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FLOWER IMAGE SEGMENTATION USING WATERSHED AND MARKER CONTROLLED WATERSHED TRANSFORM DOMAIN ALGORITHMS

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ABSTRACT

Watershed and marker-controlled watershed transform domain methods are the one of the powerful tools for image segmentation. Segmentation and recognition are two primary stages in the development of a fully digitized flower identifier for real time use. This paper limits the following discussion to flower image segmentation only. The objective of this work is to study and explore flower detection and segmentation algorithms with watershed transform. Two variants of watershed transform with morphological gradients and wavelet coefficients are proposed. The flower segmentation problem uses watershed and marker-controlled watershed algorithm during the initial phases. This transformed into a wavelet based fusion model with binary flower images in the later stages giving reasonable segmentation outputs. The segmentation results are analysed both visually and mathematically. The average segmentation distance error (SDE) and structural similarity index (SSIM) on Oxford university flower dataset is around 0.485 and 0.786 respectively.

Keywords: flower image segmentation, watershed transform, marker controlled watershed transform, segmentation distance error, structural similarity index.

1. INTRODUCTION

Flowers induce instantaneous and elongated effects on emotions, mood, behaviours and memory of both male and female human beings [1]. The authors studied extensively about the reactions flowers cause during their contact with humans in three different ways and concluded that human happiness is directly linked to flowers.

This is the reason for a 30% increase in world floriculture market every year and a 25% in India per annum [2]. The other side of the story is the losses incurred as they don't last long after they are cut form the plant. The storage, temperature, sorting, packaging and transportation are some of the causes for a market loss of nearly 25% every year [3].

The world consists of close to 250,000 species of flowers. Classification of these species is largely at the discretion of the botanists. Even the people involved in floral trade are unable to classify them correctly. An image is enough to classify the floral content with the help a guide book and an expert botanist.

People still find it difficult to identify a flower species when they come across one. If they have a name of the flower it is easy to find information about the flower species using google search engine. But the link between the photographed flower picture and the name of the flower is missing. Hence, this thesis investigates the first two steps in the process of automatic classification of flora from images of flowers captured by digital cameras.

Computer vision based algorithms can determine the quality of flower during its journey from blossoming to final consumer market. In this work we limit ourselves to the first two stages of development of a complete floral quality tester using computer vision models.

The first and most complicated task is to extract the flower to lower dimensional subspace for classification. The binary segmentation of the flower is performed by using a higher dimensional feature subspace consisting of colour, texture and shape characteristics of the image objects.

The second task is to classify the segmented flowers which are represented as features. Classification can be attempted using multiple algorithms such as K-Means, fuzzy C-Means, support vector machines (SVM), artificial neural networks (ANN) [4] [5] and deep learning architectures.

Vision computing applications are growing at an enormous pace in the last decade and agriculture [6] is no exception. Pest detection, grading [7], lesion estimation [8], yield prediction [9] and flower quality estimation [10] leading to good harvesting are the major areas [11]. For floral image processing, very little research progress is observed.

This work exclusively uses standard image processing techniques for flower segmentation. The objective of this paper is to study and explore flower detection and segmentation algorithms with watershed transform. Two variants of watershed transform with morphological gradients and wavelet coefficients are proposed.

Segmenting a flower image captured in the wild poses many challenges in the form of brightness, contrast, scale, resolution, orientation and occlusions. The objective is to test the robustness of the segmentation algorithms on flower images and design methods to make them immune to such capturing effects.

The watershed transform is simple, intuitive and always gives full division of the regions in the image. However, when applied to complex images like flower images captured in the wild, it is affected over segmentation and high noise sensitivity. This paper presents an improvement to the watershed transform by involving pre- knowledge in its calculations.

The pre - knowledge about the region of interest is provided in two ways. One is in the form of morphological markers calculated on the region of interest of the object and two, using the wavelet coefficients. In the marker based watershed, the algorithm is informed about the flower's location using the markers generated from the original flower images using morphological operations.

In wavelet coefficient based model, wavelet coefficients in high frequency are thresholded and applied as a pre - knowledge to the watershed algorithm. Performance of these two algorithms is tested multiple times on the two flower image datasets.

The performance measures are structural similarity index (SSIM) [12] and segmentation distance error (SDE) [13]. Results show an improvement in the basic watershed algorithm is achieved in both marker controlled and wavelet based watershed models for flower image segmentation.

2. RELATED WORK

In [11], a standard visual vocabulary of flower species is created as images in multiple variations under a single flower name as label. The dataset is named as Oxford University flower dataset (OUFD) [14] and on the similar lines we have created a flower dataset named as KL University Flower Dataset (KUFD). The OUFD consists of 102 species of flower and KUFD has 32 species of flowers respectively.

The flower image segmentation and recognition is a sub area under object detection and classification from unconstraint images. Here unconstraint images are captures done with multiple types of cameras unconditionally. Object detection is a segmentation problem and recognition is a classification problem.

