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SEGMENTING MODULATED LINE TEXTURES WITH S-GABOR FILTERS

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ABSTRACT

This paper describes a novel technique for segmenting frequency modulated line-textures. Textures of this sort abound in nature and are typified by growth patterns in which the deposition rate varies over time. The basic idea underpinning the technique is to use the S-Gabor kernel as a frequency modulated channel response function. According to this channel model, the central frequency changes exponentially with distance from the centre of the kernel. In order to segment the resulting texture response, we use fuzzy clustering to locate peaks in the Fourier power spectrum. In this way we estimate both the centre-frequency and the modulation parameters of the filter bank. We illustrate the effectiveness of our technique on the segmentation of growth patterns on fish scales.

1. INTRODUCTION

Gabor filters have been widely exploited to compute a multi-channel representation of the raw image data in the characterisation not only of edge and line features, but also of regular texture [1, 2]. The Gabor function serves well as a channel model when the features to be detected are regular in width, orientation, phase and frequency. However, if the target features are more complex then a more sophisticated channel model is required. One example of such a situation is provided by textures which rather than having a regular spatial frequency, exhibit frequency modulation. Examples from nature are common, especially where deposition rates (of bone, wood or sediment) vary over time (seasonal, diurnal or geological). Of particular interest for the application in hand is the detection of growth patterns in fish scales. Here growth-lines are deposited with a spatial frequency which varies with time (see figure 1). The characterisation of these patterns requires either a very dense disposition of frequency channels or a frequency-modulated channel model.

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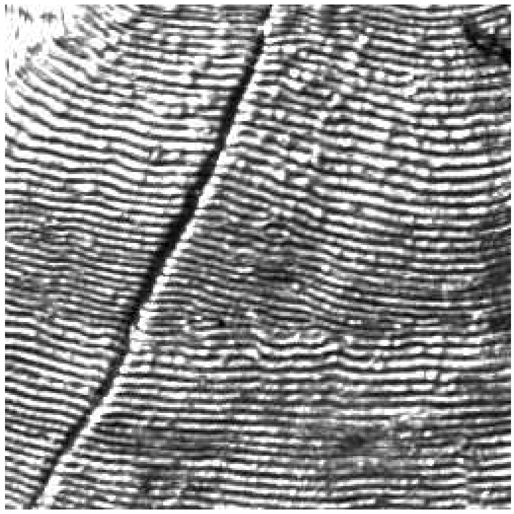


Figure 1: Part of a fish scale.

If modulated textures are to be segmented, two problems need to be solved. Firstly, a wavelet basis function needs to be found that can represent frequency modulated textures. Since they are associated with a fixed central frequency, the standard Gabor functions are unsuitable since a large number of filters must be deployed to cover the required frequency range. It is for this reason that we turn to the frequency modulated S-Gabor kernel [3]. This filter differs from its canonical Gabor counterpart by virtue of the fact that the centre-frequency undergoes exponential decay with a predefined amplitude and lifetime. With a suitable filter-basis to hand, the second requirement is for an effective means of estimating the parameters of the modulation function. In our texture segmentation application, this involves determining the range of frequencies which are present in the modulated line patterns. Because of the uncertainty and potential overlap of peaks in the power spectrum, we opt to use a fuzzy clustering technique.

2. S-GABOR FILTERS

The S-Gabor function recently suggested by Heitger et al [3] modulates the central spatial frequency ν of its Gabor counterpart through a process of exponential decay. If x and y denote the spatial co-ordinates, then the so called S-Gabor functions with horizontal orientation having spatial width w are as follows

$$C_{0,w}(x,y) = \exp[-\frac{1}{2}(\frac{x^2}{w_x^2} + \frac{y^2}{w_y^2})]\cos[2\pi\nu x\psi(x)] \quad (1)$$

$$S_{0,w}(x,y) = \exp[-\frac{1}{2}(\frac{x^2}{w_x^2} + \frac{y^2}{w_y^2})]\sin[2\pi\nu x\psi(x)] \quad (2)$$

The modulating function imposes an exponential attenuation on the spatial frequency

$$\psi(x) = 1 - k(1 - \exp[-\lambda\frac{x^2}{w_x^2}]) \quad (3)$$

A cosine-phase S-Gabor filter tuned for line-texture segmentation is shown in figure 2

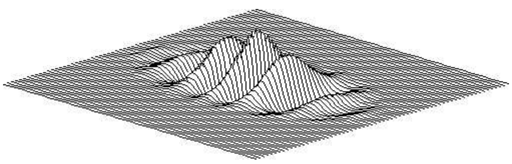


Figure 2: S-Gabor filter. $\nu = 0.15$, $w_x = 9$, $\lambda = 1$ and $k = 0.3$

The spatial scale w of the Gabor function and the decay constant λ are effectively determined by the width of the line structures that constitute the texture pattern. Our texture segmentation problem therefore reduces to one of estimating the central frequency ν and the attenuation amplitude k.

