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A Review Paper on Gabor Filter Algorithm & Its Applications

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***Abstract*— In applications of image analysis and computer vision, Gabor filters have maintained their popularity in feature extraction. The reason behind this is that the resemblance between Gabor filter and receptive field of simple cells in visual cortex. Being successful in applications like face detection, iris recognition, fingerprint matching; where, Gabor feature based processes are amongst the best performers. The Gabor features can be derived by applying signal processing techniques both in time and frequency domain. The models like human preattentive texture perception have been proposed which involves steps like convolution, inhibition and texture boundary detection. Texture features are based on the local power spectrum obtained by a bank of Gabor filters. The concept of sparseness to generate novel contextual multiresolution texture descriptors are described. In this paper we present the detailed study about the Gabor filter and its application.**

***Index Terms*— Gabor filter, Gabor energy, image quality assessment, Gabor features, multiresolution techniques, segmentation, textured images..**

I. Introduction

In imaging science, image processing is any form of signal processing for which the input is an image, such as a photograph or video frame; the output of image processing may be either an image or a set of characteristics or parameters related to the image. Most image-processing techniques involve treating the image as a two-dimensional signal and applying standard signal-processing techniques to it. Image processing usually refers to digital image processing, but optical and analog image processing also are possible.

An image defined in the "real world" is considered to be a function of two real variables, for example, a(x,y) with a as the amplitude (e.g. brightness) of the image at the real coordinate position (x,y).

The goal of this manipulation can be divided into three categories:

- Image Processing (image in to image out)
- Image Analysis (image in to measurements out)
- Image Understanding (image in to high-level description out)

An image may be considered to contain sub-images sometimes referred to as regions-of-interest, ROIs, or simply regions. This concept reflects the fact that images frequently contain collections of objects each of which can be the basis for a region. In a sophisticated image processing system it should be possible to apply specific image processing operations to selected regions. Thus one part of an image (region) might be processed to suppress motion blur while another part might be processed to improve color rendition.

Sequence of image processing: Most usually, image processing systems require that the images be available in digitized form, that is, arrays of finite length binary words. For digitization, the given Image is sampled on a discrete grid and each sample or pixel is quantized using a finite number of bits. The digitized image is processed by a computer. To display a digital image, it is first converted into analog signal, which is scanned on to a display.

1.1 What is Gabor Filter?

In image processing, a Gabor filter, named after Dennis Gabor, is a linear filter used for edge detection. Frequency and orientation representations of Gabor filters are similar to those of the human visual system, and they have been found to be particularly appropriate for texture representation and discrimination. In the spatial domain, a 2D Gabor filter is a Gaussian kernel function modulated by a sinusoidal plane wave. Simple cells in the visual cortex of mammalian brains can be modeled by Gabor functions. Thus, image analysis with Gabor filters is thought to be similar to perception in the human visual system.

1.2 Applications of 2-D Gabor filters

In image processing In document image processing, Gabor features are ideal for identifying the script of a word in a multilingual document.[9] Gabor filters with different frequencies and with orientations in different directions have been used to localize and extract text-only regions from complex document images (both gray and colour), since text is rich in high frequency components, whereas pictures are relatively smooth in nature. It has also been applied for facial expression recognition Gabor filters have also been widely used in pattern analysis applications. For example, it has been used to study the directionality distribution inside the porous spongy trabecular bone in the spine.[14] The Gabor space is very useful in image processing applications such as optical character recognition, iris recognition and fingerprint recognition. Relations between activations for a specific spatial location are very distinctive between objects in an image. Furthermore, important activations can be extracted from the Gabor space in order to create a sparse object representation.

1.3 What is a texture? A measurement of the variation of the intensity of a surface, quantifying properties such as regularity, smoothness and coarseness. You can also explain with term is color map. Texture is mapped onto an already available surface. A surface texture is created by the regular repetition of an element or pattern, called surface texel, on a surface. In computer graphics there are deterministic (regular) and statistical (irregular) texture It's often used as a region descriptor in image analysis and computer vision. The three principal approaches used to describe texture are structural, spectral and statistical. Apart from the level of gray and color texture is a spatial belief indicating what characterizes the visual homogeneity of given zone of an image in a in infinte(true) image which generate another image based on the original texture and finally analyze these two fragments by classifying them in a different or a same category. In other words we can also say that the main objective is to decide if texture samples belong to the same family by comparing them. By using filter-bank model the process is bring to conclusion, dividing and decomposing of an input image into numerous output image is prepared by a set of linear image filters working in parallel which is used by the filter-bank model. These filters gives rise to concept of joint space/ spatial-frequency decomposition by simultaneously concentrate on local spatial interactions and on particular range of frequencies.

