TEXTURE IMAGE SEGMENTATION USING FRACTIONAL DISCRIMINATION FUNCTIONS

J. You¹ S. Hungenahally² A. Sattar¹

¹School of Computer & Information Technology
Griffith University, Brisbane, Qld., Australia 4111

²School of Microelectronic Engineering
Griffith University, Brisbane, Qld., Australia 4111

ABSTRACT

This paper presents an approach to texture image segmentation using a family of fractional discrimination functions. In contrast to the conventional methods, the proposed functions provide uniform treatment of the existing functions and operators for selective feature extraction. The effectiveness of fractional discrimination functions for texture feature detection is demonstrated in the presence of noise and texture variation.

Key words and phrases: Feature extraction, fractional discrimination, texture classification, image segmentation.

1. INTRODUCTION

The analysis of texture is an important consideration in the development and application of computer vision system since visual texture is a fundamental property identifying the surface structure in scenes. However, the characterization of complex texture, necessary for both image segmentation and texture classification, remains a difficult and challenging problem. Traditional approaches to texture analysis involves extracting texture features to constitute a feature space and then performing stochastic search within this feature space to determine a complex classifier[2]. The aim of feature extraction is to represent an image by a set of numerical 'features' so as to remove redundancy from the data and reduce the features dimension. For the classification to be useful, it must be reliable and computationally attractive, which means the choice of the textural features or the models must be as compact as possible, and yet as discriminating as possible.

Historically, structural and statistical approaches have been adopted for texture feature extraction[5],[9],[12]. The structural approach assumes the texture is characterised by some primitives following a placement rule.

In this view, to describe a texture one needs to describe both the primitives and the placement rule. The description should be sufficiently flexible that a class of equivalent textures can be generated by using similar primitives in similar relationships. Although there has been reported progress in this area[5], the approach is restricted by the complications encountered in determining the primitives and the placement rules that operate on these primitives. Therefore, textures suitable for structural analysis have been confined to quite regular textures rather than more natural textures in practice.

In the statistical approach, texture is regarded as a sample from a probability distribution on the image space and defined by a stochastic model or characterized by a set of statistical features. The most common features used in practice are based on the tonal properties and the pattern properties[12]. These are measured from first- and second-order statistics and have been used as discriminators between textures. Though these features have been widely used in the classification and segmentation of textured images, they cannot cope with changes in rotation and scale.

Unlike the usual approaches involving feature extraction and classification rule construction, the special interest of our proposed method is to determine a simple discrimination operation which directly functions as a classifier in a single stage. In this paper we introduce a family of fractional discrimination functions which selectively extract local information from the image while preserving its global features. Such functions perform global scale tuning in conjunction with local feature enhancement for effective identification and localisation of visual information. Section 2 highlights the fractional discrimination functions for texture feature extraction and Section 3 details the implementation procedure. Section 4 presents the experimental results and the concluding remarks are drawn in Section 5.

2. FRACTIONAL DISCRIMINATION FUNCTIONS

The concept of fractional derivatives is the approximation of the non-integer derivatives to a continuous domain with the converge to the first-, second- and finite-order derivatives. The fractional derivative of a constant is not always equal to zero. Based on the different approaches to define such fractional derivatives, different fractional discrimination functions will be developed. In the work reported here, we adopted the following idea in the area of fractional calculus to define the fractional differentiation.

Let $f(\xi)$ represent any function in the domain of ξ , $D^\nu f(\xi)$ refer to as the fractional differentiation of function $f(\xi)$ at the order of ν , where ν is any real positive number. If gamma function is used, we have

$$D^{-\nu} f(\xi) = \frac{1}{\Gamma(\nu)} \int_c^\xi (\xi - t)^{\nu-1} f(t) dt$$

where c and ξ are the lower and upper limits of the integral. Accordingly, if $\nu = m - \mu > 0$ and $\mu > 0$, we have

$$D^\mu f(\xi) = D^m [D^{-\nu} f(\xi)], \text{ where } \xi > 0.$$

Consequently, we can define the fractional discrimination functions by combining the aggregation function $\alpha(\xi)$ with the fractional discrete derivatives.

