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TEXTUREIMAGESEGMENTATIONUSINGMORPHOLOGYINWAVELETTRANSFORMS

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Texture Image Segmentation using Morphology in Wavelet Transforms

K. Venkata Subbaiah [α] & V. Vijay Kumar [σ]

Abstract- One of the essential and crucial steps for image understanding, interpretation, analysis and recognition is the image segmentation. This paper advocates a new segmentation scheme using morphology on wavelet decomposed images. The present paper provides a good segmentation on natural images and textures by dividing an image into non overlapping regions, which are homogenous in terms of certain features such as texture, spatial coordinates etc. using simple morphological operations. Morphological enhancement technique based on Top Hat transforms enhances the local contrast in this paper. The morphological treatment and followed by Otsu's threshold overcomes the problem of noise and thin gaps, and also smooth the final regions. The experimental results on four different databases demonstrate the success of the proposed method, compared to many other methods.

Keywords: morphology, top hat transform, local contrast, otsu threshold.

I. Introduction

Research on texture segmentation has been carried out for decades; this is because image analysis, description, illustration, classification, image understanding and restoration are largely dependent on the segmentation results. The texture segmentation plays a vital role in a variety of applications such as medical imaging, textile designs, identification of human faces and expressions, various military applications, remote sensing, robot vision, cartography, identification of vehicles and quality assurance in industries etc. The texture is still a relatively poorly understood phenomenon. It is very easy and natural for human being to understand a texture; it is extremely difficult to define it. That's why many researchers attempted to define texture based on their application and a catalogue of texture definitions is available in literature [1].Texture segmentation [2, 3, 4, 5] break ups an image texture into dissimilar areas depending on a variety of attributes. The attributes can be texture, pixel intensities, color, shape or any other feature of interest according to the particular application. Researchers contributed significantly to the problem of image segmentation in the literature [6, 7, 8, 9, 10,11]. Color is one of the important attribute of the texture and there are many segmentation schemes that are based on color [10, 12, 3, 14, 15, 16, 17].

The segmentation methods based on wavelets [18], hidden Markov models [19],multichannel filtering [20], quadtree [21], fractal dimension [22], feature smoo thing [23], split-and-merge methods [24], autoregressive models [25], pyramid node linking [26], local linear transforms [27], Markov random field models [28], and selective feature smoothing with clustering [29] are proposed in the literature. The above methods [18-29] attained fine results for texture like mosaics (a tiny set of fine-grained texture); and failed to achieve a precise segmentation for natural texture images. The present paper considered Brodtaz and other natural textures and implemented segmentation on wavelet based images using morphological and thresholding techniques to obtain better results.

Edge-based [30, 31], region-based [32] and pixel-based segmentation [33] methods are also popular in the literature. Region-based segmentation can identify partitions in a given image. The region based methods [34, 41-43] arepopular in literature. The segmentation methods based on normalized cuts are also proposed [35-40] and among these, the multi scale normalized cut approach [39] obtained a precise segmentation. The histogram based [44-48] methods, fall in to pixel based segmentation approaches. Thetextonor shape based methods [49-52] also attained good results. The exactness of segmentation method is highly dependent on i) Type of textures ii) The type of attributes considered iii) The way the attributes are evaluated (global, local or region wise etc.). This indicates that segmentation methods are application dependent. The present paper initially decomposes the texture images using wavelet transforms. The segmentation scheme is applied on the decomposed image and quality assessment parameters are evaluated. The present paper is organized as follows: The section 2 describes the related work. The section 3 and 4 describes the proposed method and results and discussions respectively. The section five describes the conclusions.

II. Related Work

a) Mathematical Morphology (MM)

Mathematical morphology (MM) is the popular and wide spread non-linear theoretical model and widely used for image investigation, processing, analysis, and

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other applications. Mathematical morphology refers to image components like topology, shape, connectivity etc. The morphological operations are very simple, easy to understand, compute and analyze because they are basically derived from algebraic operators and it is proposed by Matheron and Serra and it is an extension of Minkowski's set theory [53], [54]. Morphology is gained much attention in solving and analyzing image processing problems related to geometrical variations and aspects of the image, whereas most of the non-morphological image processing methods are mostly unsuccessful in this aspect. These methods have additional advantages in dealing with textures, because the texture is basically nonlinear in nature. The morphology basically deals with shape or topological properties of objects. That is the reason they are most significant in segmentation problems. Using morphological operations one can easily represent or capture the various dissimilarities between geometrical properties such as size, connectivity, shape, which are considered as essential feature parameters that are basically needed to partition or segment an image texture. Many researchers used morphological operations extensively in various computer vision and pattern recognition applications like: preprocessing, boundary detection, removal of noise, image segmentation, image enhancement, image smoothening, image understanding and analysis of images. The main reason for the popular usage of mathematical morphology in image processing is they are based on dilation and erosion operations, which can be implemented in binary and gray leveldomains.

b) Gray Value Morphological Processing

The dilation operation, in gray level is given by equation 1. The images grow in size by dilation. The erosion is given by the following equation 2. The image size is reduced in size, based on the specifications of the structure element (SE). The morphological gray level opening and closing are defined in equations 3 and 4.

$$Dilation = \max_{[j,k]\epsilon Q}\{P[m-j,n-k]\} = \max_{Q} P \qquad (1)$$

$$Erosion = \min_{[j,k]\in Q}\{P[m-j,n-k]\} = \min_{Q}(P) \qquad (2)$$

$$Opening - O_G(P,Q) = \max_{Q}\left(\min_{Q}(P)\right) \qquad (3)$$

$$Opening - O_G(P,Q) = \min_{Q}\left(\max_{Q}(P)\right) \qquad (4)$$

Where P and Q are the original image and structuring element.

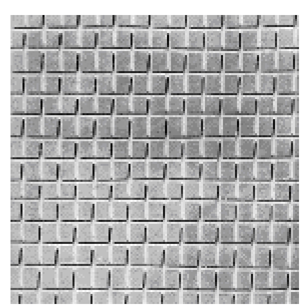
The Structuring element Q contains fixed number pixels, which are bounded and convex in nature. The erosion followed by dilation is called morphological opening. In opening the erosion of an image removes all structures that cannot fit inside. Further shrinks all other structures. Then by dilating the result of the erosion with the same structuring element, the structures that are survived by the erosion (were shrunken, not deleted) will be restored. Opening generally smoothes the contour of an image, splits slim isthmuses, and overcomes from thin protrusions affect. The closing smooth the image removes minute holes, and fills gaps in the contour. This retains the uniformity of a local region.

