MULTI SCALE REPRESENTATION FOR REMOTELY SENSED IMAGES USING FAST ANISOTROPIC DIFFUSION FILTERING

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ABSTRACT

Object based image analysis has gained on the traditional per-pixel multi-spectral based approaches. The main pitfall of using anisotropic diffusion for creating a multi scale representation of a remotely sensed image remains the computational burden. Producing the coarser scales in a multi scale representation or, diffusing spatially large images involves significant time and resources. This paper proposes a fast approach for anisotropic diffusion that overcomes spatial size limitations by distributing the diffusion as individual sub-processes over several overlapping sub-images. The overlap areas are synchronized at specific diffusion time ensuring that the fast approximation does not deviate too much from its single process equivalent. This demonstrated for an image, which can be diffused using a traditional sequential approach. In addition, experimental data for very large images that can not efficiently be processed using a sequential approach is illustrated.

***Index Terms*—** Image enhancement, anisotropic diffusion, (very) high resolution images, multi-process, parallel computing

1. INTRODUCTION

In recent years, the use of multi scale representation for the analysis of remotely sensed images has received increasing interest [1, 2, 3]. These approaches acknowledge the fact that the analysis of images depends on the scale of the objects of interest. Multi scale representations based on scale space theory encapsulates two concepts: scale space filtering and the linking strategy which deals with the methodology that relates signal structure at different scales. Scale space filtering concerns the mechanism that embeds the signal into a one-parameter family of derived signals for which the signal content is simplified. The parameter describes the scale or resolution at which the signal is represented. The main idea is that the amount of local extrema in the signal and its derivatives should decrease with scale. Initially linear or Gaussian scale-space was preferred, however inherent drawbacks such as the dislocation of feature and the similar treatment of noise and important signal structure lead toward non-linear scale-spaces filters. Anisotropic diffusion is an established technique for image enhancement and multi scale representation. Although originally proposed for gray-scale images [4, 5], it has been long extended to color [6, 7], multi [8] and hyperspectral [9, 10] images. Furthermore, fast numerical approximations and parallelization [11, 12] schemes have improved computation times significantly. However, dealing with high resolution images remains challenging.

2. ANISOTROPIC DIFFUSION

The focus lies on edge-affected diffusion processes in which the diffusion is locally adaptive aiming to favor intra-region instead of inter-region smoothing, thus overcoming the dislocation of region boundaries. The mathematical form of this type of process [5, 6] is given by:

$$\begin{aligned} &\forall i = 1, 2, \ldots, M \text{ and } \forall t \in \mathbb{R}_+ : \\ &\qquad \partial_t \mathbf{u}^{(i)}(t) = \operatorname{div}\left[g(|\nabla_{\sigma^r}\mathbf{u}(t)|)\nabla\mathbf{u}^{(i)}(t)\right] \end{aligned} \tag{1}$$

The scale-space image $\mathbf{u}$ is obtained by evolving the above PDE using the original M-bands image $\mathbf{f}(\mathbf{x}) = \{f^{(1)}(\mathbf{x}),\ldots, f^{(M)}(\mathbf{x})\}, \forall \mathbf{x} \in \Omega \subset \mathbb{Z}^2$, as the initial condition for the scale parameter $t = 0$, in conjunction with homogeneous *von Neumann* boundary conditions, where $\mathbf{x}$ denotes a 2D position vector on the image plane Ω. Note that $|\nabla_{\sigma^r}\mathbf{u}(t)|$ is the regularized vector-valued gradient magnitude obtained by convolving the image with a Gaussian kernel of size σ^r [5], and g is the diffusivity function, which is a bounded, positive, decreasing function that discriminates the different diffusion models. The time sampling start from the naturally sampling of the scale-space image [13]:

$$t_j = \left\{ \begin{array}{cl} 0 & \text{if} \quad j = 0 \\ \exp\left[2(j-1)\tau\right] & \text{if} \quad j > 0 \end{array} \right. \tag{2}$$

where τ denotes the time step considered for time discretization. A compact version of the scale space stack may be extracted from the sampled set of scales: Let $\{t_0, t_1, \ldots, t_{end}\}$ represent the set of discrete times/scale obtained via scale space sampling, then the purpose of scale selection is to obtain a subset of discrete scales $\mathcal{S} = \{s_0, s_1, \ldots s_{\text{end}}\}$, where the localization scale $s_0 = t_j$ is the scale for which $\mathbf{u}(t_j)$

contains a minimum amount of noise whilst retaining all important image features at their exact location. For image enhancement the identification of the scale s_0 suffices.

