IMAGE SEGMENTATION USING GABOR FILTER AND WAVELET TRANSFORM

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ABSTRACT

This paper describes the various methods for the segmentation purpose like as using Gabor transforms and wavelet transform. The texture segmentation is the important tasks in the machine vision and the computer application. Among the existing texture segmentation methods, those relying on Markov random fields have retained substantial interest and have proved to be very efficient in supervised mode. This paper introduces a formulation which allows using wavelet-based image segmentation. This formulation can be used in supervised, unsupervised, or semi supervised modes. The main obstacle to using wavelet-based priors for segmentation, that they’re aimed at representing real values, rather than discrete labels, as needed for segmentation. We are trying to compare between Gabor filter and wavelet transform using various algorithms. The goals are to improve textured image segmentation results, especially along the borders of regions; and to take into account the spatial relationship among pixels to improve the segmentation of region interiors.

KEYWORDS: Gabor Filter, Wavelet Transform, Clustering, MRF, Neural Network, Genetic Algorithms, Selectionist Relaxation

INTRODUCTION

An important task of an image analysis system is to segment the given image into meaningful regions and to label the individual regions. Textured image segmentation consists in partitioning an image into regions that are homogeneous with regards to some texture measure. Classification of natural textures is difficult for several reasons. We can try to compare between Gabor transform texture output and the wavelet transform texture output using the various algorithms applying to both methods such as in our first part the texture input image is filtered and extract by applying the 2-D Gabor filter with different orientations and scales. The clustering and MRF model are used to segment the image into different parts. In the second section of this paper the HAAR wavelet transform is used to decompose the image after that the train neural network is apply for the segmentation purpose. The Genetic algorithm is for the optimization. The third method, we are implemented in this paper is wavelet transform using hill-climbing algorithm.

LITERATURE REVIEW

[1] Describe a new hidden Markov random field model, which we call hierarchical multi-data model, and which is based on triplet of random fields (two hidden random fields and one observed field) in order to capture inter-scale and within-scale dependencies between various scales of resolution of wavelet-based texture features. The Gabor filter is applying into different orientation and scales such as 0, 30, 60, 90, 120, 150 degree rotations. Development of image features, and feature models, as relevant and informative as possible for segmentation. Classicalexamples for texture segmentation include Gabor features [2], wavelets-based features [3], [4], Markov random field models [5], [6]

GABOR BASED APPROACH

A Gabor filter is a linear filter whose impulse response is defined by a harmonic function multiplied by a
Gaussian function. Because of the multiplication-convolution property (Convolution theorem), the Fourier transform of a Gabor filter's impulse response is the convolution of the Fourier transform of the harmonic function and the Fourier transform of the Gaussian function. A 2-D Gabor filter is an oriented complex sinusoidal grating modulated by a two-dimensional (2-D) Gaussian function. GEF's were first defined by Gabor and later extended to 2-D by Daugman

\[ h(x, y) = g(x', y') \exp[j2\pi(ux + vy)] \]  

(1)

Where \((x', y') = (x \cos \theta + y \sin \theta, -x \sin \theta + y \cos \theta)\) represent rotated spatial-domain rectilinear coordinates. Let \((u, v)\) denote frequency-domain rectilinear coordinates, \((U, V)\) represents a particular 2-D frequency. The complex exponential is a 2-D complex sinusoid at frequency.

The complex exponential is a 2-D complex sinusoid at frequency \( F = \sqrt{u^2 + v^2} \) and \( \tan^{-1} \frac{v}{u} \) specifies the orientation of the sinusoid. The function \( g(x, y) \) is the 2-D Gaussian

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

(2)

Where \( \sigma_x \) and \( \sigma_y \) characterize the spatial extent and bandwidth of the filter. Thus, the GEF is a Gaussian that is modulated by a complex sinusoid. It can be shown that the Fourier transform of \((x, y)\) is given by

\[ H(u, v) = \exp \left[ -\frac{1}{2} \left( (\sigma_u |u - U|)^2 + (\sigma_v |v - V|)^2 \right) \right] \]  

(3)

Where, \( |(u - U)|, |(v - V)| = [(u - U)\cos \theta + (v - V)\sin \theta, -(u - U)\sin \theta + (v - V)\cos \theta] \).