III. Methodology

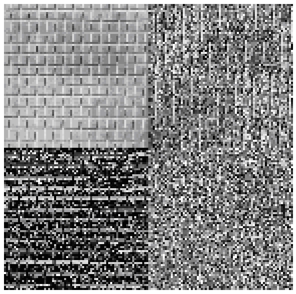
To derive precise segmentation the present paper initially converts the color image in to gray level image using HSV color quantization. The present paper then convert the gray level image into discrete wavelet transform (DWT) using Harr wavelet transform.

a) Wavelet transforms

The mathematical function that is used to divide a given function into components of different frequency is called wavelet transform. And each component is studied by wavelets with a resolution that matches its scale. An image signal is passed through an analysis filter bank followed by a decimation operation and analyzed in wavelet transforms. This filter bank consists of a low pass and a high pass filter at each decomposition stage. The low pass filter, corresponds to an averaging operation. The low pass filters extracts the coarse information of a signal. The high pass filter extracts the detail information of the signal and it represents to a differencing operation. The image will be divided i.e., decomposed into four sub-bands i.e. denoted by low-low (LL), high-low (HL), low-high (LH) and high-high (HH). The LH1, HL1 and HH1 sub bands correspond to the detail images i.e., finest scale wavelet coefficients. The LL1 sub-band corresponds to approximation image (coarse level coefficients). By decomposing LL1 sub band alone, the next coarse level of wavelet coefficients will be obtained and they are denoted as LL2, LH2, HL2, and HH2. Similarly, to obtain further decomposition, LL2 will be used. The features obtained from these DWT transformed images are useful for texture analysis, namely segmentation. The



(a)



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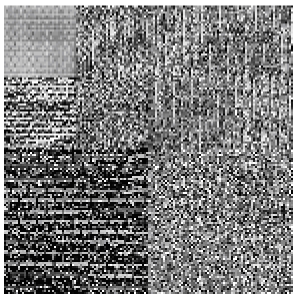
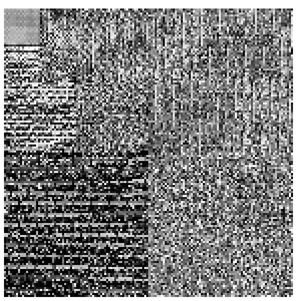


(c)



(d)

Figure 1: Shows the 1-level, 2- level and 3-level wavelet transformed image.

Figure 1(a) Original Brodatz Texture (b) Level-1 Wavelet Transformed Brodatz Texture (c) Level-2 Wavelet Transformed Brodatz Texture (d) Level-3 Wavelet Transformed Brodatz Texture.

b) Identification of interior regions by Top-hat transform

Initially the image is converted in to DWT image. To recognize details of interior regions and to improve the contrast of the image texture, morphological treatment is given by using Top Hat transform (THT). This paper used THT, instead of Histogram Equalization (HE) to deal with the natural textures with high and low mean brightness values; The present paper also overcomes the enhancement disadvantages that arises from the global content of the image. HE may produce over enhancement and saturation artifacts [55, 56]. That is why researchers are focusing on upgrading of the conventional histogram equalization. To overcome this present paper derive contrast enhancement based on THT of morphology. The THT is used to extract image features. There two types THTs: white top hat transforms (WTH) and black top hat transformation (BTH). The morphological WTH is applied to take out bright or over intensity features of texture mage. It is derived from equation 5.

$$P_{WTH} = P - (P \circ Q) \tag{5}$$

To extract the darker features of image texture the BTH is used and it is derived by equation 6.

$$P_{BTH} = (P \bullet Q) - P \tag{6}$$

To increase the contrast between the black and white regions of image the present paper derived a new contrast enhancement using MM operations as given below.

$$P_{CE} = P + P_{WHT} - P \tag{7}$$

where, P is the original image. P_{CE} is the final enhanced image. P_{WHT} represents the extracted white image regions. P_b represents the extracted black image regions.

To derive the uniform local regions of the texture image, closing operation is applied in this paper. This has connected the objects that are nearer to each other and it has filled small gaps.

c) Thresholding by Otsu method

To set upwell defined boundaries in the texture image, Otsu thresholding is applied in this paper. One of the important steps in segmentation is thresholding. Thresholding divides the texture image in to two or more units. Threshold will be chosen based on intensity attribute of the objects, sizes of the objects, number of different types of objects appearing in an image etc. One should have proper knowledge about the images and the application to choose the threshold. The Otsu method [57] is based on discriminate analysis. This method [57] selects the threshold by limiting the within-class variance of the two groups of pixels separated by the thresholding operator. A measure of region homogeneity is variance. The OTSU thresholddoes not depend on modeling the probability density functions and it is based on a bimodal distribution of gray-level values. The OTSU threshold operation performs the division of image pixels into two classes C0 and C1 (e.g., objects and background) at gray level.

IV. Results and Discussions

The performance of the texture segmentation schemes can be assessed by subjective evaluation, supervised and non-supervised evaluation: Comparing the approximate segmentation results with various other segmentation approaches is called subjective evaluation; The segmented output, is compared with the original image in supervised evaluation. The above two assessments are impractical and not popular because they are not automatic and requires human interaction. In “unsupervised approaches” [58, 59] comparison with ground truth or original images is not required. And they take less time in evaluating the performance of the segmentation method. The proposed segmentation scheme is assessed by unsupervised parameters like: Discrepancy, Entropy, Standard deviation, internal region contrast as given below. The value of these indicates the following: If the value of discrepancy is high, then it indicates a better segmentation. Using entropy value one can recognize the Over segmentation and under segmentations. Over segmentation will be resulted if entropy value less than 1 and if it is above 1.5 then represents under segmentation. A better segmentation is estimated with lower values of standard deviation. Region uniformity should not be disturbed while segmenting. If the segmented image results a low internal contrast then it indicates a high uniformity.

$$Discrepancy = \sum_{r=1}^{n}\sum_{c=1}^{m}(A(r,c) - B(r,c)) \quad (8)$$

Where A(r,c) and B(r,c) represents the gray level original and segmented image.

Entropy of an image is given as

$$Entropy = -\sum_{r}\sum_{c} B(r,c)log\big(B(r,c)\big) \quad (9)$$

Where B is segmented image

Standard deviation of a given vector is expressed as

$$\text{Standared deviation S} = \left[\frac{1}{n-1}\sum_{i=1}^{n}(x_i - \bar{x})^2\right]^{\frac{1}{2}} \quad (10)$$

Where x_i and $\bar{x}$ are the value of vector and average of all values.

