TOPOGRAPHIC GRAY LEVEL MULTISCALE ANALYSIS AND ITS APPLICATION TO HISTOGRAM MODIFICATION

Chu He[1], Xin-Ping Deng[1], Gui-Song Xia[2], Wen Yang[1] and Hong Sun[1]

School of Electronic Information, Wuhan University, Wuhan 430079, P.R.China [1]
LTCI, CNRS, TELECOM ParisTech 46 rue Barrault, 75013 Paris, France [2]

ABSTRACT

This paper describes a framework for multi-scale gray level analysis of images. It defines scales based on gray levels and organizes the basic "atoms" with a topographic map. The aim of this approach is to separate a large number of pixels concentrating in a narrow range of gray values. The main advantage of the methodology is that it allows manipulating pixels according to gray levels and spatial relations simultaneously. We apply it to histogram modification of Synthetic Aperture Radar (SAR) images. The experiments on displaying and classification prove the superiority of the approach.

Index Terms— Level set, topographic map, multiscale, synthetic aperture radar

1. INTRODUCTION

It is well-accepted by now that vision is an inherently multiscale phenomenon and the visual task is to represent and interpret intensity fields replete with singularities. Moreover, it has been suggested that an efficient representation might be the key to many image processing tasks, including compression, de-noising, feature extraction and inverse problems [1]. Many multiscale analysis tools have been proposed to achieve robust representation, including Fourier series and wavelets. It's worth noticing that most of them share the same remark: applying operations on small spatial neighborhood of pixels at different scales [2]. We name this kind of methods Spatial Multiscale Analysis (SMA). However, in some case, the gray level of image concentrates in a narrow range, because of different reasons, such as illumination conditions. For instance, the images taken by Synthetic Aperture Radar (SAR) always fall in a narrow value range, even through the data format is 16-bit [3]. In those, it is of great interest to implement a multi-scale analysis to image gray level, similar to multi-scale analysis of image spatial information.

In this paper, we present a dual operation of SMA, called Topographic Gray level Multiscale Analysis (TGMA) and apply it to histogram modification [4]. Fig.1 shows the comparison between SMA and TGMA. The TGMA involves two central components: decomposition and reconstruction. In the decomposition, a topographic map [5] is first built out of the image. It is structured in a scale-space tree, in which tree nodes corresponds to the level line shapes [6]. The topographic map then is divided into two trees further by applying a pair of complementary operations. This is similar to applying a low pass filter and a high pass filter to the signal in wavelet analysis. The subdividing continues until a certain depth is achieved. We can apply sorting, merging, thresholding and other operations on shapes in each tree like dealing with the wavelet coefficients. The reconstruction is to recover the image from a group of topographic maps.

In Synthetic Aperture Radar (SAR) image processing, it needs to compress the 16-bit SAR data into 8 bits in order to display them on computers or to reduce the computation complexity of methods. Histogram equalization and computing square root are two widely used ways on this task. However, they fail to preserve the original histogram characteristics, which is one of the most efficient characteristics of SAR data. Aiming at keeping the shape of original histogram, we apply the scheme of TGMA to the gray level compression. It allows us to assign values to pixels based on both gray levels and spatial relations (shapes) in the histogram modification. Thus, a more precise depiction can be achieved.

2. TOPOGRAPHIC GRAY LEVEL MULTISCALE ANALYSIS (TGMA)

In this section, the procedure of TGMA is detailed. First we show the basic "atoms" in TGMA, level line shapes. Also, the topographic map that organizes these shapes in a tree structure is briefly recalled. Then we present the algorithm to subdivide topographic maps based on gray levels. As we shall see, the process shares a same thinking with wavelet analysis.