Thus, from (3), the GEF’s frequency response has the shape of a Gaussian. The Gaussians major and minor axis widths are determined by \( \sigma_x \) and \( \sigma_y \), it is rotated by an angle \( \theta \) with respect to the positive u-axis and it is centered about the frequency \((U, V)\). Thus, the GEF acts as a bandpass filter. In most cases, letting \( \sigma_x = \sigma_y = \sigma \) is a reasonable design choice. If it assumed that \( \sigma_x = \sigma_y = \sigma \), then the parameter \( \theta \) is not needed and the equation of GEF simplifies to

\[ h(x, y) = \frac{1}{2\pi \sigma^2} \exp \left[ \frac{x^2 + y^2}{2\sigma^2} \right] \exp[j2\pi(Ux + Vy)] \]  

(4)

We now define the Gabor Filter \( \hat{O} \) by

\[ m(x, y) = \hat{O}(i(x, y)) = [i(x, y) \otimes h(x, y)] \]  

(5)

Where \( i \) is the input image and \( m \) is the output.

An important property of the 2-D Gabor filters is their ability to represent the image both in spatial and spatial frequency domains optimally by achieving the theoretical lower bound of joint uncertainty [7], depending upon the chosen metric [8]. This is equivalent to achieving maximum possible joint resolution in the two domains [9], providing simultaneous spectral and spatial localization.

![Figure 1: System Structure](image)

**WAVELET-BASED APPROACH**

A wavelet is a wave-like oscillation with amplitude that starts out at zero, increases, and then decreases back to
zero. It can be viewed as a “brief oscillation” similar to oscillations recorded by a seismograph or heart monitor. Wavelets are crafted to exhibit specific properties that make them useful for signal processing. A typical wavelet texture features extraction scheme is to the texture image decomposed with the Haar wavelet transform.

![System Structure](image)

**Figure 2: System Structure**

**Haar Wavelet for Image Decomposition**

Haar wavelet is a sequence of functions. It is the simplest wavelet transform. It is a compression process. The Haar wavelet’s mother wavelet function $\psi(t)$ can be described as

$$
\Psi(t) = \begin{cases} 
1 & 0 \leq t < 1/2 \\
-1 & 1/2 \leq t < 1 \\
0 & \text{otherwise}
\end{cases}
$$

and its scaling function $\phi(t)$ can be described as

$$
\phi(t) = \begin{cases} 
1 & 0 \leq t < 1 \\
0 & \text{otherwise}
\end{cases}
$$

**PROPOSED METHDOLOGY**

In this paper, we are implemented three methods. In first method the texture image taken as input. This texture image extracted using the Gabor filtering in various scales and orientation. The Gaussian filter is used for the smooth that texture image. From this the mean and standard deviation calculated. The k-mean clustering used for the segmentation. Markov Random Field (MRF) is used to sharpen that segmented image. In second part of this paper, the wavelet transform is used for the image decomposition. The Haar wavelet is used at two level decomposition. The Artificial Neural network is used to train and segment that textured image. In third part, the wavelet transform is used to decompose the image and the Hill-Climbing Algorithm is used to segmentation.

**RESULTS AND DISCUSSIONS**

The main objectives of this work are: a) to improve segmentation results, especially along the borders of regions; and b) to take into account the spatial relationship of pixels in the process of textured image segmentation. We are trying to compare between wavelet and Gabor transform. The original input images is shown in figure (3.a), (4.a), (5.a). The output of the Gabor filter without Markov Random Fields is shown in figure (3.b), (4.b), (5.b), and with Markov Random field is shown in figure (3.c), (4.c), (5.c). The output of the wavelet transform using neural network is shown in the figure (3.d), (4.d), (5.d). The output of wavelet using Hill-climbing algorithm is shown in figure (3.e), (4.e), (5.e).
CONCLUSIONS

From our experiments, we see that our methods could achieve the image segmentation purpose. For simple images with just a little texture inside, the result is quite good. The result from the Gabor filter using MRF is better than the Gabor filter using only K-mean clustering. The result from the wavelet and the neural network is better than the wavelet and Hill-climbing Algorithm.

REFERENCES

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