3. FUZZY CLUSTERING OF THE FOURIER POWER SPECTRUM

Examples of frequency domain texture analysis are provided by Bovik [4] and Tan [5] who search the Gabor Power Spectrum. The basic idea is that peaks correspond to the centre-frequencies and orientations of the dominant image textures. Peaks formed by regular line textures are clear and spike-like in comparison with the more vague peak formed by frequency-modulated textures (see figure 3), which makes robust identification of the peak more difficult. Moreover, the width of the peak can provide information about the range of frequencies in the texture. Because it is tailored to locating only the modes of compact peaks in the power-spectrum, the algorithm adopted in [5] is not appropriate for our application involving frequency modulated textures. Instead we require a means of determining both the centres and widths of diffuse structures in the Gabor power spectrum.

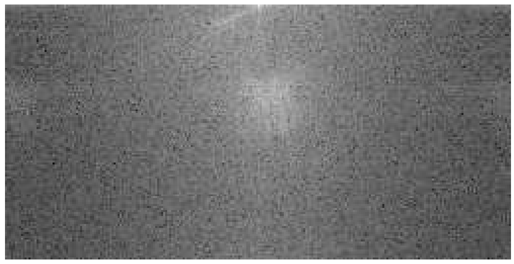


Figure 3: Power Spectrum of the image in figure 1. The range of circulus frequencies is represented by the width of the peak

It is for these reasons that we require more sophisticated means of learning the structure of the Gabor power spectrum. Specifically, the novelty of the work presented here resides in the use of fuzzy clustering to compute not only the central frequencies ν of the filters, but also their associated modulation parameter k. We use the Gustavson Kessel Fuzzy Clustering (GKFC) algorithm [6] to label the peak which represents the growth-line frequency range in the power spectrum. Our requirements in locating peaks in the power spectrum are to be able to specify *a priori* the acceptable density of significant clusters and to be able to assign irrelevant structure to a background (or noise) category.

3.1. Gustavson-Kessel Algorithm

The idea of specifying the weight of membership (between 0 and 1) of a data point to two or more clusters imposed on the data set is central to fuzzy clustering. The membership of each datum i to a cluster j is proportional to some measure of distance $d_{i,j}$ to the centre of that cluster. Suppose that $\mathbf{X} = \{\mathbf{x}_j | j = 1..N\}$ is a set of N data points. If the dimensionality of the parameter space is n then each member of the data-set $\mathbf{x}_j$ is an n-dimensional measurement-vector. $\mathbf{V} = \{\mathbf{v}_i | i = 1..C\}$ is a set of cluster centres $\mathbf{v}_i$ in the n-dimensional parameter space. The fuzzy class membership weights are determined by the set of distances $d_{i,j}$ between the data points and and the cluster-centres. The fuzzy-memberships are recorded in the $C \times N$

matrix $\mathbf{U} = [u_{i,j}]$. For each datum, the membership-weights sum to unity over the set of clusters, i.e.

$$\sum_{i=1}^{C} u_{ij} = 1 \quad \text{for all} \quad j = 1..N \tag{3}$$

Fuzzy clustering is an iterative process whose goal is the minimization of the following objective function:

$$J(\mathbf{U}, \mathbf{V} : \mathbf{X}) = \sum_{i=1}^{C} \sum_{j=1}^{N} (u_{ij})^m d^2(\mathbf{x}_j, \mathbf{v}_i) \tag{4}$$

where m is a constant known as the "fuzzifier". The algorithm proceeds as follows:

Gustafson-Kessel Fuzzy Clustering

Fix C, the number of clusters $2 \leq C < N$. Fix m, the fuzzifier $m \in (1, \infty)$. Fix the C volume constraints $\rho \in (0, \infty)$. Initialise $\mathbf{U}$ and $\mathbf{V}$. Set iteration counter $l = 1$.

REPEAT

Calculate fuzzy scatter matrices $\mathbf{S}$ with $\mathbf{U}$,$\mathbf{V}$ and

$$\mathbf{S}_i = \sum_{k=1}^{n} (U_{ik})^m (\mathbf{x}_k - \mathbf{v}_i)(\mathbf{x}_k - \mathbf{v}_i)^T \tag{5}$$

Calculate inverses and determinants of each $\mathbf{S}$
Calculate the norm-inducing matrices $\mathbf{A}$:

$$\mathbf{A}_i = [\rho_i det(\mathbf{S}_i)]^{\frac{1}{n}} (\mathbf{S}_i^{-1}), \quad 1 \leq i \leq C \tag{6}$$

Update $\mathbf{U}$ using $\mathbf{V}$,
distance $d_{ik} = |\mathbf{x}_j - \mathbf{v}_i| \mathbf{A}_i |\mathbf{x}_j - \mathbf{v}_i|^T$ and

$$u_{ik} = \frac{1}{[\sum_{j=1}^{C} (\frac{d_{ik}}{d_{jk}})^{\frac{2}{(m-1)}}]} \tag{7}$$

Update $\mathbf{V}$ with $\mathbf{U}$ and

$$\mathbf{v}_i = \frac{\sum_{k=1}^{n} (u_{ik})^m \mathbf{x}_k}{\sum_{k=1}^{n} (u_{ik})^m} \quad \text{for all} \quad i \tag{8}$$

Increment l

UNTIL

$$||U^{(l+1)} - U_{(l)}|| \leq \varepsilon \tag{9}$$

Before proceeding to describe our texture segmentation method, it is worth commenting on some of the advantages of our fuzzy-clustering strategy. In the first-instance, since we specify the maximum acceptable density of clusters, we do not need to perform any separate cluster merging. A single cluster prototype was capable of describing all the data points in the target cluster because of the underlying ellipsoidal distribution.