2.1. Level line shape and topographic map

Given an image u, with Ω denoting the image domain, the family of sets

$$X_{\lambda}(u) = \{x \in \Omega, u(x) \geq \lambda\} \quad (1)$$

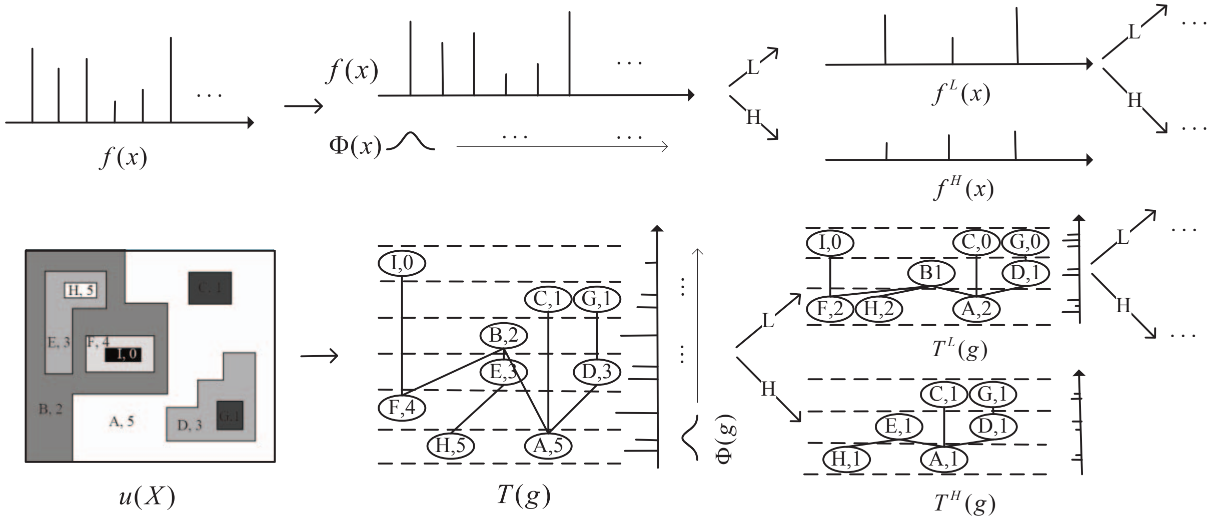

Fig.1 The comparison between spatial multiscale analysis and topographic gray level multiscale analysis.

$$Y^{\mu}(u) = \{x \in \Omega,\ u(x) \le \mu\} \tag{2}$$

for all λ, μ in the range of gray levels are called upper level sets and lower level sets respectively. Note that level sets are nested: if λ is larger than ρ, then $X_{\lambda}(u)$ is include in $X_{\rho}(u)$. Level lines are defined as the connected components of the topological boundaries of these sets [5]. Now, a level line can contain several level lines thanks to the inclusions of level sets. In [6], Monasse *et. al* draw on the notion of *level line shape* to denote the level line and its contained "holes". The size (number of pixels), gray level of pixels and other shape attributes then can be computed. Level line shapes play a role in TGMA analogous to the role player by dyadic squares in wavelet analysis.

Topographic map has a tree structure, in which tree nodes corresponds to the level line shapes. As argued in [5], it is an efficient way to represent images thanks to its

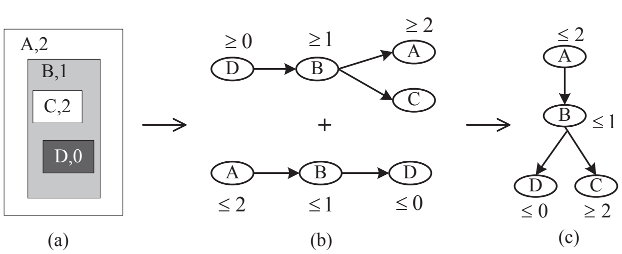

Fig.2 The procedure of building topographic map. (a) the synthetic image; (b) two trees corresponding to upper level sets and lower level sets; (c) the topographic map after merging two trees in (b).

contrast invariance and stability. There are three steps to build the topographic map out of an image according to [6]. First, the upper level sets and lower level sets of an input image are computed. Then two trees can be built based on the inclusions of these sets, giving consideration to the "holes". At last, find the holes of a shape in the other tree corresponding to it, whose descendants are merged into the current shape too. The procedure is illustrated in Fig. 2.