Review works on object detection and classification show multiple segmentation, feature extraction and classification techniques popular in computer vision are used [15] [16] [17]. Image segmentation has been researched extensively till date with more iterative based algorithm with learning capabilities on unconstrained images [18] [19].

Image segmentation is an integral part of all computer vision related fields such as agriculture [20] [21], gesture analysis [22] [23], medical imaging [24], human action recognition [25] [26], mechanical defect detection [27], garment defect identification [28], etc.

The segmentation algorithms are classified as supervised and unsupervised. The unsupervised algorithms are non-iterative models that does not use some form of knowledge about the object being segmented [29]. Unsupervised algorithms generally use gradient metrics on pixels to separate objects from background. The most popular model is active contours, which is formulated as an iterative algorithm with a reference gradient model [30].

Other popular semi supervised model is Grab cuts, a graph based algorithm, which models foreground and background of the objects as graph nodes. This algorithm requires user to point markers on the image as foreground and background pixels prior to segmentation [31].

The major problem in floral image segmentation can be understood. The same flower class is described by multiple color models in nature. Hence the initial flower segmentation algorithms focused on using some attribute of the flower for segmentation.

The early models of flower image segmentation focused on edge flow technique, where nearest neighbourhood edge following algorithm tries to identify and follow flower edge [32]. Boundary of the flower is used as feature for classification of a flower [33]. The success of these algorithms is limited by their inability to locate flower edges in the presence of background clutter.

The next phase of algorithms used color attribute of the flower as a segmentation parameter [34]. In [35], color patches from flower images are used as a reference color for color similarity measure and the obtained similarity score extracts the flower in the image. Statistical color models were constructed from color combinations which are iterative matched to the actual flower colors [36].

Hierarchical approach on color maps arranges different color components in ascending or descending order. The ordered color information is thresholded to extract the flower from the image [37]. Multiple color maps such as HSV (Hue, Saturation, Value) and Lab color spaces are explored in this work.

The color based models produced reasonably good segmentations as the flowers are rich in natural color [38]. However, the color capturing sensors and the required brightness quotient during capture played an important role in determining the quality of the segmentation algorithms.

The watershed algorithm [39] considers an image as a topographic alleviation, each pixel's height is related to its gray values and imagine rain falling on the image, then the watersheds are lines that separate the water bodies formed on the terrain. The basic watershed transform uses image gradient magnitudes to locate the boundaries of water bodies.

This simple, fast linear algorithm divides the image into regions even under poor image contrasts, thus avoiding the need for any kind of contour joining. Many variants of watershed algorithms are proposed in literature with multiscale frameworks [40].

However, the drawbacks exists due to over segmentation, sensitivity to noise, meagre boundaries detection in low contrast regions and poor apprehension of thin segments. In this paper, we propose two modified watershed models with morphological markers and wavelet markers for flower image segmentation.

3. METHODOLOGY

3.1. Watershed transform for image segmentation

Figure-1 shows an example of watershed transformation on the flower image.

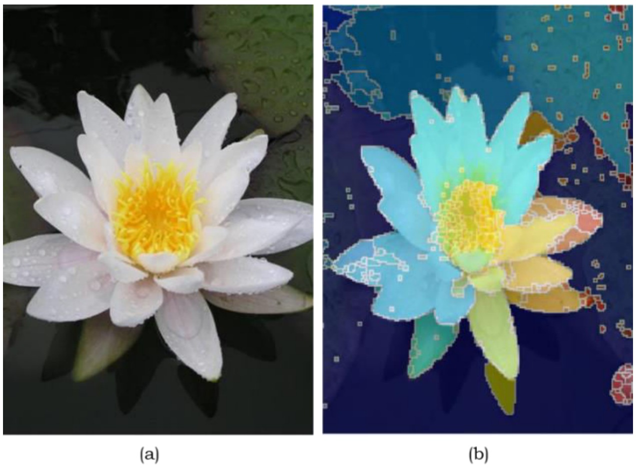

Figure-1. (a) Original flower image, (b) Its watershed transform.

The output of watershed transform in Figure-1(b) has numerous closed and connected regions. The boundaries of these regions follow the image contours. The amalgamation of all the regions produces the original image. The significance of the watershed transformation lies in its ability to form closed boundaries.

Traditional edge based models for discontinuous object contours, which require more than one operation to form a connected boundary. The boundaries of output regions represent contours of object in the image. This is in contrast with split and merge models using simple regular sectioning resulting in unstable outputs.

The union of all regions form the original image. The disadvantage of watershed transformation on natural images is over segmentation. This segmented output is unacceptable as it becomes difficult to extract the flower from the image for recognition.

In order to produce better segmentation of objects, some form of pre- and post-processing methods are required. Some methods are: region merging [41], hierarchal watersheds [41], marker based watershed [42], morphological filtering [43] and adaptive smoothing [44]. All these methods have their own set of advantages and disadvantages when comes to object detection and segmentation in images captured in the wild.

