RECONSTRUCTION OF DIGITAL IMAGES BY COMBINING MULTIPLE GRADIENTS

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ABSTRACT

Up to now, many algorithms have been introduced for computing reconstruction in grayscale images. But the execution time is required by the known grayscale reconstruction algorithms make their practical use rather cumbersome on conventional computers. A new algorithm is introduced to bridge this gap and reconstruct the image in better way. This is based on the notion of regional maxima, regional minima, most significant value in the region and regional sorted Meddle values and uses different gradient algorithms constructed based on regional maxima, regional minima and regional sorted Meddle values for reconstruction. The existing study shows that the watershed by foreground markers is able to segment real and simple images containing few irregularities in a better way than the standard watershed segmentation algorithms. This method is based on markers and simple morphology, which allows a regularization of the watersheds. But it is not a flexible approach for further optimization parameters. The algorithm is able to segment or extract desired parts of only simple gray-scale images. To overcome these draw backs here new method is propose for real and multiple scale images by combining multiple gradient operators.

Key words: *Reconstruction, discrete grid, background markers and watershed transformation*

1. INTRODUCTION

The discrete grid $G \subset Z^2 \times Z^2$ provides the neighborhood relationships between pixels: p is a neighbor of q if and only if $(p, q) \in G$. Here, we shall use square grids, either in 4 - or in 8 - connectivity or the hexagonal grid. Note however that the algorithms described below work for any grid, in any dimension. The distance induced by G on Z^2 is denoted d_G: $d_G(p, q)$ is the minimal number of edges of the grid to cross to go from pixel p to pixel q. In 4-connectivity, this distance is often called city-block distance whereas in 8-connectivity, it is the chessboard distance [1,2]. The elementary ball in distance d_G is denoted B_G, or simply B. We denote by $N_G(p)$ the set of the neighbors of pixel p for grid G [3,4] . In the following, we often consider two disjoined subsets of $N_G(p)$, denoted $N_G^+(p)$ and $N_G^-(p)$. $N_G^+(p)$ is the set of the neighbors of p which are reached before p during a raster scanning of the image (left to right and top to bottom) and N_G^- (p) consists of the neighbors of p which are reached after p.

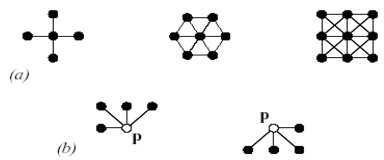


Figure 1.1: (a) The elementary ball B in 4 -, 6 - and 8 - connectivity;(b) N_G^+ (p) and N_G^-(p) in 8 – connectivity

2. GRAYSCALE RECONSTRUCTION:

Let J and I be two grayscale images defined on the same domain, taking their values in the discrete set {0, 1….. N - 1} and such that J≤ I (i.e., for each pixel p ∈ D_I; J(p) 0≤ I(p)). The grayscale reconstruction $\rho_I(J)$ of I from J is given by:

$\forall$ p ∈ D_I , ρ_I (J)(p) = max{ k ∈ [0 , N-1] | p ∈ $\rho_{T_k(I)}$ (T_k(J)) }.

3. DILATION-BASED GRAY-SCALE IMAGE RECONSTRUCTION

The former definition does not provide any interesting computational method to determine grayscale reconstruction in digital images[7,8]. Indeed, even if a fully optimized binary reconstruction algorithm is used, one has to apply it 256 times to determine grayscale reconstruction for images on 8 bits. Therefore, it is most useful to introduce this transformation using the geodesic dilations. Following the threshold decomposition principle, one can easily define the elementary geodesic dilation $\partial_I^{(1)}$(J) of grayscale image J ≤ I “under" I:

$$\partial_I^{(1)}(J) = (J \oplus B) \wedge I ,$$

In this equation, $\wedge$ stands for the point wise minimum and $J \oplus B$ is the dilation of J by at structuring element B [9, 10]. These two notions are the direct extension to the grayscale case of respectively intersection and binary dilation by B. The grayscale geodesic dilation of size n ≥ 0 is then given by:

$$\partial_I^{(n)}(J)= \partial_I^{(1)} o\, \partial_I^{(1)}\, o……….o\, \partial_I^{(1)}(J)$$

This leads to a second definition of grayscale reconstruction:

4. EROSION-BASED GRAY-SCALE RECONSTRUCTION:

The grayscale reconstruction ρ_I (J) of I from J is obtained by iterating grayscale geodesic dilations of J “under” I until stability is reached, i.e:

$$\rho_I(J) = \vee_{n\geq 1} \partial_I^{(n)}(J).$$

It is straightforward to verify that both this definition correspond to the same transformation. Similarly, the elementary geodesic erosion $\varepsilon_I^{(1)}$(J) of grayscale image J ≥ I “above" I is given by

$$\varepsilon_I^{(1)}(J)=(J \Theta B) \vee I,$$

where $\vee$ stands for the point wise maximum and $J \Theta B$ is the erosion of J by at structuring element B [7,8] The grayscale geodesic erosion of size n≥0 is then given by:

$$\varepsilon_I^{(n)}(J)= \varepsilon_I^{(1)}\, o\, \varepsilon_I^{(1)}\, o\, ………o\, \varepsilon_I^{(1)}(J).$$