2.2. Decomposition and reconstruction

To our best knowledge, most classical multiscale analysis tools have coarse-to-fine scales defined spatially, for example, the wavelengths in Fourier series and the side lengths of dyadic squares in wavelets. Instead, we define scales based on gray levels. As we shall see, the goal of TGMA is to represent an image with level line shapes and apply shape operations on these scales. The SMA, on the other hand, is for the gray level operations on spatial neighborhood. That is, TGMA can be viewed as the dual operation of SMA. As shown in Fig.1, the TGMA decomposition works as follows.

1) Build the topographic map $T(g)$ using the algorithm described above.

$$X \leftarrow \{X_i(u), 1 \le i \le \Omega\} \tag{3}$$

$$Y \leftarrow \{Y^i(u), 1 \le i \le \Omega\} \tag{4}$$

$$T(g) \leftarrow merge(X, Y) \tag{5}$$

To make it intuitive, we arrange the shapes from the top down according to the gray level values instead of the parent-child relations.

2) Sort the shapes at the same gray level. Let S be the set of shapes at gray level g. Calculate the distances between each shape and its parent.

$$D \leftarrow \{distance(s, parent(s)) : s \in S\} \tag{6}$$

Then sort the shapes in S according to these distances.

$$(i, j) \leftarrow \arg_{(i,j)}\{D(i) > D(j), i < j\} \tag{7}$$

$$t \leftarrow S(i) \;\; S(i) \leftarrow S(j) \;\; S(j) \leftarrow t \tag{8}$$

3) Apply shape operations. The operation on the shapes can be viewed as the generalized convolution of the topographic map and operation function.

$$T^L(g) \leftarrow T(g) * \Phi(g) \tag{9}$$

$$T^H(g) \leftarrow T(g) * \psi(g) \tag{10}$$

In this paper, the function $\Phi(g)$ works in a similar way as a low pass filter, that is, it keeps several shapes in the front of S.

4) Repeat step 3 until the terminal condition is satisfied.

The TGMA reconstruction is to build an image out of the shapes according to their properties and inclusions after operations.

3. APPLICATIONS

Histogram modification is one of the basic and most useful operations in image processing, especially when processing images like SAR data, to which the distribution of pixel values is an important feature. However, operations on histogram containing 2^{16} bins cost a lot of computation load, therefore, it is necessary to compress the gray levels into 8 bits. There are two most common ways to do this: histogram equalization and computing square root. As we know, both of them fail to separate pixels having same gray values and keep the original histogram characteristics. In this paper, we apply the TGMA to the histogram preserving gray level compression.

3.1. Histogram modification

The goal in this experiment is to compress histogram of SAR images to improve the visual effect using TGMA. We choose a 4-looks SIR-C/X-SAR image (256*256 pixels) that covers Matterhorn, Switzerland. Fig. 3 (a) shows the original histogram. By mapping gray levels to different values according to the shapes, we generate a new histogram, see Fig.3 (b). We name the new histogram TGMA histogram. Fig.3 (c) and (d) are the histogram and displaying image after traditional histogram equalization. The result of histogram equalization on the TGMA histogram and corresponding displaying image are shown in Fig. 3 (e) and (f). Although Fig.3 (f) does not differ much with Fig. 3 (d), the histogram after TGMA is more close to a uniform distribution. In Fig.3 (g), a histogram specification result that keeps the same distribution as the original one is shown. Fig.3 (h) is the displaying image.