For a gray scale image $I(x,y)$ of arbitrary size having no plateaus outside the minima, the lower slope $LS(x,y)$ of I at a pixel (x,y) is defined as

$$LS(x,y) = \max_{(x_1,y_1)\subset N_G(x,y)\cup(x,y)} \left(\frac{I(x,y)-I(x_1,y_1)}{d(x,y,x_1,y_1)} \right) \qquad (1)$$

Where, $N_G(x,y)$ is a neighbourhood of pixel at location (x,y) on a grid G and (x_1,y_1) is another pixel in the neighbourhood. $d(x,y,x_1,y_1)$ is the Euclidian distance metric between (x,y) and (x_1,y_1). The term inside the brackets is a directed gradient of the pixel (x,y). The Lower slope $LS(x,y)$ defines the steepest slope relation between voxels.

The lower neighbours of the lower slope for each pixel (p) in the image is a set of lower neighbours $\Gamma(p)$

$$\Gamma(p) = p' \in N(p) \left| \frac{I(p)-I(p')}{d(p,p')} \right. \qquad (2)$$

The set of lower neighbours are set of pixels in the neighbourhood of p, where the directed gradient of the pixel equals its lower slope. At this point let us assume pixel $(x_1,y_1)=(q)$ to define the steepest descent. A pixel p is said to belong to the downstream of pixel q, if there exists a path π of steepest descent between p and q. Consequently, a pixel q is said to be upstream of pixel p if there exists a path in reverse from q to p. Using this, a catchment basin $Cb(m_i)$ is defined for region minimum m_i in the image is a set of points in the upstream of m_i. The watershed pixels are the pixels which are in the upstream of at least two minima that do not belong to any catchment basins.

The watershed transform is calculated on the absolute gradient of the image as the gradient magnitudes represent high values at the contours of objects in the image. This causes problems to thin segments in the image that are commonly formed in natural and medical images.

3.2. Marker controlled watershed segmentation

The most common difficulty in watershed transformation on natural images is over segmentation. The solution is usually provided with pre-knowledge to control the over segmentation. This pre – knowledge is to access the local minimum point for segmentation using an external marker. This enables the catchment basin minimum point to propagate near to the marked region instead of the gradient magnitude minimums in the image.

The previous works show a multitude of methods to create markers from the image's region of interest pixels. The most popular and widely used is morphological filter based marker extraction. However, the process is affected by the size of the structuring element designed in morphological filtering algorithm.The results of marker controlled watershed show a remarkable improvement compared to the traditional watershed transform. This section presents the modification carried on traditional watershed algorithm in the form of flower markers.

The prior information advantage for image object segmentation with compromising the original characteristics of the watershed transform is achieved in this work using morphological markers(MM) and wavelet markers (WM).

Watershed transform uses closed contours which are expressed as ridges around the object of interest. The marker points are pixels in a binary image with single marker occupying a set of connected pixels or a set of

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markers distributed over connected pixels. The connected markers should be placed inside the object of interest.

The number of markers decides the number of segmentation regions in the output of watershed transform. The segmented output consists of watershed regions ordered as befitting ridges thereby bifurcating each object into segments. The selection of markers can be accomplished through human intervention or through automation. However, automated models provide high throughput experimentation.

3.3.1. Creating morphological markers

Morphological models use two models to reconstruct the image markers: (i) image dilation approach and image erosion approach. Let I_{xy} and J_{xy} are two images in the spatial domain with $x, y \in \mathbf{R}^{+}$ and $I_{xy} > J_{xy}$. The marker reconstruction of I_{xy} from J_{xy} with iteratively dilating J_{xy} on the image I_{xy} for all pixels using the following expression

$$d_I\left(J\right) = \bigcup_{n \geq 1} \delta^{(n)} J \tag{3}$$

Where the dilation is defined as

$$\delta^{(I)}\left(J\right) = \left(J \oplus b\right) \bigcap I \tag{4}$$

With b as structuring element of size I and $\bigcap$ gives pixel wise minimum.

The dilated output is then eroded by repeating simple erosions of J above I till the operation is stabilized with

$$e_I\left(J\right) = \bigcap_{n \geq 1} \varepsilon^{(n)} J \tag{5}$$

Where the erosion operator is given by

$$\varepsilon^{(I)}\left(J\right) = \left(J \ominus b\right) \bigcup I \tag{6}$$

From the eroded image $\varepsilon^{(I)}\left(J\right)$, local minima points are extracted to act as markers or pointers to the regions of low contrast. The local minima or markers are extracted by computing the background region and foreground regions. The foreground markers point to the local minima of the region of interest in the image.

Maxpooling is applied on the eroded image and the regions of max pixels in the object region are marked. Connected components in the neighbourhood of 8 is used to remove the noisy regional minimums that doses not contribute to the global minima.

Next background pixels close to the object edges are identified and eliminated by image thinning. Finally, the background and foreground markers are added in binary domain, which is given as pre-knowledge to the watershed transform. Figure-2 shows the mixture of foreground and background markers for three flower images.