Let D^μ denote the fractional discrete derivative operator (FDD). The fractional discrete derivative is performed by convolving the coefficients of FDD with the given image. The FDD coefficients for the order from 0.1 to 1.0 can be determined based on a Maclaurin series expansion of $(1 - x)^p$, $p < 1.0$. Higher order of FDD coefficients can be derived by repeated convolutions of the lower order of FDDs. The details of the related calculation are given in [14]. The fractional discrimination functions gradually phase out the contrasts and eventually result in a peak or zero-crossing map for the 1st and 2nd-order operation. As a result, subtle features in an image will be extracted at different resolutions in terms of various fractional-orders, which is very powerful in texture feature extraction. Table 1 lists the coefficients of the fractional discrete derivatives of orders up to 1.0, where the trailing end coefficients are truncated as their magnitude is very small compared to the first one. The accuracy of this definition heavily relies on the number of co-efficients used. From the mathematical point of view, an infinite number of co-efficients will result in high accuracy.

Table 1: Coefficients of the fractional discrete derivatives of orders up to 1.0

order	1	2	3	4	5	6	7
0.0	1.0	-0.1	-0.028	-0.016	-0.013	-0.011	-0.009
0.2	1.0	-0.2	-0.08	-0.048	-0.033	-0.025	-0.016
0.3	1.0	-0.3	-0.105	-0.05	-0.040	-0.029	-0.023
0.4	1.0	-0.4	-0.120	-0.064	-0.041	-0.029	-0.022
0.5	1.0	-0.5	-0.125	-0.062	-0.039	-0.027	0.020
0.6	1.0	-0.6	-0.120	-0.056	-0.033	-0.022	-0.016
0.7	1.0	-0.7	-0.105	-0.045	-0.026	-0.017	-0.002
0.8	1.0	-0.8	-0.08	-0.032	-0.017	-0.011	-0.007
0.9	1.0	-0.9	-0.045	-0.016	-0.008	-0.005	-0.003
1.0	1.0	-1.0	0	0	0	0	0

3. IMPLEMENTATION

The key issue to the success of our fractional discrimination functions for texture image segmentation is how to choose three parameters (shape, size and order) associated with those functions. We adopted a tuning scheme to dynamically determine the related parameters to optimise the results. The following are the main steps:

- Initialisation

An initial discrimination function is tentatively chosen based on the nature of visual information present in the image, such as texture, portrait, scene, noisy, resolution.

- Shape

Determine the shape of the function from the standard library including rectangular, sinusoidal, triangular, exponential and Gaussian. As the degree of aggregation η which measures the goodness of the aggregation operation of the discrimination function depends on two factors: one is the window of aggregation and the other is the shape of the aggregation weighting function. The degree of aggregation increases with an increase in the window of aggregation. For a fixed window size, we choose the shape which gives the lowest η if the image is not very noisy else choose the shape which gives the highest η . In the case wherein η does not vary much a triangular shape is chosen.

- Size

Once the shape of function is determined, the choice of the size of the function reflected in its width is optimised based on the entropy and contrast sensitivity for the processed image. The entropy and contrast sensitivity also vary with the order of discrimination.

- Order

In the event of subtle contrast enhancements use fractional discrimination of orders up to 3 with a 0.1 resolution and vary the width and shape parameter to observe perceptually significant features.

In general, the process to choose a discrimination function is very subjective and dependent on the type of image information. An automated process for the determination of the shape, size and order of the discrimination by tuning the parameters based on results from the higher level recognition algorithms.

4. EXPERIMENTAL RESULTS

The fractional discrimination function detailed in this paper can be used for feature enhancement in different region boundaries for texture image segmentation. Figure 1 shows our comparative studies by detecting the coast line of the map of Australia which consists of two different but visually similar textures. Figure 1(a) is the original image with different textured regions. Figure 1(b)-1(c) are the segmented images by means of Prewitt edge detector and fractional discrimination function respectively. The advantage of our fractional functions to image enhancement is further demonstrated in Figure 2, where Figure 2(a) is the original spine image with noise, Figure 2(b) - Figure 2(f) are the series of enhanced images corresponding to the fractional order of 0, 0.2, 0.4, 0.5, 0.8 and 0.9. The gradual transition between the original image and the first-order image enhancement makes it useful for medical diagnosis. Table 2 lists some statistical measurements for the comparison of the performance at different fractional order.