4. EXPERIMENTS

Our interest in segmenting modulated line textures originates in the analysis of patterns on fish-scales. Fish age can be estimated by counting the number of bunches of closely-spaced growth rings on their scales. These bunches are called *annuli* because they are formed once a year as the fish lives through a winter. In figure 1, an annulus runs across the centre of the image. At present, annuli are identified manually, but the development of an automated system would be of great assistance to fisheries management.

The methods outlined above were used to identify annuli in fish scale images as follows. The Fourier power spectrum of a fish scale image was computed. This was segmented using the GKFC algorithm. A three- cluster partition was imposed on the power spectrum, two of which were used to capture high and low frequency noise features. The frequency range was determined from the width of the modulation-peak. An example of a partition is shown in figure 4. Identification of the frequency width is robust, even though a few pixels that are not part of the modulation-peak are mis-labelled.

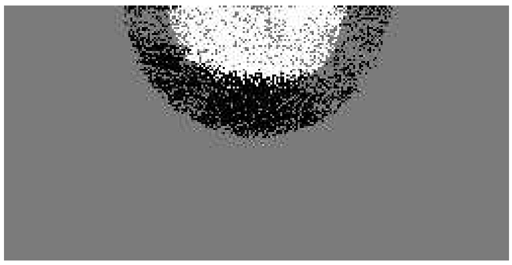
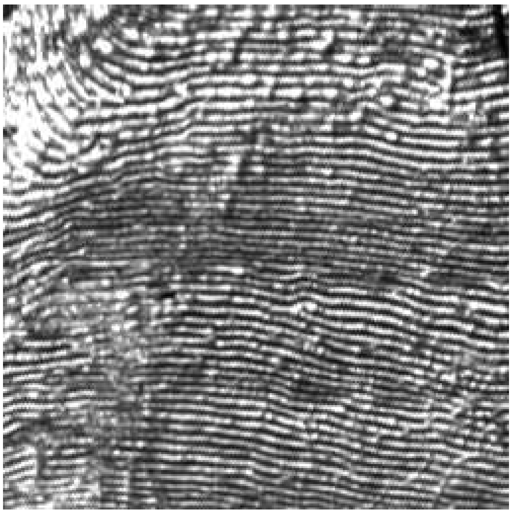


Figure 4: A segmented power spectrum

For each ν, the maximum and minimum values of the frequency attenuation parameter k could then be determined. Suppose that ν_{max} is the maximum extent of the Gabor-peak of frequency ν and ν_{min} is the minimum extent. For any value of ν between these limits, the minimum value of the attenuation parameter is equal to $k_{min} = \frac{(\nu - \nu_{max})}{\nu}$ while the maximum value is equal to $k_{max} = \frac{(\nu - \nu_{min})}{\nu}$.

Since the spatial frequency of growth lines on fish scales does not fluctuate evenly between ν_{max} and ν_{min}, we selected four values of ν set to divide up the frequency width equally. For each ν, two filters were specified, one with $k = k_{max}$ and one with $k = k_{min}$.



(a)

(b)

Figure 5: (a) Test image and (b) segmentation using S-Gabor filters

Segmentation of the fish scale image is achieved by applying a filter bank to the raw image data and determining the most significant channel response. Each pixel is characterised by a vector whose elements are the set of channel filter responses. The mean class-vectors for annuli and background pixels are computed using the contents of the fuzzy clusters located in the training data. We assign image pixels to texture class which minimises the Mahalanobis distance.

5. CONCLUSIONS

We have demonstrated how fuzzy clustering can be used to identify regions of interest in power spectra of textured images. Fuzzy clustering allows unsupervised texture segmentation of more complex images than those specified by Bovik. We have demonstrated that more detailed analysis of the power spectrum is one way to design a more powerful Gabor filter-bank.

The efficiency of a multi-channel segmentation algorithm is dependent upon the number of channels in the filter bank. Where the segmentation is used to discriminate between textures which differ only by a very small (unknown) change in spatial frequency, methods such as those described by Tan [5] or Bovik [4] would require a large number of canonical Gabor filters to guarantee discrimination. The nature of power spectra of modulated texture images is such that conventional peak finding is of only limited success in determining the frequency range. Efficiency is not the only potential advantage that S-Gabor filters offer over canonical Gabor filters. In our application example, it is local minima which characterise regions of interest - not the frequency *per se*. S-Gabor filters can be tuned to detect such features.

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