Figure-2. Marker regions using morphological marker algorithm.

In summary, foreground objects were created using morphological operations such dilation based gray scale reconstruction and erosion based gray scale reconstruction models. Regional maxpooling is applied to extract the smooth edges of the objects in the floral images. Background markers are identified by thinning the pixels near to the object edges. However, the results are effected by intensity of the pixels in the image, this work proposes a novel wavelet based marker design algorithm for better segmentation.

3.3.2. Creating wavelet markers

Wavelet transform uses multiresolution approach to separate the image pixels in spatial domain to frequency domain. The work in [45] discusses in detail the wavelet transforms and its properties. The present work, proposes to these characteristics to define the markers for watershed

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image transform. To understand the model, we present in fig.3, the results of discrete wavelet transform on a flower image at level 1.

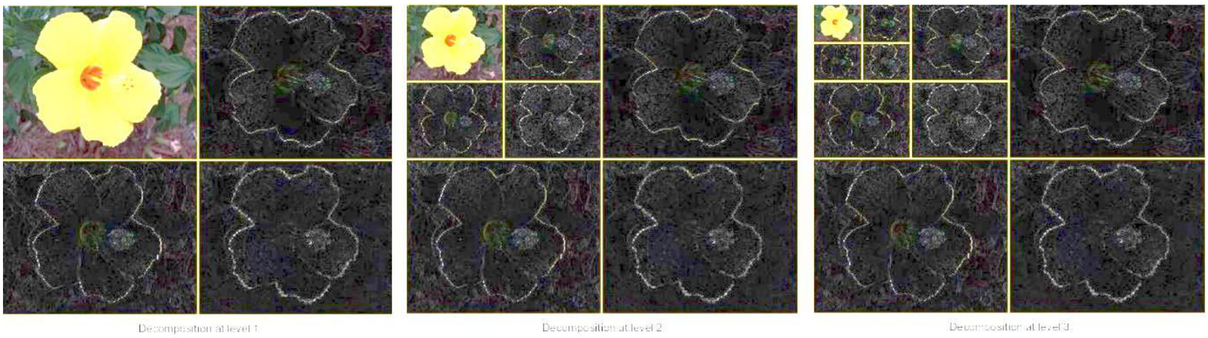

Figure-3. Wavelet decompositions at level 1, 2 and 3 for a flower image.

The top left image is called approximated component and the remaining three are called horizontal, vertical and diagonal coefficients. The virtue of this method is its ability to differentiate between low frequency and high frequency regions. The proposed wavelet markers are calculated by using approximate the detailed components. The averaged detailed wavelet coefficients are used as regions in the foreground and the approximate coefficients mark the background regions.

Figure-4. Proposed wavelet markers on flower images.

Averaging and maxpooling on the three detailed components extract the boundary regions of the flower image which define the foreground markers. The background regions are marked by thresholding and minpooling on the low frequency average wavelet coefficients. Figure-4 shows the results generated with proposed wavelet markers on three different flower images.

Compared to the morphological markers, wavelet markers are rich in information about foreground and background regions in the images. This gives watershed transform a large local region to extract local minimum. In the next section, results of segmentation are discussed exclusively by comparing the proposed wavelet markers against the popular flower image segmentation outputs with watershed transform and morphological marker based watershed transform.

4. RESULTS AND DISCUSSIONS

To validate the methods discussed in this thesis, we use both visual identification and quantitative analysis on the segmented outputs. The performance indices are structural similarity index (SSIM) and segmentation distance error (SDE).

Performance of the proposed segmentation model is measured with segmentation distance error (SDE) [12] defined as

$$SDE = \frac{\left\|(\varphi_F - \varphi_D)\right\|_2^2}{\left\|(\varphi_D)\right\|_2^2} \tag{7}$$

where φ_F is the final contour enclosing the flower and φ_D is the desired contour obtained from the ground truth of

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flower image. SDE gives the normalized error between the desired contour and final contour. The value of SDE ranges from 0 to
1, where a zero indicates a 100% exact segmentation.

To quantify the results further, we choose structural similarity index measure (SSIM) [13] and image quality index (IQI) [13] on the extracted flower image from proposed algorithm and ground truth (GT) model.

SSIM calculates the similarity is shape between the extracted flower and ground truth flower. SSIM formulation is based on literature in [13] as

$$SSIM = \frac{(2\mu_F\mu_D + C_F)(2\sigma_{FD} + C_D)}{(\mu_F^2 + \mu_D^2 + C_F)(\sigma_F^2 + \sigma_D^2 + C_D)} \quad (8)$$

Where C_F, C_D are contrast information for the segments given by $C = (KL)^2$ for $K <<1$ and L is the dynamic range of pixels in the image. μ_F and μ_D are mean values of pixels in the respective flower image regions. σ_F and σ_D are variances of pixels and σ_{FD} is the covariance matrix. SSIM calculations will help in making decisions on the structural similarity of the segmented flower. Image Quality Index (IQI) is SSIM with $C_F = C_D = 0$. This parameter is useful in determining the pixel variations between the extracted and ground truth flower image. With no contrast terms in eq'n 8, means IQI tests the correlation between the pixels in the images. With these performance measures, testing the proposed wavelet marker controlled watershed segmentation algorithm is analyzed.