Table 2: Statistical measurements at different fractional order

order	Mean	SDV	Skewness	Entropy	SNR
0.0	129.91	46.65	-2.24	3.58	0.00
0.2	131.75	47.43	-2.21	3.79	22.78
0.3	136.32	50.08	-2.16	3.72	19.57
0.4	138.79	50.55	-2.18	3.90	19.28
0.5	133.48	47.87	-2.21	3.75	23.01
0.6	134.07	48.01	-2.22	3.50	23.91
0.7	134.29	48.08	-2.22	3.70	22.92
0.8	137.47	48.14	-2.22	3.81	22.91
0.9	134.68	48.20	-2.22	3.91	22.86

5. CONCLUDING REMARKS

Image feature extraction is a complex problem which requires the successful enhancement and detection of edge features within their context. The extraction of local features in the framework of global scales is not

easily achieved by existing methods both in the spatial domain and frequency domain. The fractional discrimination functions introduced in this paper provide solutions to extract features dynamically at various conditions. The functions perform robust (in the presence of noise), selective (band limited) and contextual feature enhancement. The effectiveness of our approach is demonstrated by medical image enhancement and texture image segmentation. Our initial testing results will open other topics for our further research, such as perceptual sub-band coding of images, multi-dimensional, multi-spectral and multi-resolution image decomposition for image representation.

6. REFERENCES

- [1] L.S. Davis, "A survey of edge detection techniques", *Comput. Graphics Image Process.*, Vol. 3, pp. 248-270, 1975.
- [2] J.J. Koenderink and A.J. van Doorn, "Receptive Field Assembly Pattern Specificity", *J. Visual Comm. Image Rep.*, Vol. 3, pp. 1-2, 1992.
- [3] T.M. Caelli and D. Reye, On the classification of image regions by colour, texture and shape. *Pattern Recognition* 26, 1993, 461-470.
- [4] F.S. Cohen, Z. Fan and M.A. Patel, Classification of Rotated and Scaled Textured Images Using Gaussian Markov Random Field Models. *IEEE Trans. Pattern Anal. Machine Intell.* 13, 1991, 192-202.
- [5] R.M. Haralick, Statistical and structural approaches to texture. *Proc. IEEE*, 67, 1979, 786-804.
- [6] R.L. Kashyap and A. Khotanzad, A model based method for rotation invariant texture classification. *IEEE Trans. Pattern Anal. Machine Intell.* 8, 1986, 472-481.
- [7] K.I. Laws, Textured Image Segmentation, Ph.D Thesis, University of Southern California, January 1980.
- [8] J. Mao and A. Jain, Texture classification and segmentation using multiresolution simultaneous autoregressive models. *Pattern Recognition* 25, 1992, 173-188.
- [9] S. Peleg, J. Naor, R. Hartley and D. Avnir, Multiple resolution texture analysis and classification. *IEEE Trans. Pattern Anal. Machine Intell.* 6, 1984, 518-527.

- [10] M. Pietikäinen, A. Rosenfeld, and L.S. Davis, Experiments with texture classification using averages of local pattern matches. *IEEE Trans. Syst., Man, Cybern.* 13, 1983, 421-425.
- [11] M. Unser, Local linear transforms for texture measurements. *Signal Processing* 11, 1986, 61-79.
- [12] H. Wechsler and T. Citron, Feature extraction for texture classification. *Pattern Recognition* 12, 1980, 301-311.
- [13] J.S. Weszka, C.R. Dyer and A. Rosenfeld, A Comparative study of texture measures for terrain classification. *IEEE Trans. Syst., Man, Cybern.* 6, 1976, 269-285.
- [14] S. Hunganehally, *On discrimination functions for image feature extraction*, Ph.D thesis, Griffith University, 1996.

(a) texture image
(two-texture composite)

(b) edge image
(Prewitt operator)

(c) enhanced image
(fractional function)

Figure 1: Comparison of feature points for texture segmentation

(a) original image

(b) fractional order = 0.2

(c) fractional order = 0.4

(d) fractional order = 0.5

(e) fractional order = 0.8

(f) fractional order = 0.9

Figure 2: Fractional discrimination operation