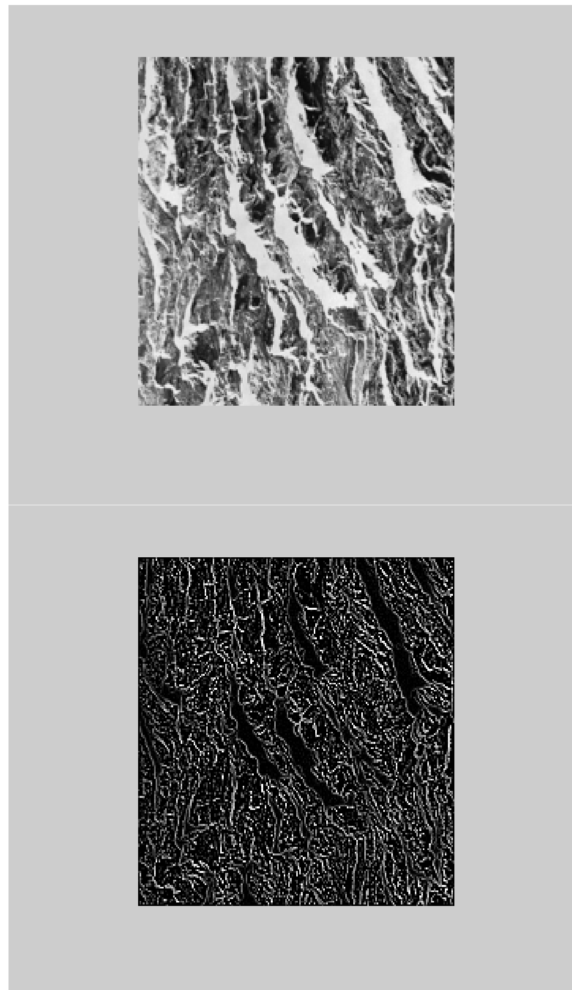
Internal region contrast is defined as

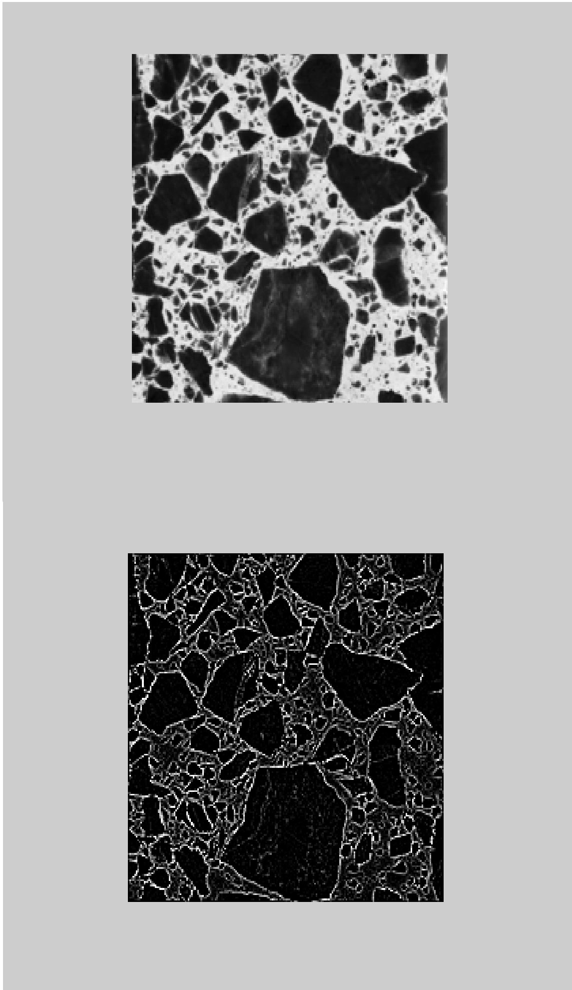
$$\text{Internal region contrast } I_j = \frac{1}{S_j}\sum_{s\in R_j} \max\{cont(s,t), t \in N_s \cap Rj \quad (11)$$

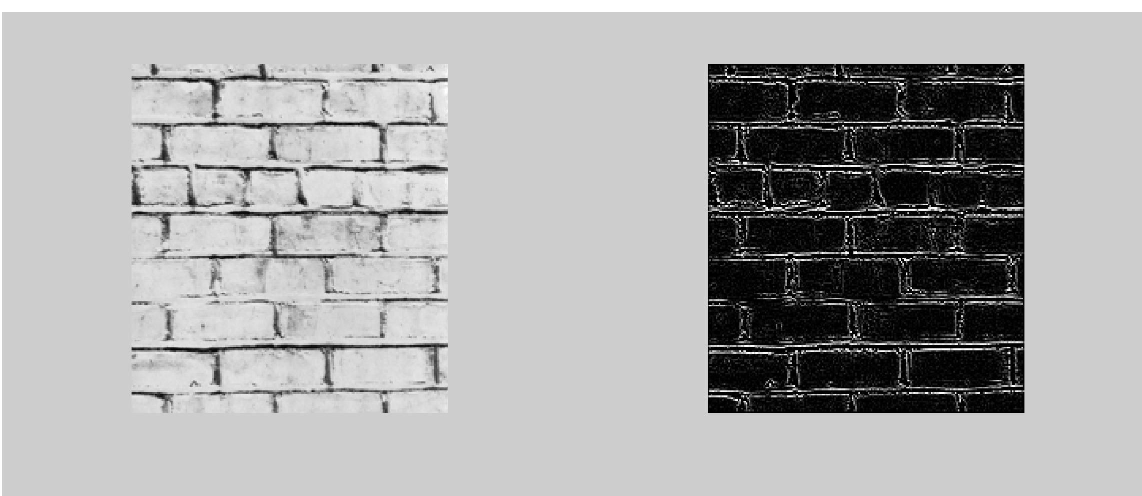
Where N(s) is the neighborhood and contrast (s,t) = $|C_x(s) - C_x(t)|$ is the contrast of pixel ‘s’ and ‘t’. The region uniformity is measured by internal contrast, I_j. The I_j represents “region average Max Contrast”.

The present method is tested on Brodtaz [60], Oxford flowers [61], Wang [62] and standard images from Google (Lena, Camera man, House, Mandrill, and Ship) [63]. The experiments are carried out by considering 100 images from each data base, thus it results a total of 400images.There are 1,000 natural images in Wang database and these images are selected manually from Corel stock photo database. These images are divided into 10 categories (each category consists 100 images). There are 17 classes (80 images per class) in Oxford flower database. There are 112 texture images in the Brodatz album with different background intensities. The proposed method is compared with three existing methods ISLGHEM [64], automatic thresholding method [65], wavelet based watershed method [66] and MULBP method [67]. To show the performance, the proposed integrated DWT segmentation scheme is applied on input images and results are shown in Fig.2, 3, 4 and 5 for Brodatz, Oxford, Wang and standard database textures respectively. The following are noted from the segmented outputs and they clearly establish the following facts.