Three experiments were designed with the oxford university flower dataset OUFD [14]. The 1st experiment uses only watershed transform with externally added local minima in the form of markers. Experiment 2 is testing with morphological markers and experiment 3 is with the proposed wavelet markers.

4.1. Exp - 1: Watershed with no external minima

The watershed transform is applied on all the images in the flower dataset and a few results are shown in Figure-5.

Figure-5. Results of Exp-1 on OUFD with watershed segmentation (a) Original flower image, (b) Gray scale image, (c) gradient magnitude and (d) watershed segmented with color coded regions.

The results show no clear region of the flower being extracted from Figure-5(d) using the traditional watershed transform. This effect is due to the dependency of segmentation result on the pixel values which define the gradient magnitude. The local minima in watershed transform is set with the max pooled regions in the gradiented image. The results were not even close to the ground truth (GT) images of flowers and hence we shift to marker controlled watershed transform. The 2^{nd} experiment simulates the morphological marker based watershed transform.

4.2. Exp - 2: Watershed with morphological markers

Figure-6 shows the results of intermediate morphological operations on a flower image.

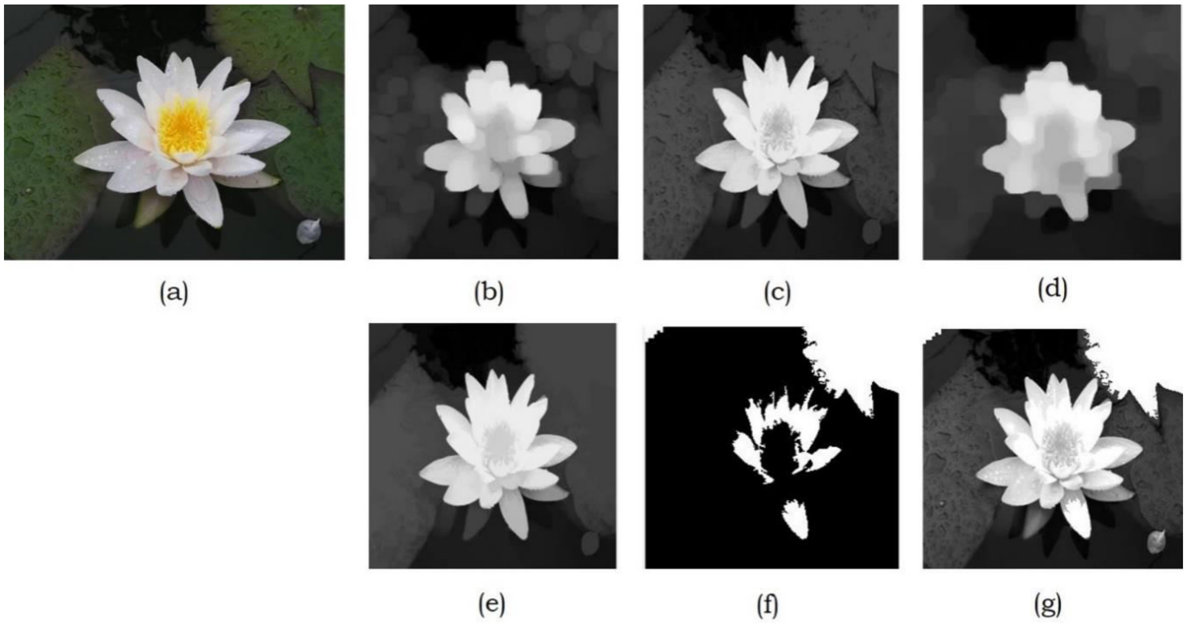

Figure-6. Morphological marker creation for watershed transform (a) Original image, (b) closing operation, (c) reconstructed gray scale image, (d) opening operation, (e) reconstructed gray scale image, (f) foreground and background markers and (g) marker projections on original gray scale image.

The morphological operations with maxpooling gives the necessary local minima points that control the segmentation flow between ridges in the watershed transform. The experimental results on OUFD for a few samples is shown in Figure-7.

Visual comparison of Figures 6 and 7, the morphological marker controlled watershed is definitely showing better segmentation regions compared to the traditional watershed model. However, improvements can be achieved by carefully controlling the morphological parameters. To make the segmentation process independent of thresholds and structuring elements in morphological operations, a novel watershed controlled algorithm is proposed with wavelet based markers.

