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# Implementation of Graph Based Image Segmentation Technique

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**ABSTRACT**:This paper presents the implementation of graph-based image segmentation technique using MATLAB codes.Here, the segmentation problem is solved in a spatially discrete space by the well-organized tools from graph theory. After the literature review, the problem is formulated regarding graph representation of image and threshold function. The boundaries between the regions are determined as per the segmentation criteria and the segmented regions are labeled with random colors. In our approach, the image is pre-processed by discrete wavelet transform and coherence filter before graph segmentation. The experiments are carried out on a number of images and compared. The obtained results are encouraging.

**KEYWORDS:**Digital Image Segmentation; Graph Theory; Image Processing; Preprocessing; Threshold; Wavelet Transform

## I.INTRODUCTION

Among the various existing segmentation approaches, graph theoretic approach found to have several good features in practical applications. The graph theoretic approach organizes the image elements into mathematically sound structures. It makes the formulation of the problem more flexible and the computation more resourceful. The problem is modeled in terms of partitioning a graph into several sub-graphs; such that each of them represents a meaningful object of interest in the image. The segmentation problem is then solved in a spatially discrete space by the efficient tools from graph theory [1].

A general example of partitioning a graph into several sub-graphs and labeling the different components, which are obtained after partitioning, is shown in Figure 1 and Figure 2. There are various criteria to measure the quality of segmentation results, but in general, it is believed that the elements in a component are supposed to be homogenous, and elements in different components to be heterogeneous. In the Figure 1, let the squares represent the pixels, the lines connecting two pixels be edges, and the number indicated on the edges be edge weights. The algorithm should first sort the edges into non-decreasing edge weights. As shown in the Figure 1, the edge weights shown in red color are relatively high as compared to other edge weights. A threshold function can be introduced here to control the degree to which the difference between components must be larger than the difference within a component. Depending upon the threshold function the boundaries are determined and the graph is partitioned into sub-graphs. The thick lines show labeling discontinuities between neighboring pixels. In other words, the thick lines partitions the graphs into three sub-graphs and hence three components are obtained. The corresponding vertices are labeled with random colors as shown in Figure 2.

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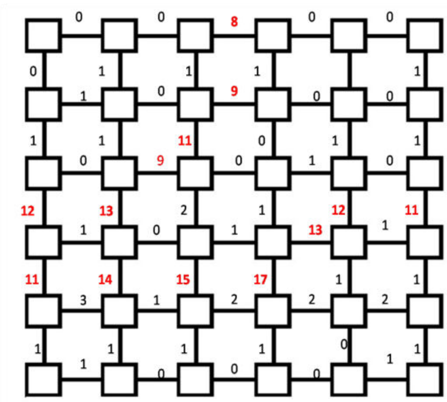

Figure 1: An example of partitioning the graph into sub-graphs. The graph maintains the 4-neighborhood system. The squares represent the pixels, the lines connecting two pixels are edges, and the number indicated on the edges are edge weights. The higher edge weights are identified.

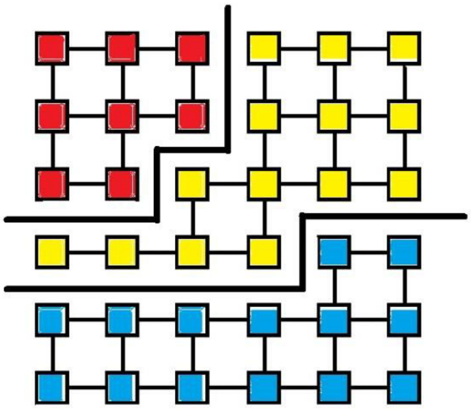

Figure 2: The graph is separated into three sub graphs. Labeling assigns random colors to each region. Thick lines show labeling discontinuities between neighboring pixels

## II. GRAPH BASED SEGMENTATION

- Let $G = (V, E)$ be an undirected graph
- Vertices $v_i \in V$, the set of elements to be segmented
- Edges $(v_i, v_j) \in E$ corresponding to pairs of neighboring vertices.
- Each edge $(v_i, v_j) \in E$ has a corresponding weight $w((v_i, v_j))$ which is a non-negative measure of the dissimilarity between neighboring elements $v_i$&$v_j$.
- In the case of mentioned approach, the elements in $V$ are pixels and the weight of an edge is the difference in intensity between the two pixels connected by that edge.