1. The WHT enhanced the contrast of the local DWT regions of images.
2. The small holes are filled by the morphological treatment.
3. The Otsu threshold established local boundaries of the image effectively and also removed unwanted non-significant portions of the image.







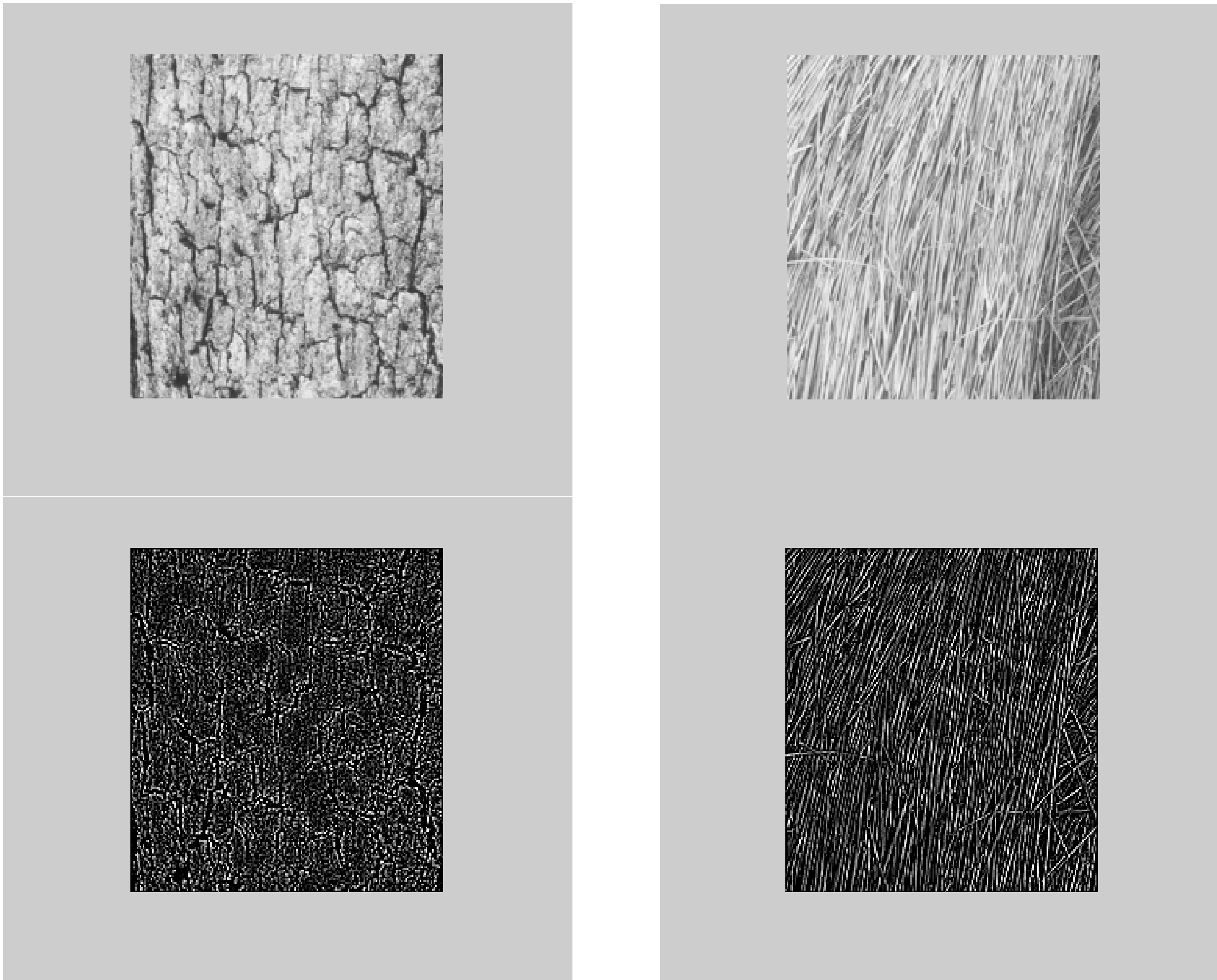


Figure 2: The segmented output Brodatz texture images by the proposed method.

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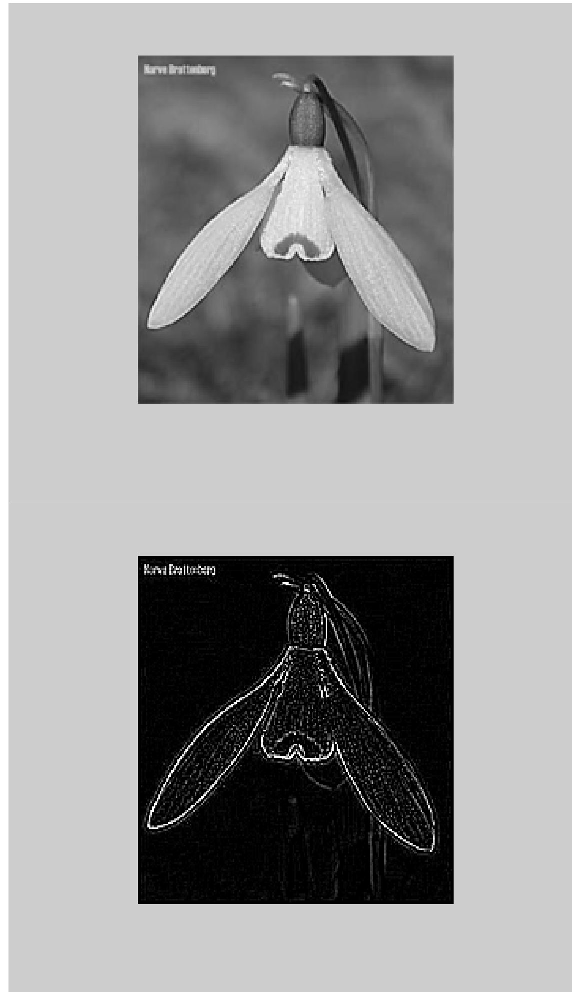
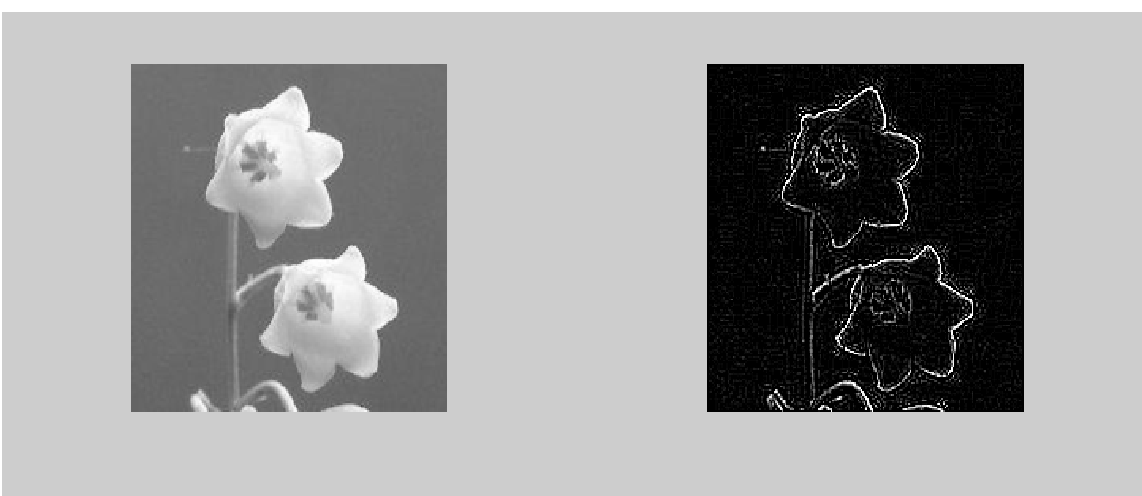