3. FAST APPROXIMATION

In some application domains the pixel resolution of the imagery is so high that an image cannot be processed as a whole. In such circumstances, the image is commonly divided into sub-images, i.e. tiles, that often have a degree of overlap. These sub-images are processed separately whereafter the final results are reintegrated. The proposed fast approximation scheme adopts this methodology. But instead of integrating the final results, the overlap areas are regularly synchronized ensuring that the diffusion can occur across the tiles.

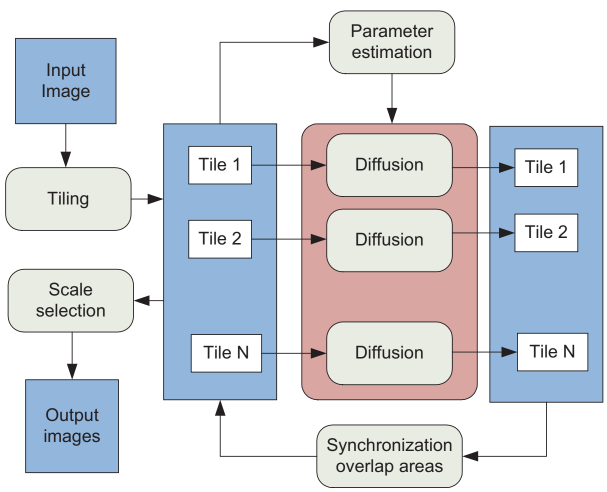

Fig. 1. Flowchart of the proposed scheme.

Figure 3 show a flowchart of the proposed scheme. Once the parameters of the anisotropic diffusion are estimated on the full image, the iterative procedure starts. The latter consist of two steps: (i) For each sub-image we calculate the next diffusion scale t_j (2) via the AOS-based numerical approximation [7] of (1) using as many concurrent processes as efficiently possible. (ii) Once all sub-images are processed, the overlap areas are synchronized. Hereafter the estimations needed for the scale selection are performed [8]. This procedure repeats until either the desired amount of diffusion scales is reached or a stopping criterion is met.

For tile synchronization, we adopt an approach that seamlessly rejoins the tiles. For this purpose, a weighted sum of the overlapping pixel values for which the weights are inversely proportional to the distance of the respective tile center, is adopted. The overlap areas are synchronized at specific diffusion times and should ensure that the fast approximation does not deviate too much from its single process equivalent. In this way we obtain a fast approximation for anisotropic diffusion that significantly alleviates the limitations with respect to spatial size whilst retaining a high degree of accuracy with respect to its single process equivalent.

4. EXPERIMENTAL RESULTS AND DISCUSSION

The experiments are conducted on a Intel(R)Xeon(R)CPU E5345@2.33GHz with 8GB of RAM. For the 4-band 1022 x 1023 image shown, in Fig. 2(), the scale-space representation containing 60 scales, i.e. $t_0, \ldots t_{60}$, is obtain using (a) a sequential AOS based implementation of (1) and, (b) the proposed fast approximation [1]. The quality of the fast diffusion approximation is very high in the finer scales. For the very coarse scales (Fig.2(i)-(j)) one can observe the appearance of the underlying tiles. The latter is due to the fact that the synchronization is performed at each sampled time step t_j, which is increasing exponentially. The latter can be remedied by increasing the amount of synchronization steps at the coarser scales. Fig. 2(c) illustrates a scale-space representation for which the synchronization step is triggered more frequently at the coarser scales. The quality of the approximation increases significantly however, so does the computation time. In our experiments, we limited we used tiles of 256x256 with an overlap of 32 pixels. The amount of concurrent process was limited to 16. The sequential diffusion method based on the AOS numerical scheme needed 1795 seconds, the proposed method created the 60 scales in 791 seconds. Remark, that when the bulk of the computation for time occurs at the coarser scales. In the case of image enhancement, i.e. when only the scale s_0 is needed, the 140 seconds for three approaches. Nonetheless, the key advantage of the proposed method is the fact that it is able to process very high resolution images and that the computational time can be reduced in case the that amount of concurrent processes can be increased efficiently.

5. CONCLUSIONS

This work proposes a fast approach for anisotropic diffusion based enhancement and scale-space representation of very high resolution images. It overcomes spatial size limitations by distributing the diffusion as individual sub-processes over several overlapping sub-images. In this way multi scale representations obtained via nonlinear anisotropic diffusion filtering can be achieved efficiently.

6. REFERENCES

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(a) (b) (c)

Fig. 2. Multi scale representation: (a) Sequential diffusion implementation using AOS, (b) Multi-process scheme, (c) Multi-process scheme with augmented diffusion quality. From top to bottom: $t_0, t_{21}, t_{27}, t_{33}, t_{43}, t_{52}$.

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