Wavelet-Based Marker Controlled Watershed Transformation

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***Abstract*—A new method for the generation of superpixels which can be implemented using watershed transformation and also threshold based estimation for image denoising in the wavelet transform domain. Recovery of the image from its noisy atmosphere is also an area of interest in this paper. Our method aims at the extraction process of local and global impression of a given image by giving priority to image denoising also. We propose a gradient-based segmenting adherity property of the segmented image. We also show this as an efficient method to achieve the regularity and adherence property of the segmented image. Since we are dealing with marker controlled Watershed transformation technique, the problem of over-segmentation can be avoided to a great extreme.. Partial- thresholding to smoothness and preservation of better image details can be also seen in this work. Better PSNR, MSNR and correlation parameter can be achieved through wavelet thresholding. Here, we try to showcase 'markerpixels' as an efficient tool for the creation of superpixels using Watershed transformation and also wavelet transformation process for denoised waterpixel segments. Thus a combination of wavelet based- controlled watershed segmentation can be seen through this work. Soft-thresholding and hard-thresholding are used for image denoising. By this work, it is shown that this method offer better PSNR and MSE.**

***Index Terms*—markers, watershed, threshold based denoising.**

I. Introduction

Superpixel segmenting has its own applications in many fields of imaging. Segmenting the various objects along its boundary is very important since the resultant superpixels can be used as the material for other works in different fields. Superpixels having a large pixel size and containing more number of pixel values is helpful in fields of recognition and detection.

Technique meant for distinguishing the objects from their own backgrounds inorder to change the real image to distinguishable manner for easiness its analysis is Segmentation. While dealing with noisy image segmenting is a challenging process. An image in its 2D form can be depicted as f(x,y). But the problem is that, during its transmission and acquisition process, it may get corrupted. Since wavelet transformation deals with frequency

Fig. 1.Merkerpixels illustration. First one shows the orginal image and the later one shows the Markerpixels

decomposition, it attempts to reduce the noise level by preserving the useful signal characteristics. A non-linear technique is thresholding and it acts on each coefficient. The coefficient changes with the threshold value. Replacement of coefficients which are noisy in nature by zero may lead to reconstruction with useful signal features and little noise.

Before segmenting process, the image is subjected to denoising. It is an usual scene that the image that are captured from the nature, may contain a lot of noise. So it is essential to remove or reduce the noise before the segmentation is done. Segmenting of the image that contain infinite noise content may lead to improper segmentation, that is image with irregular segments. Wavelets have its own importance in watersheding process.

The main part of this paper is to perform segmentation by considering the regularity and adherence. In this work the most prior task is to perform perfect segmentation process, that is the formation of superpixels. Classical watershed algorithms produce segments as a result of segmenting from the boundary regions, but the resultant output may not show regularness and adherity (see Fig. 1). Adaptive marker controlled watershedding obeys these conditions but it wouldnot produce the perfect denoised image. Thus it is salient to produce superpixels without any noise or blurred contents. Filtering is the mostly used noise removal process. Whereas wavelet based thresholding method is a very good option for that. In the following sections we describe briefly about the working.

II. DISCRETE WAVELET TRANSFORMATION

Using WT, an image is splitted into a set of wavelet basis functions. 2^n sets of coefficients, will be produced as a result of n-levels of decomposition by wavelet packet decomposition. That is, for a 2-level decomposition there will be 4- coefficients and 7 subbands (see Fig. 2). In general, we can say that for N-level decomposition, there we get (3N+1) sub bands and 2^N coefficients. The figure shows 3- level decomposition process using WT. Another useful thing to be noted is that, suitable basis functions selection should be done, that allow changes in time extension.

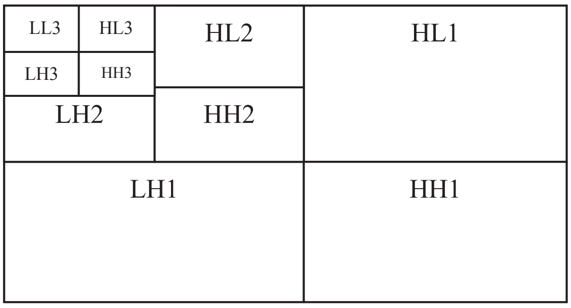

Fig. 2. Three-level subband decomposition

III. METHODOLOGY

The entire work can be divided into two sections.