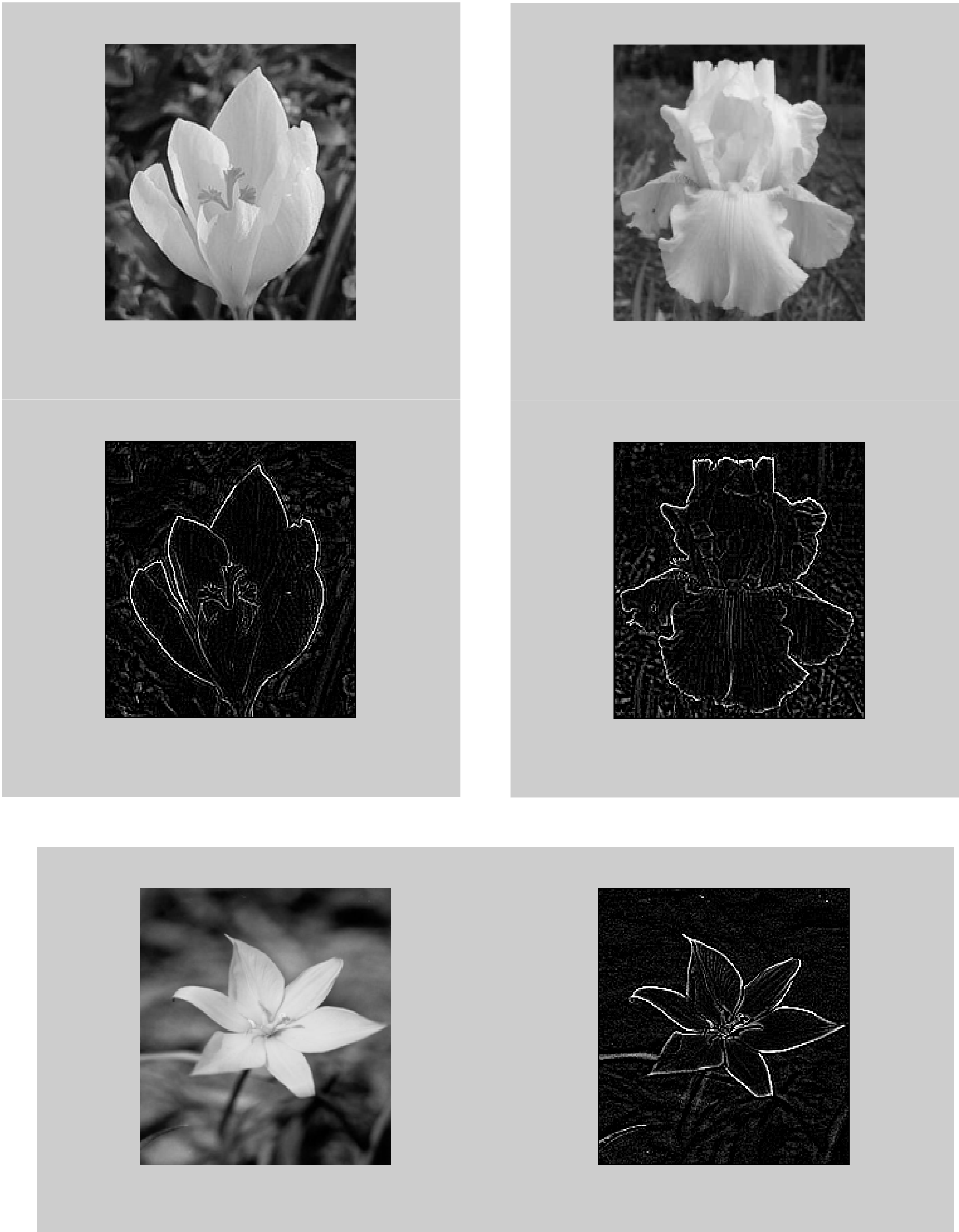
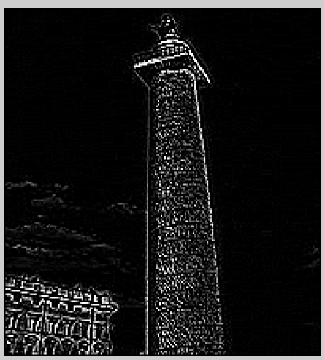
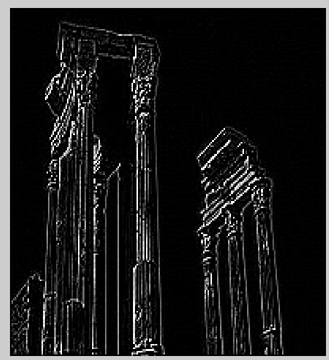
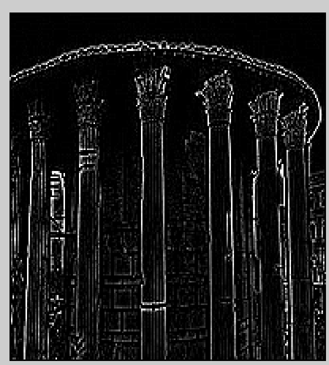


Figure 3: The segmented output Oxford flower texture images by the proposed method.