3.2. Classification

As stressed above, the distribution features are considered to be effective in SAR image processing. In this part, we present a classification experiment to show the advantage of TGMA in histogram compression. The test SAR image is

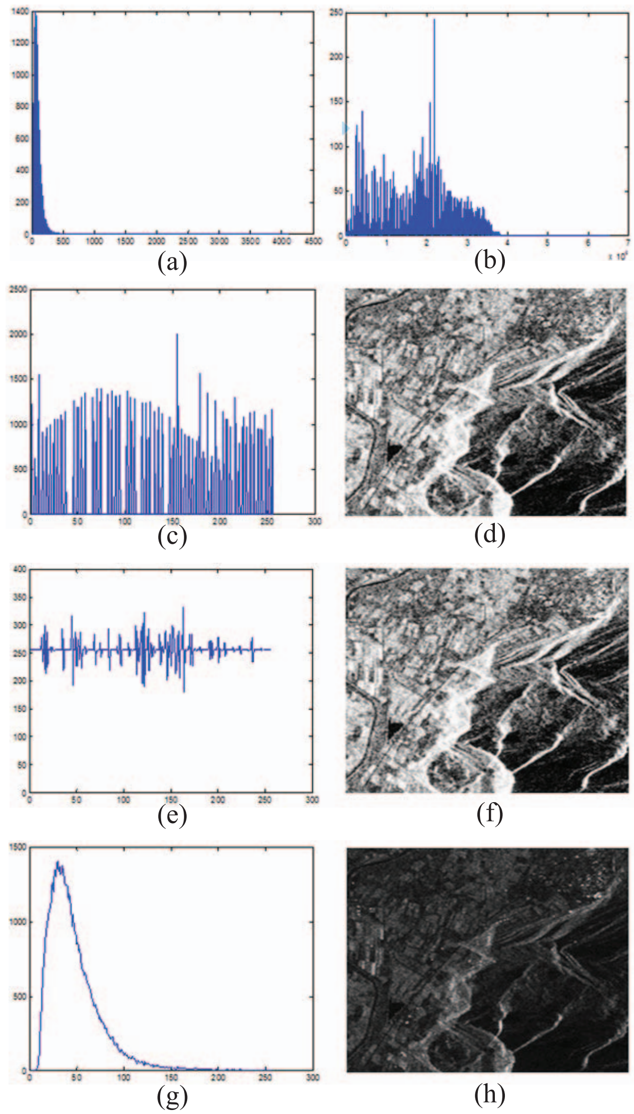

Fig.3 The results of histogram compression using TGMA. (a) the original histogram; (b) the TGMA histogram; (c) result of equalization on original histogram; (d) the displaying image corresponding to (c); (e) result of equalization on TGMA histogram; (f) the displaying image corresponding to (e); (g) result of specification on TGMA histogram; (h) the displaying image corresponding to (g).

acquired by a TerraSAR sensor over Guangzhou (South of China) with 1.25m*1.25m resolution, from which we intercept 64 images (512*512 pixels per image) to make up a test dataset. There are four classes: farmland, water, woodland, and building area shown in Fig.4. Half of the images are used for training and the remaining for testing.

We employ a supervised AdaBoost based MRF classification method. At the training stage, the images are first over-segmented into homogenous regions, called *super-*

pixels, by Meanshift over-segment algorithm [7]. Then, histogram of each super-pixels with 2^{16} bins is compressed to 2^{8} bins using TGMA. Lastly, we take the compressed histograms as distribution features to train AdaBoost classifier. Given a testing image, the probabilities of every super-pixels belonging to each class are computed by the AdaBoost classifier. Graph-Cuts optimization algorithm [8] is subsequently taken to smooth the classification results. In order to compare the performances of the distribution histograms features from TGMA, we reproduce the distribution histograms features using exponential compression (EC). Table 1 shows the classification accuracy with TGMA distribution histograms and EC distribution histograms. TGMA histograms compression can bring less distortion compared with original distribution histograms than exponential compression, so the average classification accuracy of TGMA distribution histograms is higher.

