves.

The orientation of the filter is given by θ. And the phase is given by φ. For φ equal to 0^o and 180^o the function is symmetrical (even) and for -90^o and 90^o the function is anti-symmetrical (odd).

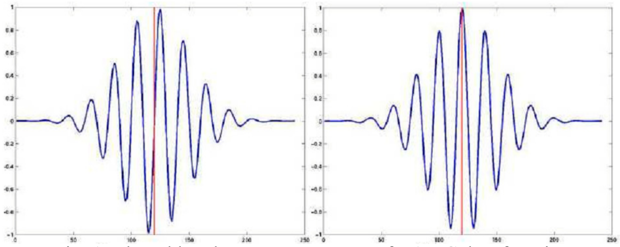


Fig. 1. The odd and even components of a 1D Gabor function

For various parameters the 2D Gabor filter will look as in the following figures:

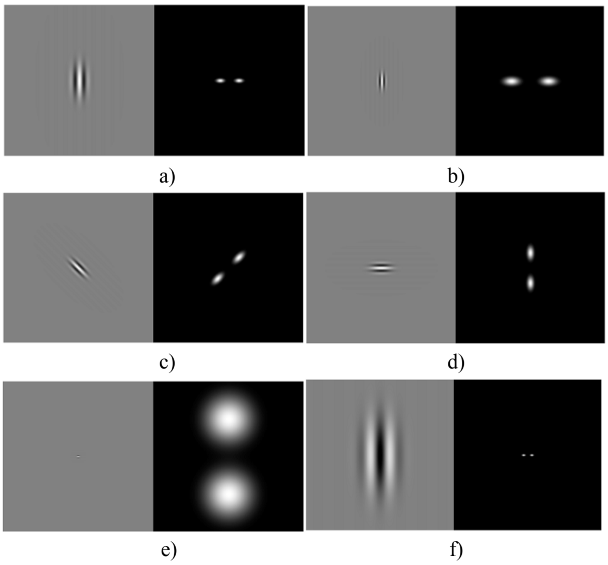


Fig. 2. Various Gabor filters

TABLE I.
GABOR FILTER PARAMETERS

Filter	Parameters				
	λ (pixels)	θ (degrees)	φ (degrees)	γ	b (octaves)
a)	16	0	0	0.5	1.0
b)	8	0	0	0.5	1.0
c)	10	45	0	0.5	1.0
d)	10	90	0	0.5	1.0
e)	4	90	0	1.0	1.5
f)	36	0	90	0.5	1.0

B. *Multi-channel Filtering*

For a single channel the process is as follows:

- the source image is convolved with the real kernel of the filter
- the source image is convolved with the imaginary kernel of the filter
- the magnitude of the channel output is used as a descriptor of applying the filter:

$$|G_{CH}(x,y)| = \sqrt{G_R^2(x,y) + G_I^2(x,y)} \qquad (9)$$

- the resulting image is smoothed with a Gaussian filter:

$$G_{\sigma,x,y} = \exp\left(-\frac{x^2+y^2}{2\sigma^2}\right) \qquad (10)$$

The process of filtering on a single channel:

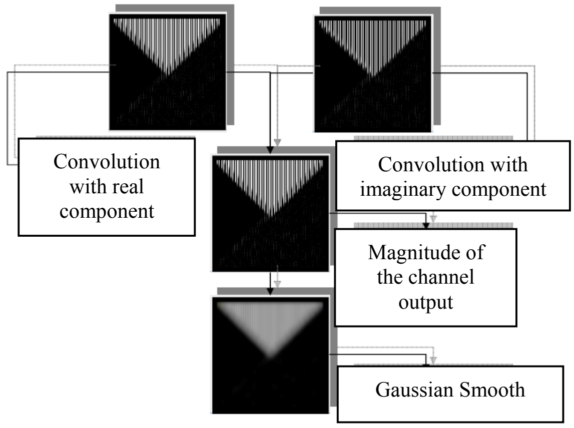


Fig. 3. Single channel filtering

For multiple channels the process is repeated for each filter.