1) Wavelet based de-noising
2) Marker controlled watershedding

Together with wavelet transformation, the watershed transformation process is very much efficient inorder to obtain superpixels with very good PSNR and MSE value. Inorder to perform wavelet based noise removal, wavelet thresholding should be done. It can be explained as follows:

$$x(t) = m(t) + n(t) \tag{1}$$

Where, m (t) denote noise-less image with Gaussian noise and N (t) denote noise.

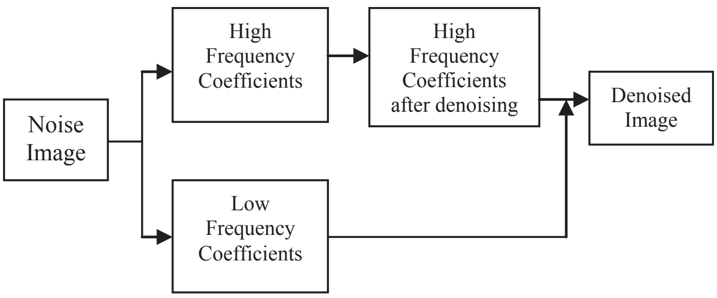

Fig. 2. Block diagram of Threshold based DWT

Let D (_,λ) represent the noise removal operator with threshold value, λ. De-noising process results in $\hat{m}(t)$, estimate value of m(t).

The thresholding process and noise removal involves the following steps:

$$y = WT(x) \tag{2}$$

$$z = D(y, \lambda) \tag{3}$$

$$\hat{m} = WT^{-1}(z) \tag{4}$$

Here, WT represent wavelet transform and WT^{-1} represent inverse phenomenon.

In general, threshold based wavelet gives best signal estimating process that is involved in noise removal process. Two types of thresholding methods involved: hard thresholding and soft thresholding. Hard thresholding is a stay or finish procedure. After hard thresholding only coefficient values greater than threshold will remain unchanged. λ vaies inaccordance with signal energy and σ^2, variance.

$$\lambda = \sqrt{2\,\sigma^2 \log N} \tag{5}$$

where N is the number of coefficients.

$$\sum \sigma = \sqrt{\max(\sigma n^2 - \sigma D^2, 0)} \tag{6}$$

$$\sigma_n^{\,2} = \frac{1}{m*n} \sum_{i,j=0}^{m,n} w_n^{\,2} \tag{7}$$

$$\sigma_D = \frac{\mathrm{median}\ (|\,w\,|)}{0.6745} \tag{8}$$

w represents the wavelet diagonal coefficient having high frequency values. σ_n represents estimated variance of sub-band coefficients.

The main section of this work deals with the superpixel segmentation process. Since marker controlled method is using, the adherity and regularity qualities can be assured. Thus the necessity for the joining of contours can be avoided. Let n_r , n_c denote the number of rows and number of columns in the hexagonal grid. S_P denote the spacing between the grid elements for hexagonal grid.

The number of superpixels can be represented as follows:

$$K = nodesperrow * nodesRows \tag{9}$$

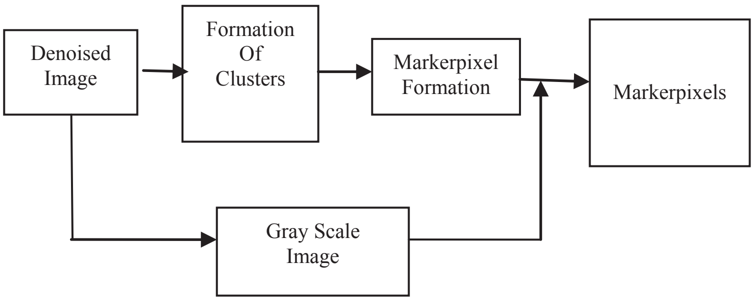

Fig. 3. Block diagram of marker controlled WS transform

By doing WS transform inaddition to some extra processes will help in proper boundary based segmentation. Since watershed is done using marker controlled approach, thus formed superpixels can be called as 'markerpixels' (see Fig. 3). Marker pixel generation can be done as follows:

- Gradient formation of the provided image.
- Clusterization of the image and representation of it as the vetrx points of a hexagonal grid.
- Spatially regularize the clusters using the updating method of distance, δ.
- Inorder to form the Mp_im , clean up the small islands within the clusters.
- On gray level image, perform WS transform inorder to obtain Ws_im.
- To obtain segmented markerpixels , add Mp_im and Ws_im.