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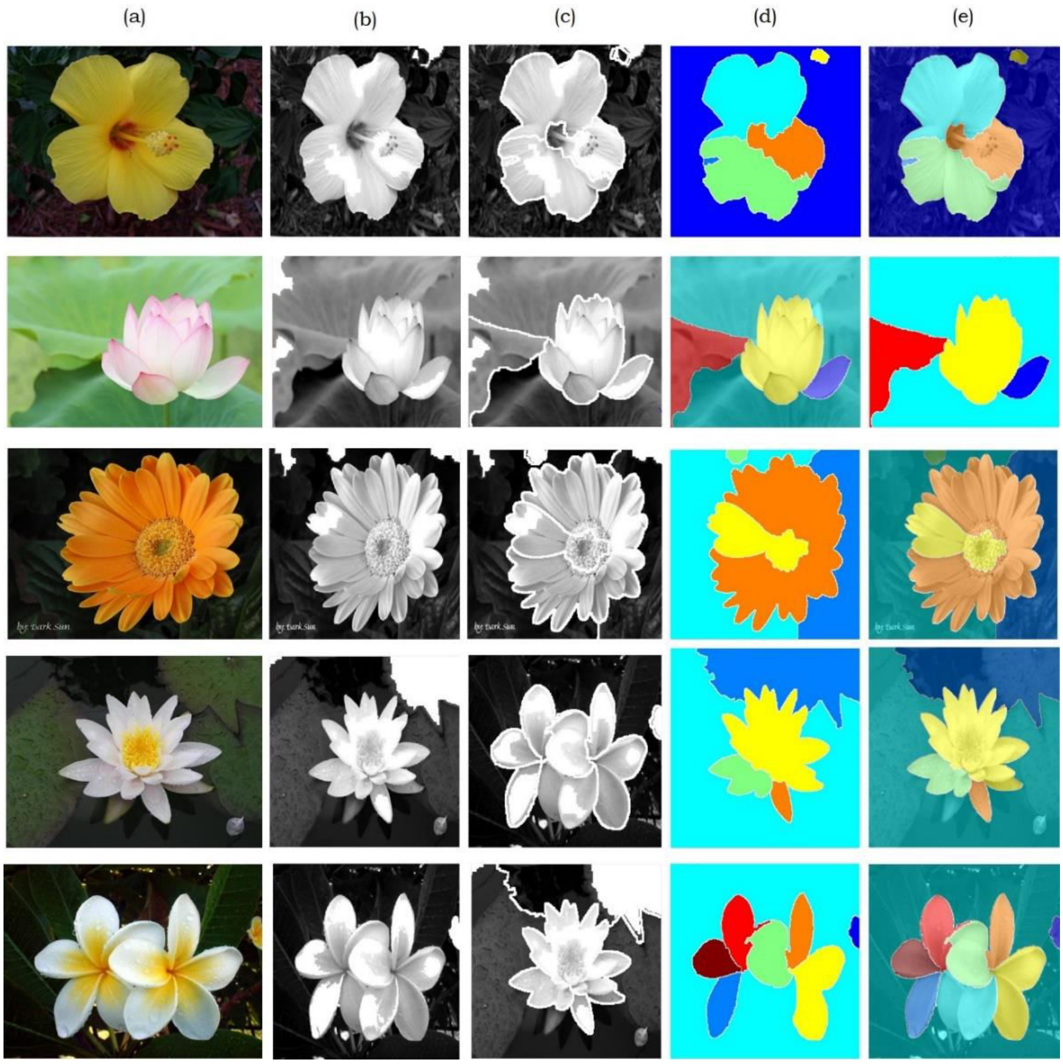

Figure-7. Morphological marker based watershed flower segmentation, (a) original, (b) imposed markers, (c) imposed boundaries, (d) watersheds segmented regions and (e) Overlapped segmented regions on original images.

4.3. Exp - 3: Watershed with wavelet markers

Wavelet transform is a multi-resolution approach transforming spatial contents into multi spectral components with a tree based filter structure. Using this multi resolution and multi spectral coefficients, this work proposes to identify foreground and background markers for watershed transform.

Exp - 3, uses wavelet markers to define local minima boundaries using the coefficients in approximate and detailed components. The results on OUFD for a few samples is shown Figure-8.

Visual analysis of Figures 6, 7 and 8 shows that the proposed wavelet marker based watershed transform has segmented out most part of the flower compared to traditional and morphological watershed transforms. This is due to the usage of low and high frequency coefficients to define markers for watershed transform. To analyze the results in an informative manner, the 3D plots of various segmented outputs are plotted in Figure-9.