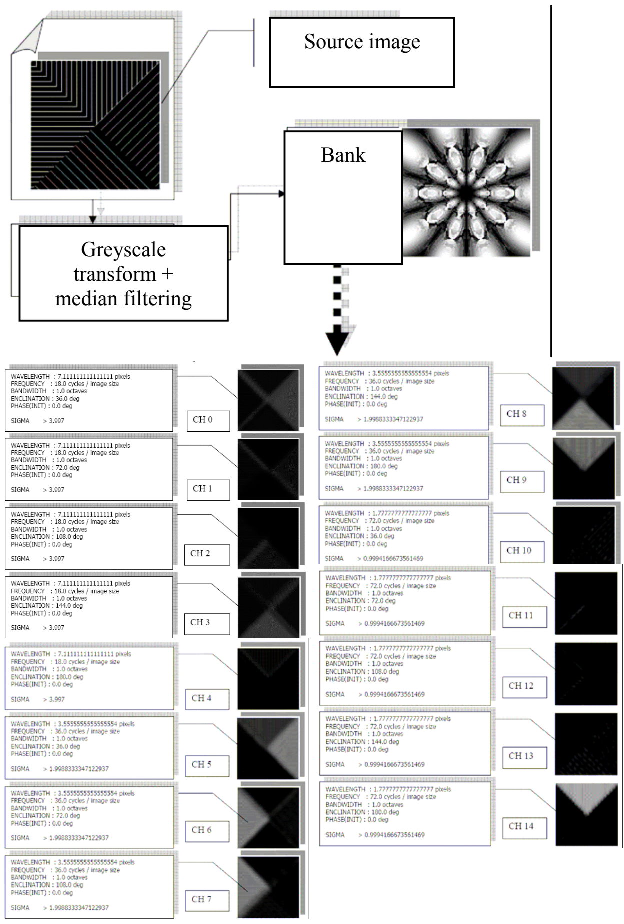


Fig. 4. Multiple channel filtering

C. *Classical Approach : The Rosette Distribution*

A number of filters are pre-selected based on the start frequency of the first filter on the x axis that is closer to the origin (center of domain).

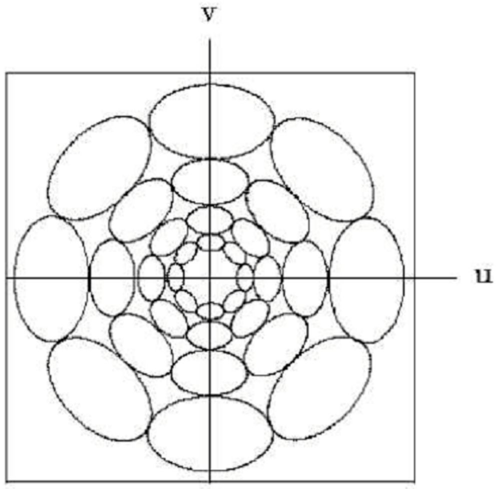


Fig. 5. The classical Rosette filter distribution

For a Rosette distribution the results are satisfactory given the number of filters in the bank is large enough. Unstable textures do not however give good results to this classic approach of segmentation. One clear advantage of the method is that it saves time by not having to regenerate the filter bank each time it's needed.

The problem in such an approach is that many filters in the bank will not discriminate a certain texture as a whole but rather certain frequencies form the texture. This indeed consist a problem if multiple textures share the same frequencies or are comprised of close frequencies for certain orientations. So by filtering in such cases portions (components) of certain textures are discriminated together making them more similar in the feature vector space.

We present a supervised (for the moment) approach to try to eliminate this problem. Rather than having a filter bank that covers the whole frequency spectrum on all orientations, we opted on using the best evolutionary *n* filters for each texture that discriminate that certain texture in the image and suppress the others.

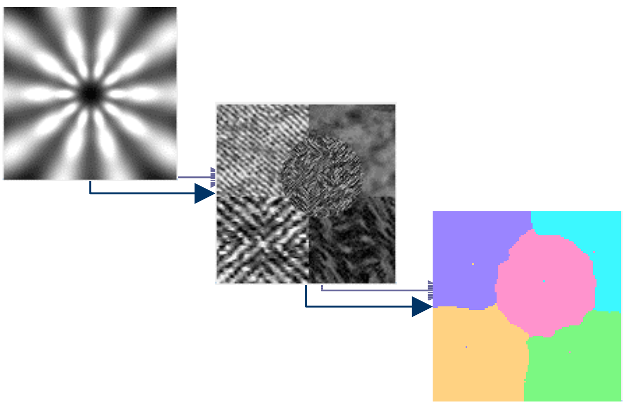


Fig. 6. The classical Rosette filter distribution. Texture segmentation.

D. *Evolutionary Approach.*

The implementation was realized using the JGAP (Java Genetic Algorithms Package) java library. The standard genetic operators where used (reproduction, crossover and mutation). The chromosome is defined as follows:

TABLE II.
THE CHROMOSOME

Central Frequency	Orientation	Aspect Ratio	Bandwidth
1 / λ	**θ**	**γ**	**b**

By varying the following genes we optimized the filter bank. The genes that produce the best results in terms of texture filtering (the fittest genes) are pushed forward.

The fitness function chosen has the following role: for each texture it selects the best *n* filters that discriminate the selected texture and suppress the rest of the present textures in the image.

$$F_{Fit} = \frac{\overline{G_R(T_D)}}{\sum_{I \neq D} \overline{G_R(T_I)}} \tag{11}$$

where $G_R(T_D)$ is the magnitude of the channel output for the texture to discriminate, and $\{T_I\,;\, I > 0\ \&\ I < N\ \&\ I \neq D\}$.