TABLE I. DEFINITION OF VARIOUS ABBREVIATIONS USED

Terms Used	Definition
WT	Wavelet Transform
λ	Threshold factor
σ	Standard deviation of noise
LL	Approximation
LH	Vertical Band
HL	Horizontal Band
HH	Diagonal Sub-band
MP	Markerpixels
Mp_im	Markerpixel Image
k	Number of markerpixels
N	Number of Coefficients
Ws_im	Watershed Image

IV. ALGORITHMS

(A) Algorithm for Image Denoising

- Read a corrupted input image (guassian noise containing image) and perform N-level decomposition using WT.
- Calculate the noise variance σ^2.
- Compute the thrsholding value, λ using the standard deviation.
- Then apply thrsholding to remove noise in the high frequency coefficients.
- Perform merging operation to combine both low high frequency coefficients.
- Inverse WT is done inorder to reconstruct the desired image (denoised image)

(B) Algorithm for Markerpixel Generation

- Hexagonal grid formation of the gradient based image.
- Definition of spacing after converting the image to Lab space.

$$S_P = \frac{\sqrt{nr - nc}}{k + \sqrt{3/2}}$$

- Compute

  K = nodesperrow * nodeRows
- Allote memory by initializing label, distance and clusters.
- Updation of label by varying the distances.
- After spatial regularization, perform WS transform to produce Ws_im.
- Combine Mp_im and Ws_im inorder to obtain 'markerpixels'.

V. RESULT

Fig. 4. Denoising using soft-thresholding

Fig. 4. Denoising using Hard-thresholding

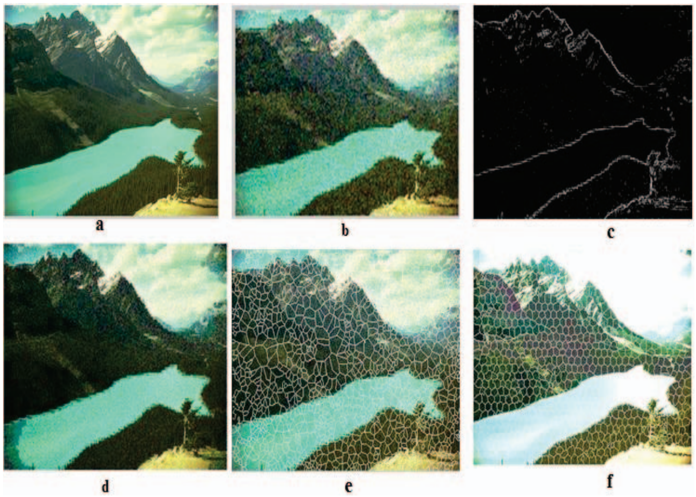

Fig.2. Wavelet based marker controlled watershed for Markerpixel generation: (a) Original image ; (b) Noised Image; (c) Lab gradient; (d) watershed image; (e) Markerpixels having adherity property; (f) Markerpixels having regularity property

TABLE II. WAVELET THRSHOLDING OF DIFFERENT LEVELS

Type of Noise	Wavelet	Thresholding	Level of Decomposition	PSNR
Guassian	Haar	Hard	1	68.108
			2	68.781
			3	69.891
		Soft	1	67.84
			2	67.89
			3	68.77
Speckle	Haar	Hard	1	68.56
			2	68.78
			3	69.56
		Soft	1	68.001
			2	67.894
			3	70.88

VI. COMPARISON OF THE PROPOSED METHOD WITH THE EXISTING METHOD

The existing methods offer more computational efficiency and quality by providing comparatively a large PSNR value . The existing methods mentioned in [9] and [10] have not mentioned about the PSNR value of the segmented image. Through this work, the denoising process is given an important value since it handles the requirement of a denoised image for segmentation. The works referred in this works were focused only on the segmentation process. And also it gave importance to the reduction of oversegmentation. Since the segmentation of image with regularness and adherence is very much useful in object detection and recognition process, it is very much essential to make the image to be segmented, a denoised one. Through this work, both the requirement of denoising and segmenting is achieved. The segmenting process used over here follow a different path than that ones used in [8] and [9]. On comparing with the existing method, the proposed method has a great value in the field of digital image processing.

VII. CONCLUSION

Using the combined usage of wavelet and watershedding helps to avoid the computing cost. Here, through this work, segmentation can be made by using the denoising technique efficiently and easily. Thresholding the coefficients lead to achievement of a very good denoising task. The usage marker segmentation of watershed avoid the problem of oversegmentation, thus leads to segmentation through the boundary region. Also the regularity in the segmentation can also be achieved through this method. Here , we can see the reduction of thousands to a limited superpixel counts. The markerpixel thus we created can be used in many other fields of signal processing. Hence it behaves like a very good tool in the field of image processing.

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