1.4 Introduction to Image Texture:

An image texture is a set of metrics calculated in image processing designed to quantify the perceived texture of an image. Image texture gives us information about the spatial arrangement of color or intensities in an image or selected region of an image. Image textures can be artificially created or found in natural scenes captured in an image. Image textures are one way that can be used to help in segmentation or classification of images. For more accurate segmentation the most useful features are spatial frequency and an average grey level. To analyze an image texture in computer graphics, there are two ways to approach the issue: Structured Approach and Statistical Approach For more than 50 years understanding of processes occurring in the early stages of visual perception has been a primary research topic. For regular properties like color, brightness, size and the slopes of lines composing gures preattentive segmentation occurs strongly (Beck 1966, 1972, 1973, 1983; Olson and Attneave 1970). Research into the statistical properties of preattentively discriminable texture was started by 3 Julesz in early 1960's. Complex topic where psychophysics meets physiology Beck and Julesz were among the rest to deep in.

2. LITERATURE REVIEW

The module performs a linear feature reduction by using texture measurements at two successive levels of resolution. [1] Classical theories of texture perception by Julesz'-3 and Beck- 6 attribute preattentive texture discrimination to differences in first-order statistics of stimulus features such as orientation, size, and brightness of constituent elements. These theories have typically been constructed for black-and-white dot or line patterns and are not directly applicable to gray-scale images (though Voorhees and Poggio7 provide a definition of textons for gray-scale images). Experimental results describing phenomena that are not well explained by these theories have been reported. An alternative approach to texture perception is based on the responses of the linear mechanisms (psychophysically observed spatial-frequency channels and neuro-physiologically observed blob-, bar-, and edge-sensitive neurons) that have been used to explain a range of phenomena in early spatial vision. While these efforts have demonstrated that a filtering approach can explain some phenomena that are not consistent with the texton theory, a complete model has not yet been presented. Such a model should satisfy the following criteria: 1. Biological plausibility: The stages of the model should be motivated by consistent with, known physiological mechanisms of early vision. 2. Generality: The model should be general enough that it can be tested on any arbitrary gray-scale image. 3. Quantitative match with psychophysical data: The model should make a quantitative prediction about the salience of the boundary between any two textured regions. Rank ordering of the discriminability of different texture pairs should agree with that measured psychophysically. [2] Various features related to the local power spectrum of images have been proposed in the literature and used in one way or another for texture analysis, classification, and/or segmentation. In most of these studies the relation to the local spectrum is established through (intermediate) features that are obtained by filtering the input image with a set of two-dimensional(2-D) Gabor filters. Such a filter is linear and local. Its convolution kernel is a product of a Gaussian and a cosine function. The filter is characterized by a preferred orientation and a preferred spatial frequency. Roughly speaking, a 2-D Gabor filter acts as a local band-pass filter with certain optimal joint localization properties in the spatial domain and in the spatial frequency domain. Typically, an image is filtered with a set of Gabor filters of different preferred orientations and spatial frequencies that cover appropriately the spatial frequency domain, and the features obtained from a feature vector field that is further used for analysis, classification, or segmentation. Gabor feature vectors can be used directly as input to a classification or a segmentation operator or they can first be transformed into new feature vectors that are then used as such an input. [4] Texture segmentation, i.e. the partitioning of an image in to homogeneous regions based on textural cues, constitutes a significant task of many computer vision and pattern recognition applications. Texture is one of the important cussed by human beings in identifying regions of interest in an image. Motivated by psychophysical studies showing that the he brain analyzes texture based on spatial frequency information, many researchers have opted for spectral texture analysis approaches, which typically use filter banks. In a filter bank, filters are designed to focus on different ranges of frequencies and local spatial interactions, bringing about the concept of a joint space/spatial frequency decomposition. input image contains several regions with differences in local spatial frequency, those differences will hopefully appear in one or more resulting filtered images. Many filter banks have been proposed in the literature. Banks based on Gabor functions have been of particular interest, due to their optimality for minimizing the joint two dimensional uncertainty in space and frequency. Gabor filters, constructed from Gaussian functions modulated by oriented complex sinusoidal functions, were initially proposed for texture analysis. Due to their multi-scale and multi-orientation characteristics, filter banks typically yield a high-dimensional feature space. [12]. For computational cost considerations, low dimension feature spaces are preferable over high-dimension alones. Moreover, low-dimensional feature vectors decrease the complexity of the clustering or classification tasks. Methods have been proposed to extract low dimension features from Gabor filtered images by considering only sparseness of the filter bank response. The concept of sparseness, in general terms, refers to the property of being scattered, thinly distributed. In the context of data processing, it refers to the concentration of information into a small number of coefficients. For filter bank responses, high sparseness values thus refer to a small number of triggered filters. In classical signal processing applications, sparse representation has proven to be a powerful tool for acquiring, representing, and compressing high-dimensional signals. It has played an important role in the success of many machine learning algorithms and techniques. It has also been popular in computer vision applications, as sparse representations can facilitate the retrieval of semantic data from images.[12]. Due to the rapid deployment of wireless communications, video applications on mobile embedded systems such as video telephony and video streaming have grown dramatically. A major challenge in mobile video applications is how to efficiently allocate the limited energy resource in order to deliver the best video quality. A significant amount of power in mobile embedded systems is consumed by video processing and transmission. Also, error resilient video encodings demand extra energy consumption in general to combat the transmission errors in wireless video communications. Thus, it is challenging and essential for system designers to explore the possible tradeoff space and to increase the energy saving while ensuring the quality satisfaction even under dynamic network status. [Paper 6]