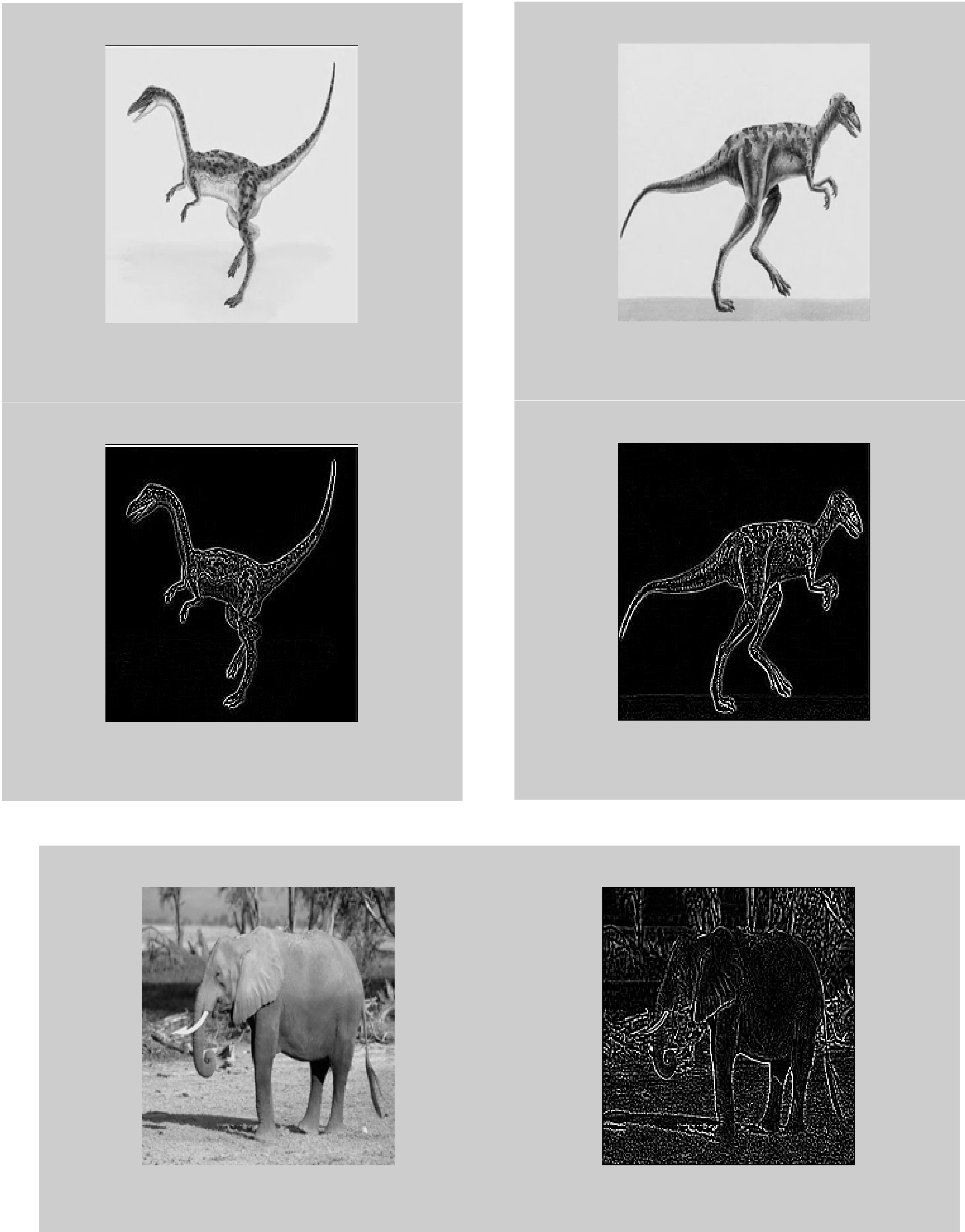
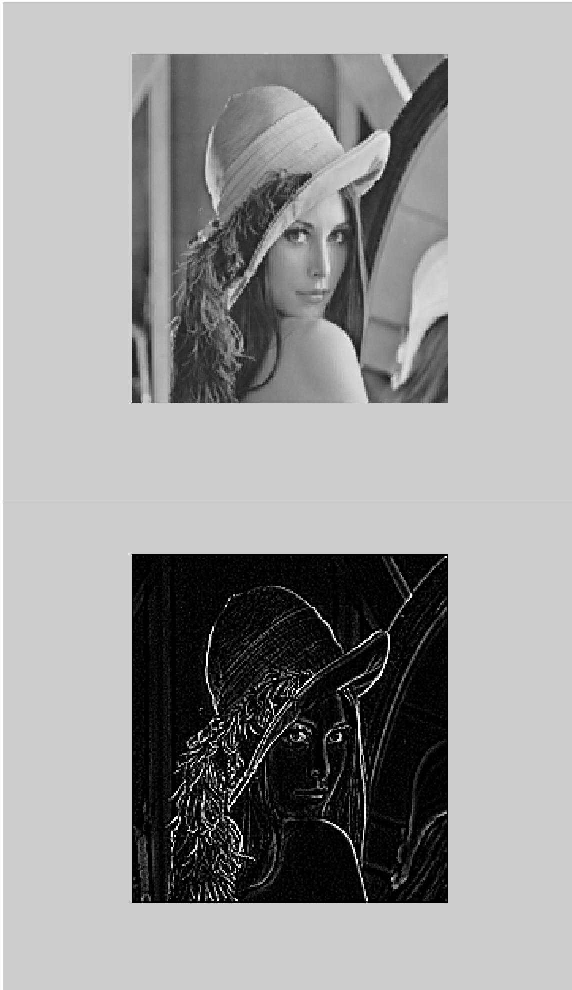


Figure 4: Final segmented texture images from Wang database.



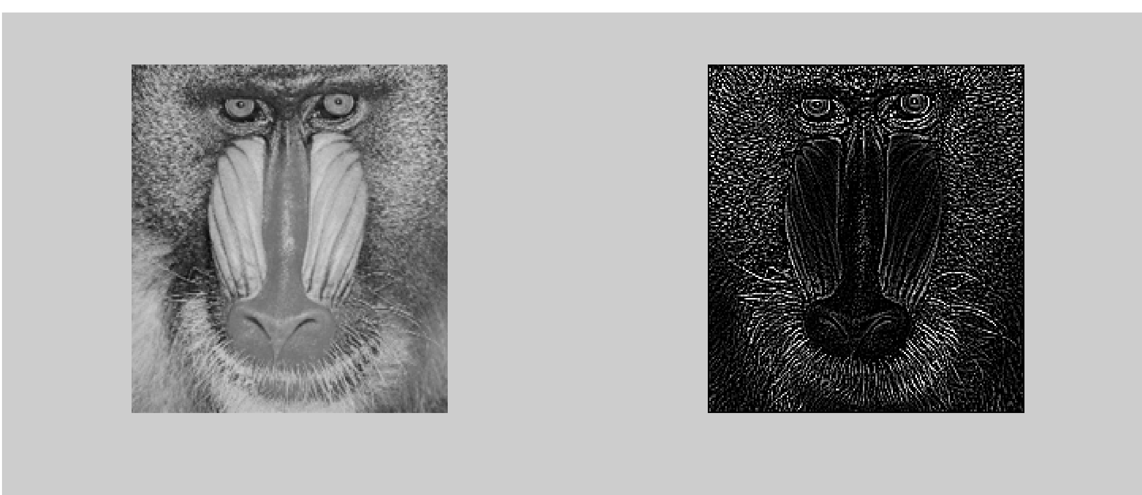


Figure 5: The segmented outputs of the standard image.