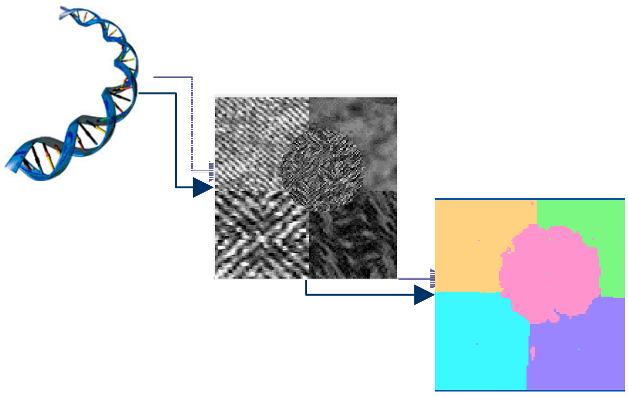


Fig. 7. The genetic filter bank. Texture segmentation.

E. *Clustering.*

The feature vector is built as follows:

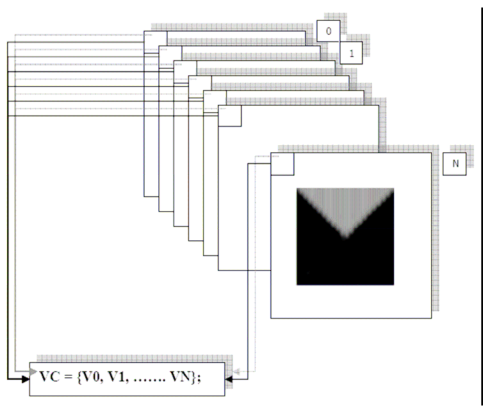


Fig. 8. Construction of the feature vector.

Each sample in the vector corresponds to the pixel value on the specified channel at the given spatial location (Cartesian coordinates).

Because usually the number of channels is quite high (average of 20 channels) this fact results in a high dimensional space that is computationally intensive to cluster.

To reduce the overhead PCA is used as a pre-clustering phase. The high dimensional feature space is transformed into a lower dimension space, experimentally 4 dimensions where used as the reduction of the original feature space, a lower reduction of the hyperspace causes the data to loose its dissimilarity resulting in poor clustering results.

We have experimented with LBG (Linde, Buzo, Gray) clustering algorithm and with the Enhanced LBG (E-LBG) (Giuseppe Patanè, Marco Russo [10]).

II. Results

A. Evolutionary approach segmentation results.

TABLE III.
TEXTURE SEGMENTATION USING GENETIC ALGORITHMS

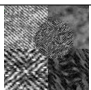
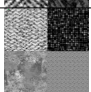
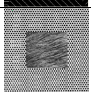
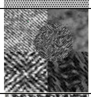
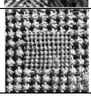
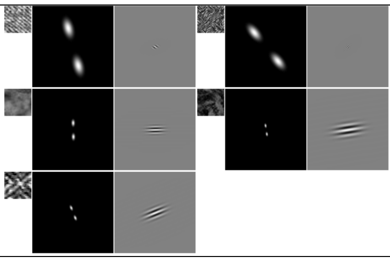
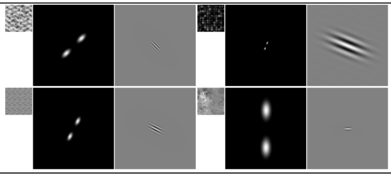
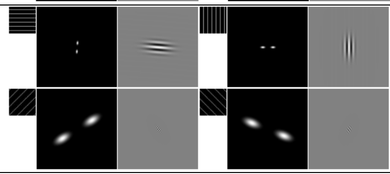
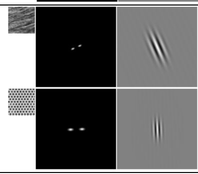
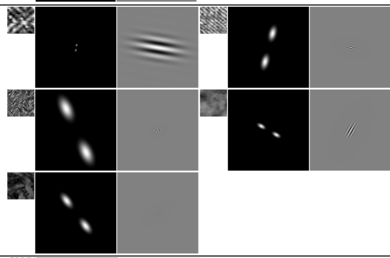
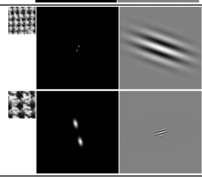
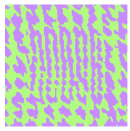
No.	Parameters					
	Texture	Initial Population	*N*	Generations	PCA	SC
1		80	4	60	4	Y
2		120	4	60	4	Y
3		80	4	60	4	Y
4		80	4	60	4	N
5		80	4	60	4	Y
6		200	4	80	4	N

TABLE IV.
OBTAINED FILTER BANKS

No.	Parameters	
	Best Filters in the Filter Bank / Texture	Result
1		
2		
3		
4		
5		
6		

By comparing results from 1 and 5 we can clearly see that the filter bank configuration can vary for real life textures due to their complex frequency components. In the case of 6 where the same texture is used but with different texton size (the inner texture is scaled down), a filter bank cannot be found for this case as the textures are the same, which is the contrary of case 4 where the two different textures can easily be discriminated from the original image.

B. Conclusions

The filter bank has to be tuned to the textures at hand in order for the method to introduce few distortions in the feature space. The major problem with Gabor filters is that a poorly selected filter will discriminate regions from multiple textures at the same time, resulting in a poor segmentation of the original image.

The method described can successfully be used to find optimum filter banks for different textures.

For future work, we plan on improving the filter function and transforming the method to a unsupervised one.

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