2.1 Feature Extraction

2.1.1 Gabor Features:

A core of Gabor filter based feature extraction is the 2D Gabor filter function expressed as,

$$\Psi(x,y) = \frac{f^2}{\pi\gamma\eta} e^{-\left(\frac{f^2}{\gamma^2}x'^2 + \frac{f^2}{\eta^2}y'^2\right)} e^{-i2\pi f x'} \quad (1)$$

$$x' = x\cos\theta + y\sin\theta$$

$$y' = -x\sin\theta + y\cos\theta$$

In the spatial domain (Eq. (1)) the Gabor filter is a complex plane wave (a 2D Fourier basis function) multiplied by an origin-centered Gaussian. f is the central frequency ofthe filter,θ the rotation angle,γsharpness (bandwidth) alongthe Gaussian major axis, and η sharpness along the minoraxis (perpendicular to the wave). In the given form, the aspectratio of the Gaussian is η/γ . This function has the followinganalytical form in the frequency domain,

$$\Psi(u,v) = e^{-\frac{\pi^2}{f^2}(\gamma^2(u'-f)^2+\eta^2v'^2)} \quad (2)$$

$$u' = u\cos\theta + v\sin\theta$$

$$v' = -u\sin\theta + v\cos\theta$$

In the frequency domain (Eq. (2)) the function is a singlereal-valued Gaussian centered at$f$. The Gabor filterin (1) and (2) is a simplified version of the general 2D form devised by Daugman from the Gabor's original 1D"elementary function". The simplified version enforces aset of filters self-similar, i.e. scaled and rotated versions ofeach other ("Gabor wavelets"), regardless of the frequency $f$and orientationθ.

Gabor features, referred to as Gabor jet, Gabor bank or multi-resolution Gabor feature, are constructed from responses of Gabor filters in (1) or (2) by using multiple filters on several frequencies f_m and orientations θ_n . Frequency in this case corresponds to scale information and is thus drawn from,

$$f_m = k^{-m} f_{max} \ , m = \{0, \ldots, M-1\} \quad (3)$$

Where, f_m is the mth frequency, $f_0 = f_{max}$ is the highest frequency desired and $k > 1$ is the frequency scaling factor. The filter orientations are drawn as,

$$\theta_n = \frac{2\pi n}{N}, \quad n = \{0, \ldots, N-1\} \quad (4)$$

Where, $\theta_n$is the $n\ th$ orientation and N is the total number of orientations. Scales of a filter bank are selected from exponential (octave) spacing and orientations from linear spacing.

a. Local Linear Transform:

The principal for this approach is to characterize the Nth order probability density function (pdf) of the pixels in a restricted neighborhood by N first order pdf's estimated along a set of suitably chosen axis. These projections are chosen by local linear transform.

This formulation establishes a correspondence between the original image $\{x_{k,l}\}$ and a N channel multivariate sequenceof local neighborhood vectors $\{x_{k,l}\}$defined forall spatial indices $\{k,l\}$. The components of the local neighborhood vector $x_{k,l}$ are the sequentially ordered graylevel values belonging to an N point neighborhood centered on the spatial position indexed by $\{k,l\}$. A locallinear transform is defined by the matrix relationship:

$$y_{k,l} = T\, x_{k,l} \quad (5)$$

Where, T is a$N * N$ non-singular transformation matrix.

b. Transform Selection:

The performance of the system depends on the transformation matrix T. The most trivial example is to consider the use the identity matrix or any of its permutations. This particular choice is the least favorable, because the statistics of the initial components of the local neighborhood vector are all identical and contain no neighborhood information. The optimal solution for analyzing a given texture was shown to be the local Karhunen-Loeve transform that diagonalizes the spatial covariance matrix. This transform has the remarkable property of producing the channel statistics that are the most different from one another; it also de-correlates the transformed coefficients, thereby justifying the approximation of the Nth order pdf by the product of N first order pdf's. The use of these solutions, however, is restricted in practice because they are texture dependent. They are therefore not applicable to unsupervised texture segmentation. Fortunately, it has been demonstrated that almost equivalent performances could be obtained with suboptimal separable transforms such as the discrete sine (DST),cosine (DCT), Hadamard (DHT), and real even Fourier(DREFT) transforms.