The present paper evaluated the above statistical parameter or unsupervised approaches on the proposed and the other methods. The results are displayed in Table 1, 2, 3 and 4 and also plotted in Fig. 6 to Fig.9.

The proposed method is compared with the existing methods [64, 65, 66, 67]. A high discrepancy rate is noted for all considered textures (14.56 to 15.66) except standard images of Google on the proposed method, which has shown low discrepancy rate of 12.19, and resulted an average value of 14.5.The average value of entropy, standard deviation and internal region contrast for the proposed methods are 1.26, 1.75 and 0.91 respectively, which clearly indicates a good segmentation. The proposed method resulted high discrepancy value and the low standard deviation over the other methods (Fig: 6 and Fig.9). This reflects a better segmentation of the proposed over the existing methods. The low value of internal contrast and a decent value of entropy also indicate the high performance of the proposed method over the existing methods.

Table 1: Average values of discrepancy.

Name of the data base	Proposed method	ISLGHEM [64]	ATM [65]	WWM[66]	MULBP method [67]
Brodatz texture	15.66	12.56	13.68	11.20	14.3
Wang	15.64	11.3	13.2	10.3	14.1
Oxford flower	14.56	11.4	12.3	10.6	13.2
Standard image	12.10	8.3	9.6	7.8	10.3
Average of all databases	14.49	10.37	11.67	9.65	12.42

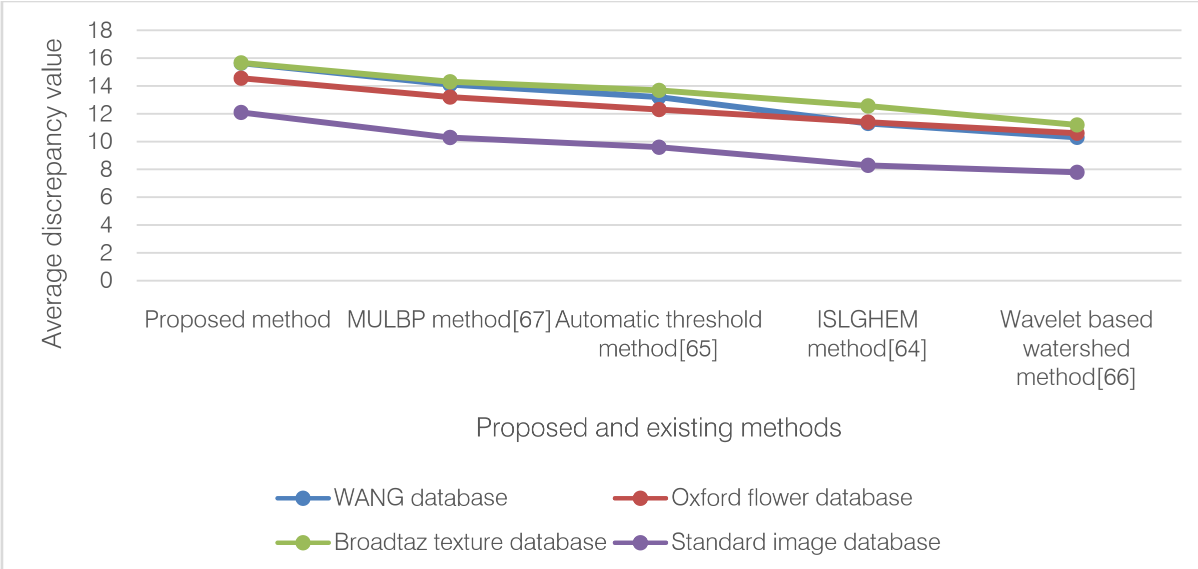


Figure 5: Comparison graph of proposed and existing methods in terms of Average discrepancy over considered databases.

Table 2: Average values of entropy.

Name of the data base	Proposed method	ISLGHEM [64]	ATM [65]	WWM [66]	MULBP method[67]
Brodatz texture	1.20	2.35	2.10	1.98	1.4
Wang	1.21	3.1	3.4	2.6	1.28
Oxford flower	1.36	2.7	3.1	2.6	1.44
Standard image	1.30	2	2.3	1.8	1.35
Average of all databases	1.26	2.475	2.85	2.225	1.36

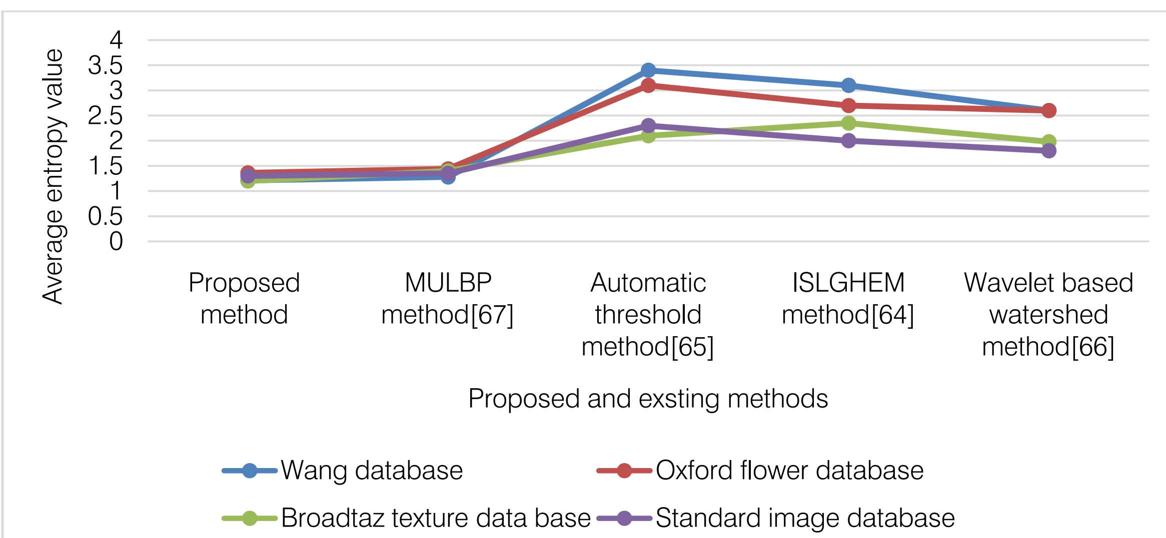


Figure 6: Comparison graph of proposed and existing methods in terms of Average entropyover considered databases.