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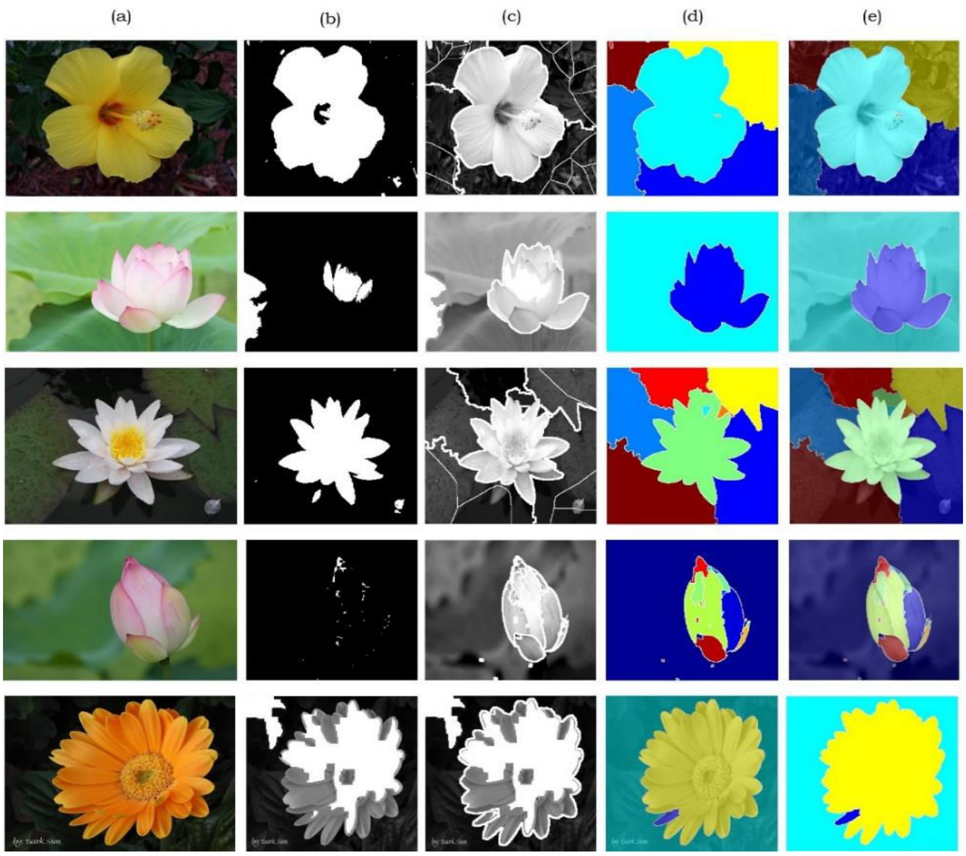


Figure-8. Wavelet marker based watershed flower segmentation, (a) original, (b) imposed markers, (c)imposed boundaries, (d) watersheds segmented regions and (e) Overlapped segmented regions on original images.

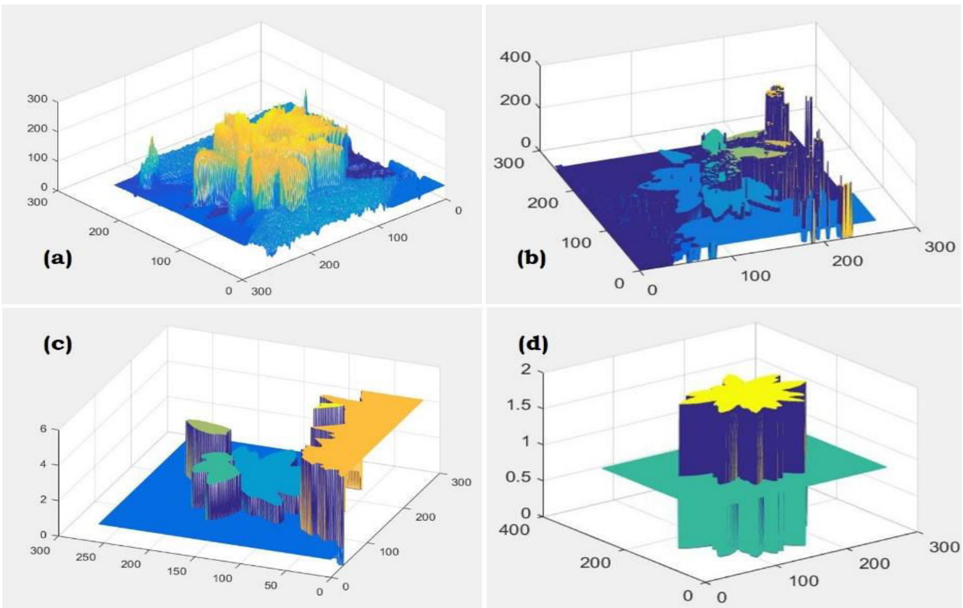


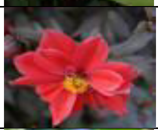
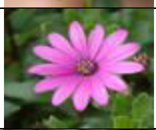
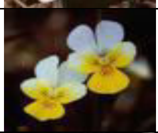
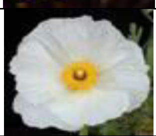
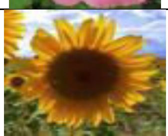
Figure-9. 3D plots of flower segmentation outputs (a) Original flower, (b) Traditional watershed transform, (c) Morphological markers and (d) Wavelet markers.