We are now able to define the dual grayscale reconstruction in terms of geodesic erosions:

5. DEFINITION FOR DUAL RECONSTRUCTION:

LET I AND J be two grayscale images defined on the same domain D_I and such that I ≤ J. The dual grayscale reconstruction ρ^*_I (J) of mask I from marker J is obtained by iterating grayscale geodesic erosions of J "above" I until stability is reached:

$$\rho^*_I (J)=\Lambda_{n\geq 1}\ \varepsilon_I^{(n)}(J).$$

6. EXISTING METHOD

This method uses simple algorithm to create foreground and background markers using morphological image reconstructions .it is erosion-based gray-scale reconstruction and followed by dilation-based gray-scale reconstruction to trace the foreground objects. Calculating the local maxima of these reconstructed images is done to get smooth edge foreground objects. Next, we superimposed these markers on original images. The background markers are created by calculating the Euclidean distance of binary version of above superimposed image [11]. The edge image is modified by morphological reconstruction with foreground and background markers. The applications of watershed transform give final segmented images of desired objects.

7.1Algorithm

(i) *Read the gray-scale image by converting color Image.*

(ii) *Apply edge detection function to generate gradient images*

(iii) *Identify foreground objects using morphological reconstruction*

(iv) *To obtain the good forward markers find the regional maxima and minima*

(v)*Superimpose the foreground marker image on the original image.*

(vi) Eliminate the noise of *the edges of the markers using edge reconstruction.*

(vii) Evaluate *the background markers.*

(viii)*Compute the watershed transform of the image.*

This is not a flexible approach for further optimization parameters. The algorithm is able to segment or extract desired parts of only simple gray-scale images. To overcome these draw backs here new method is proposed for multiple scale images by combining multiple gradient operators

8. PROPOSED METHOD

A proposed algorithm is computed based on the notion of regional maxima, regional minima, most significant value in the region and regional sorted Meddle values and uses different gradient algorithms constructed based on regional maxima, regional minima and regional sorted Meddle values for reconstruction. A pixel p of I is a local maximum for grid G if and only if its value I (p) is greater or equal to that of any of its neighbors. A pixel p of I is a local minimum for grid G if and only if its value I (p) is less than or equal to that of any of its neighbors. A pixel p of I is a local median for grid G if and only if its value I (p) is in N/2 position of the sorted grid G of its neighbors. A pixel p of I is a most significant for grid G if and only if it has more neighbors than any pixel in the grid. Next we compute gradient of middle and minima (Gmmin), gradient of middle and maxima (Gmmax), gradient of most significant and minima (Gsmin) and gradient of most significant and maxima (Gsmax). By using these gradients we can generate single value at p(x,y) location of resultant Image.

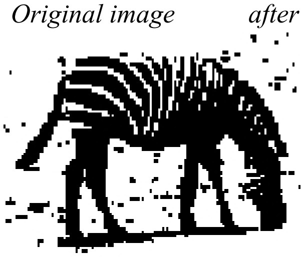
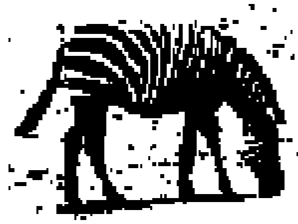
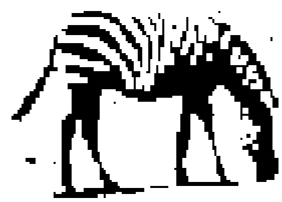
8.1 Algorithm

Step1: *Read the color image and convert it to gray-scale.*
Step2: Find region minima, region maxima, significant value and sorted middle Value
Step3: compute Gmmin, Gmmax
Step4: if Gmmin<0 and Gmmax>0 then R=significant pixel and goto
step6 Else
Compute Gsmin, Gsmax
Step5: if Gsmin> 0 and Gsmax<0 then Result=significant pixel
Else Result =sorted middle pixel
Step6: repeat step2 to step6 by convolution

9. EXPERIMENTAL RESULTS:



Original image after existing method after proposed method

Original image after existing method after proposed method



Original image after existing method after proposed method

10. CONCLUSIONS AND FUTURE WORK:

The proposed method has been proved to be a powerful and fast technique for reconstruction of images by generating both contours and regions in the image. This method removes the salt-and-pepper noise to provide smoothing of other noise that may not be impulsive and also reduces the excess thinning and thickening of object boundary. In principle, the proposed method depends on ridges to perform a proper segmentation, a property that is often fulfilled in contour detection where the boundaries of the objects are expressed as ridges. In the proposed method the crest lines always correspond to the most significant edges between the markers. So this technique is not affected by lower-contrast edges, due to noise, that could produce local minima and, thus, erroneous results, in energy minimization methods. Even if there are no strong edges between the markers, the proposed method always detects a contour in the area. This contour will be located on the pixels with higher contrast. This method all ways gives better results than conventional and existing method which is specified in this paper. Suppose mask size is larger, the complexity is increased and it may not produce better results. It is not suitable for texture reconstruction. This method may be extended for textures by combining this with stochastic model to reconstruct by generating random fields.

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