Table 3: Average values of standard deviation.

Name of the data base	Proposed method	ISLGHEM method[64]	Automatic threshold method[65]	Wavelet based watershed method[66]	MULBP method[67]
Brodatz texture database	1.5	3.8	3.3	3.6	2.1
Wang database	1.98	4.4	4.1	3.8	2.7
Oxford flower database	1.86	4.4	3.5	4.2	2.1
Standard image database	1.69	4.3	3.5	4	2.6
Average of all databases	1.75	4.3	3.85	3.9	2.55

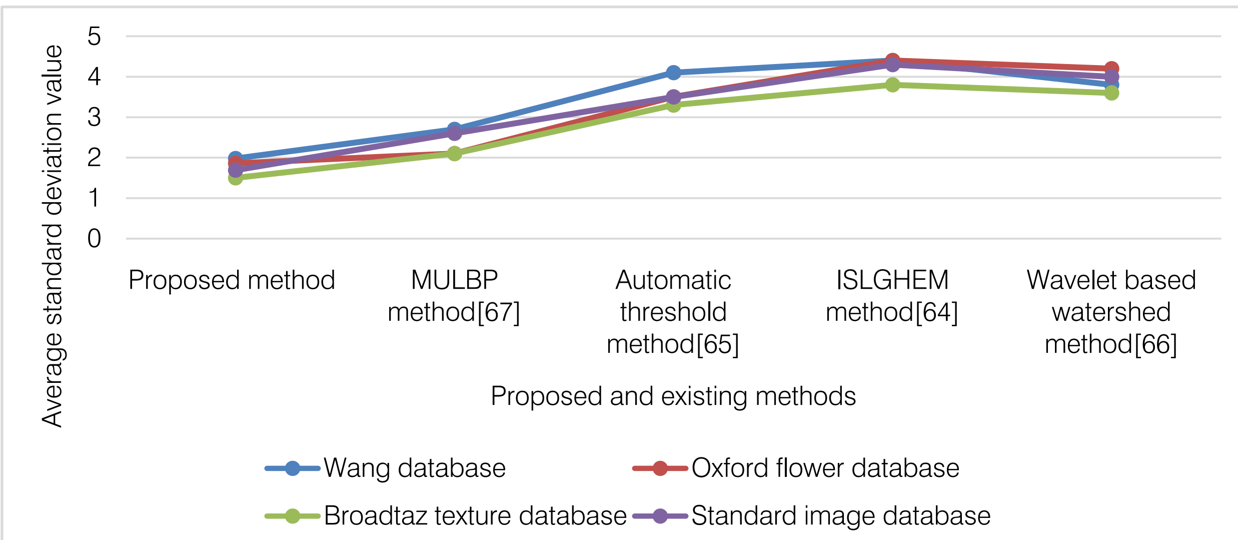


Figure 7: Comparison graph of proposed and existing methods in terms of Average standard deviation over considered databases.

Table 4: Average values of internal region contrast.

Name of the database	Proposed method	ISLGHEM method[64]	Automatic threshold method[65]	Wavelet based watershed method[66]	MULBP method[67]
Brodatz texture database	0.82	1.20	1.68	2.3	1.13
Wang database	0.89	1.8	1.4	1.9	0.90
Oxford flower database	0.86	1.5	1.8	2.6	1.10
Standard image database	1.1	2.8	2.6	3.4	1.52
Average of all databases	0.91	2.175	1.95	2.675	1.28

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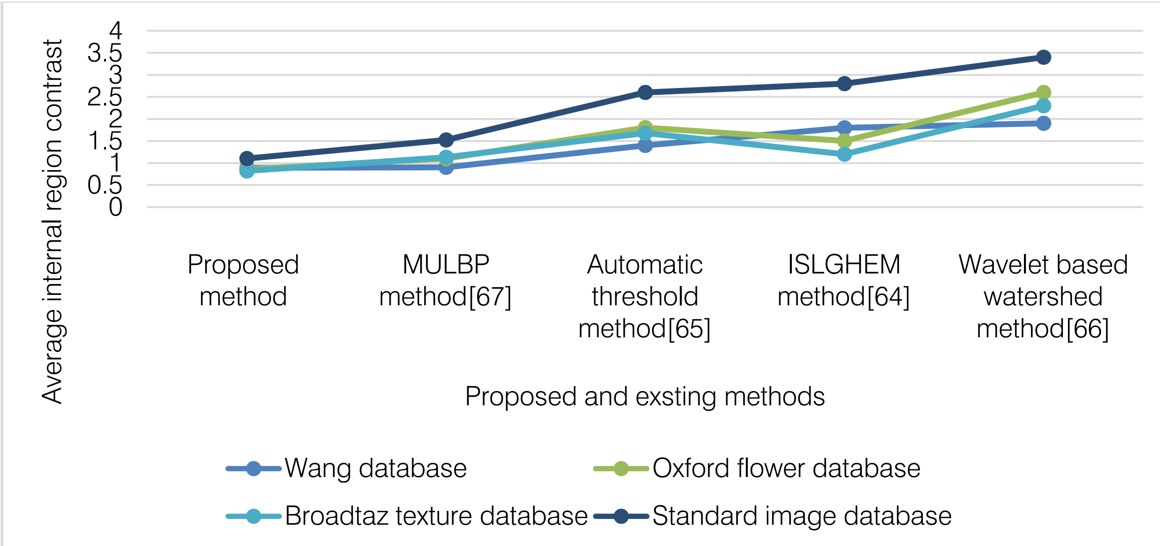

Figure 8: Comparison graph of proposed and existing methods in terms of Average internal region contrast over considered databases

V. Conclusions

The morphological operations covered the small holes with intensities and borders are connected for a better segmentation. The Otsu threshold established local boundaries efficiently and provided better contrast and also removed the unwanted local scenes of the image. The whole process of segmentation is automatic and requires no supervision. The present paper improves the contrast of sharp details in light and dark areas. The present method is experimented on the four standard databases namely Brodatz, Wang, Oxford flowers and standard images. The present method attained a good segmentation on the four datasets: however the proposed method have shown significantly high performance on Brodatz database textures when compared with other standard datasets; followed by Wang and oxford datasets. Further no over and under segmentation is reported by the present method on the considered databases. The present method is simple and suitable to real time applications because it achieved good segmentation with three basic steps.

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