The plots show that the proposed wavelet maker controlled watershed transform outperforms the morphological marker controlled watershed and traditional watershed transforms for flower image segmentation. However, there are certain drawbacks associated with the proposed wavelet marker controlled watershed.

The proposed model is prone to back ground noise as the high frequency components in the image are averaged to find the markers. Thresholding the low frequency wavelet coefficients also creates un wanted background markers giving poor segmentation outputs. Similarly, multi colors in the flower such as shown in 4th row of Figure-8 cannot be segmented into a single flower bud segment.

The qualitative analysis is accomplished using the two performance measures in eq'n 8 and 9 i.e. segmentation distance error (SDE) and structural similarity index (SSIM). The ground truth images are extracted using photoshop software which are represented in unsigned 8- bit format. The calculated values are presented in Table-1

Table-1. SDE based qualitative analysis of segmentation algorithms.

Flower image	Flower name	Traditional watershed	Morphological marker controlled watershed	Wavelet marker controlled watershed
	barbeton daisy	0.825	0.658	0.455
	bishop of llandaff	0.714	0.624	0.25
	lotus	0.789	0.609	0.321
	rose	0.815	0.821	0.419
	osteospermum	0.745	0.542	0.358
	windflower	0.712	0.587	0.524
	wild pansy	0.785	0.698	0.524
	tree poppy	0.568	0.235	0.125
	tree mallow	0.745	0.519	0.305
	sunflower	0.902	0.745	0.578
	great masterwort	0.885	0.654	0.609

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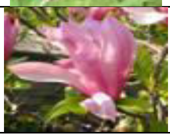
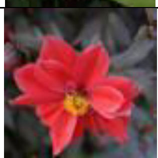
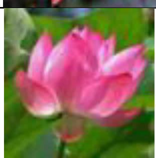
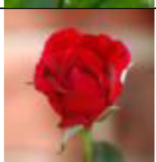
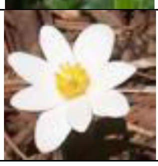
	blanket flower	0.845	0.789	0.608
	bolero deep blue	0.899	0.723	0.622
	english marigold	0.552	0.235	0.187
	sweet william	0.825	0.569	0.419
	sweet pea	0.923	0.847	0.799
	magnolia	0.944	0.874	0.812

Table-2. SSIM based qualitative analysis of segmentation algorithms.

Flower image	Flower name	Traditional watershed	Morphological marker controlled watershed	Wavelet marker controlled watershed
	barbeton daisy	0.825	0.858	0.905
	bishop of llandaff	0.799	0.824	0.901
	lotus	0.719	0.709	0.821
	rose	0.803	0.812	0.901
	osteospermum	0.745	0.875	0.899
	windflower	0.723	0.816	0.875

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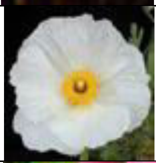
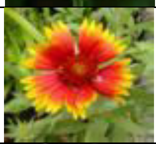
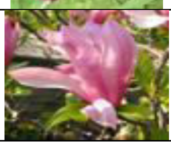
	wild pansy	0.685	0.745	0.845
	tree poppy	0.854	0.889	0.907
	tree mallow	0.753	0.823	0.895
	sunflower	0.736	0.865	0.879
	great masterwort	0.452	0.689	0.765
	blanket flower	0.526	0.689	0.735
	bolero deep blue	0.358	0.489	0.499
	english marigold	0.798	0.823	0.879
	sweet william	0.698	0.799	0.845
	sweet pea	0.489	0.589	0.625
	magnolia	0.385	0.498	0.599

The tables clearly show the robustness of wavelet markers compared to morphological markers and traditional watershed transform. The values of SDE should be minimum around 0.05 and that of SSIM should be maximum around 0.99 for a good segmentation algorithm. The values reported in the table are averaged over the entire set of images in a flower class.

For non-structured flowers with too much background clutter these algorithms have serious shortcoming and are unable to segment even 50% of the region of interest as shown in fig.10 using wavelet markers. The other two algorithms produced un even segmentation outputs which are worse than the results shown in Figure-10.

Figure-10. Wavelet marker controlled watershed segmentation with failure models.

Hence, the thesis will explore other segmentation models to extract flowers from the images which can be inputted to a recognition algorithm.

5. CONCLUSIONS

In this paper, the three flower segmentation models on naturally captured flower images are studied. Traditional watershed algorithm is good for segmentation of natural images where a local minimum is calculated based on the neighbourhood of pixels. However, calculating a local minimum is influenced by pixel values in the image. To balance the pixel variations within a region of interest, marker controlled watershed algorithms are used with morphological markers calculated from the image. However, the morphological gradients are affected by pixel variations with the interest regions. Hence, this work proposed to calculate wavelet based markers for the region of interest for watershed transform. The results an increase in segmentation regions of flowers with use of pre-defined markers with watershed transform. The wavelet based markers are selected based on high and low frequency contents in the image with precisely mapping detailed wavelet coefficients to edges and approximate coefficients to find background.

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