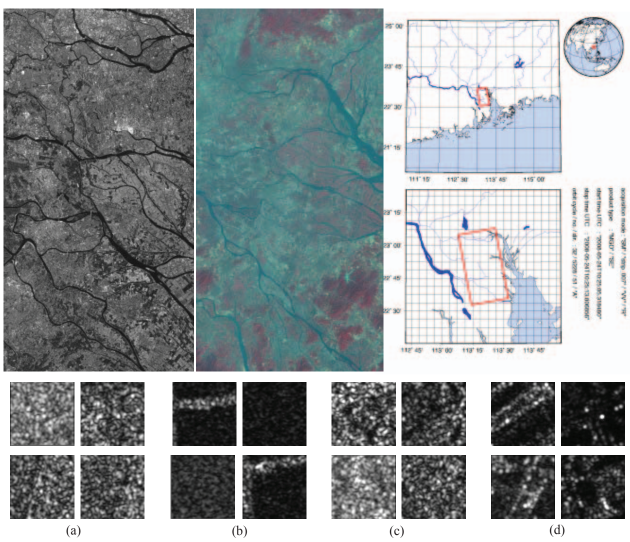

Fig.4 Images from the SAR image dataset: Top left: original SAR image; Top middle: the ordinary optics image of the SAR image; Top right: the opposition of the SAR image in the earth—Guang Zhou in China; Bottom: slices from the original SAR image, which includes four classes: (a) farmland, (b) water, (c) woodland, and (d) building area.

4. CONCLUSION

In this paper, we put the level sets, level line shapes and topographic map in a view of multiscale framework, in which scales are defined based on gray levels. According to this scheme, pixels can be separated by their gray levels and positions. It is useful in the histogram modification when large number of pixels concentrate in a narrow range of gray levels. Future work can be focused on shape operations in the topographic map. Also, image matching based on TGMA representation will be promising extension.

Table 1 Classification results

(a) Distribution histograms features from TGMA (76.32%)

Accuracy	Building	Water	Farmland	Woodland
Building	0.8889	0.0474	0.0403	0.0234
Water	0.1491	0.8056	0.0311	0.0142
Farmland	0.1082	0.0119	0.8337	0.0462
Woodland	0.2611	0.0752	0.2536	0.4101

(b) Distribution histograms features from EC (75.41%)

Accuracy	Building	Water	Farmland	Woodland
Building	0.9176	0.0324	0.0334	0.0167
Water	0.1471	0.8171	0.0243	0.0115
Farmland	0.1187	0.0140	0.8244	0.0430
Woodland	0.2948	0.0701	0.3057	0.3293

5. ACKNOWLEDGEMENTS

The work was supported by the NSFC grant (No. 60702041, 60872131) and Hi-Tech research and development program of China (863) (No. 2007AA12Z155).

6. REFERENCES

[1] M.N. Do, M. Vetterli, “The contourlet transform: an efficient directional multiresolution image representation,” *IEEE Trans. Image Processing*, vol. 11, pp. 146–158, Feb. 2002.

[2] R.C. Gonzalez, R.E. Woods, and S.L. Eddins, *Digital Image Processing Using MATLAB*, Pearson Prentice Hall Pearson Education, Inc., NewJersey, USA, 2004.

[3] C. Oliver and S. Quegan, *Understanding Synthetic Aperture Radar Images*, Norwood, MA: Artech House, USA, 1998.

[4] V. Caselles, J.–L. Lisani, J.–M. Morel, and G. Sapiro, “Shape preserving local histogram modification,” *IEEE Trans. Image Processing*, vol. 8, no. 2, pp. 220-230, Feb. 1999.

[5] V. Caselles, B. Coll, and J.-M. Morel. “Topographic maps and local contrast changes in natural images,” *International Journal of Computer Vision*, vol. 33, no. 1, pp. 5-27, 1999.

[6] P. Monasse and F. Guichard, “Fast computation of a contrast invariant image representation,” *IEEE Trans. Image Processing*, vol. 9, no. 5, pp. 860-872, 2000.

[7] D. Comaniciu, P. Meer, S. Member, “Mean Shift: A Robust Approach Toward Feature Space Analysis,” *IEEE Transactions on Pattern Analysis and Machine Intelligence*, vol 24, no.5: 603-613, 2002.

[8] Y. Boykov, O. Veksler, R. Zabih, “Fast Approximate Energy Minimization via Graph Cuts,” *IEEE Transactions on Pattern Analysis and Machine Intelligence*, vol.2, no.1 pp. 222-1 239. 2001.