c. Gabor Energy Features:

The outputs of a symmetric and an antisymmetric kernel filter in each image point can be combined in a single quantity that is called the Gabor energy. This feature is related to the model of a specific type of orientation selective neuron in the primary visual cortex called the complex cell and is defined in the following way:

$$e_{\lambda,\theta}(x,y) = \sqrt{\gamma^2_{\lambda,\theta,0}(x,y) + \gamma^2_{\lambda,\theta,-\left(\frac{1}{2}\right)\pi}(x,y)} \qquad (6)$$

Where, the terms in squareroot sign are the responses of the linear symmetric and antisymmetric Gabor filters respectively. The result is a new non-linear filter bank of 24 channels. The Gabor energy is closely related to the local power spectrum.The local power spectrum associated with a pixel in animage is defined as the squared modulus of the Fourier transformof the product of the image function and a window functionthat restricts the Fourier analysis to a neighborhood of thepixel of interest. Using a Gaussian windowing function and taking into account the Gabor feature image and (3) the followingrelation between the local power spectrum$p_{\lambda,\theta}$ and the Gaborenergy features can be proven:

$$p_{\lambda,\theta}(x,y) = {e_{\lambda,\theta}}^2(x,y) \qquad (7)$$

d. Texture Sparseness:

Hoyer's measure was selected in [13] to compute the sparseness of the Gabor descriptor. The main reason is that thismeasure possesses all but one of the desirable sparsenessmeasure attributes presented by Hurley and Rickard,failing only the "cloning" attribute (irrelevant to ourapplication). Hoyer's measure is based on the ratio between theL1 and L2 norms. We modified the original formulation toaccommodate the case of absence of texture, for which all filterbank responses would be zero (null vector):

$$sparseness(\vec{x}) = \begin{cases} 0 & \forall x_i : x_i = 0 \\ \dfrac{\sqrt{n} - \left(\dfrac{\sum x_i}{\sqrt{\sum {x_i}^2}}\right)}{\sqrt{n} - 1} & \exists x_i : x_i \neq 0 \end{cases} \qquad (8)$$

With $\vec{x}$ the feature vector formed by all filter bank responses, and n the dimensionality of $\vec{x}$. This feature maps a vector from $\mathfrak{R}^n$ to $\mathfrak{R}$. The minimal and maximal sparseness values to zero and one are measured for vectors having all equal elements and only one non-zero element, respectively. Fig. 2 shows the block diagram of the method involved in texture segmentation using sparseness.

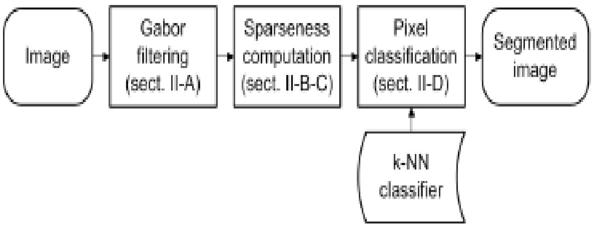

Fig. 2 Block diagram of texture segmentation using sparseness

1. Problems In Previous Research

In this section we represent all previous existing issues which are face by those previous approaches: • All previous approaches are increases the time complexity issue. • Algorithm reduces some amount of time complexity but still it will have issue of image quality. • Algorithm reduces the image quality problem, but it will increase the time complexity issue. • Previous existing Gabor filter have the issues of time complexity which will increase the entire time of texture segmentation process.

2. Future Scope on Gabor Filter

Texture Segmentation Processor is useful architecture in much application like Multimedia & Graphics but still Texture Segmentation processor faeces many problems which I discussed in research gap. So there are followings object is which I will cover in my thesis: 1. Here we will try to make novel algorithm which is fast as compare to previous algorithm. 2. Here we are presenting new algorithm for gabor filter using of error tolerant logic. 3. We will also maintain image quality up to the mark with factor improvement in time complexity. Here I will present another new approach which reduces that entire problem by the help of approximation technique. In this approach error range introduce is between 0 to 5%which is tolerable.

3. Conclusion

According to current technology future is totally based on virtual world. Right now everything is based on real data transfer and as we know for real time data transfer we need noise less system. According to this paper we did study about the previous existing gabor filter and according to that previous existing problem which is time complexity with maintain the quality level of the generated output images. The key contribution of this paper is to provide a complete information about the previous existing approaches. Here there is lot of future scope on this area , still this area is facing lots of problems which have to solve.

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