In the graph based segmentation approach, a segmentation $S$ is a partition of $V$ into components such that each component (or region) $C \in S$ corresponds to a connected component in a graph $G' = (V', E')$, where $E' \subseteq E$ and $V' \subseteq V$. As mentioned in the introduction, the elements in a component to be similar with respect to some similarity measures and elements in different components to be dissimilar. The similarity measure here means intensity values. This means that the edges connecting two pixels in the same component should have relatively low weights and the edges connecting pixels in different components should have higher weights.

A predicate, $D$, is defined here for estimating whether or not there is evidence for a boundary between two components in a segmentation. This predicate is based on measuring the dissimilarity between the pixels along the boundary of the two components relative to a measure of the dissimilarity among neighboring pixels within each of the two components. The predicate compare the differences between two components to the differences within each component and is thereby adaptive with respect to the local characteristics of the data.

Internal difference of a component $C \subseteq V$ is defined to be the largest weight in the MST of the component and is denoted by $MST(C, E)$.
That is,

$$Int(C) = \max_{e \in MST(C,E)} w(e) \quad (1)$$

It can be concluded that the given component $C$ only remains connected when edges of weight at least $Int(C)$ are considered.
The difference between the two components $C_1, C_2 \subseteq V$ is defined to be the minimum weight edge connecting the two components. That is,

$$Dif(C_1, C_2) = \min w((vi, vj)) \quad (2)$$

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$v_i \in C_1, v_j \in C_2, (v_i, v_j) \in E$

The predicate estimates if there is evidence for a boundary between a pair or components by checking if the difference between the components, *Dif* $(C_1,C_2)$, is large relative to the internal difference within at least one of the components, *Int*$(C_1)$ and *Int*$(C_2)$.

## II. THRESHOLD

A threshold function is introduced here which is used to control the degree to which the difference between two components must be larger than minimum internal difference within each component.
The threshold function τ manages the extent to which the difference between two components must be greater than their internal differences in order for there to be evidence of a boundary between them (D to be true). When D is true then the two components are not merged and, thus, remain in the final segmentation. When D is false, then the two components get merged.
For small components, Int(C) is not a good approximate of the local characteristics of the data. In the extreme case, when |C| = 1, Int(C) = 0. Therefore, a threshold function τ is used based on the size of the component,

$$\tau(C) = k / |C|$$

where |C| denotes the size of C, and k is user defined constant parameter.

## III. WORKING OF THE GRAPH BASED IMAGE SEGMENTATION APPROACH

The systematic working of the graph based approach is demonstrated by means of flow chart, prepared by us, as shown in Figure 3. The input image is considered as a graph where the pixels are vertices and the edges connecting two pixels have some weights that are the difference between the intensity values of the two pixels. These edges are initially sorted according to the non decreasing order. The segmentation process is then initialized with the consideration that each vertices belong to its own components. Now the edges connecting two vertices in the neighboring regions are evaluated. Based on the threshold value, the predicate decides whether the two regions have to be merged or to be considered as segmented. If the edges connecting two pixels of different components have less value than the threshold, then the two regions are merged together. If the edges connecting two pixels of different components have equal or larger value than the threshold then the two regions remain separated and are obtained in the final segmentation results. Similar calculation is performed for all the edges and thus the boundaries between the two pixels are determined. The regions are finally labeled with random colors so as to distinguish the adjacent regions. The above process can be interpreted with the help of following flowchart.

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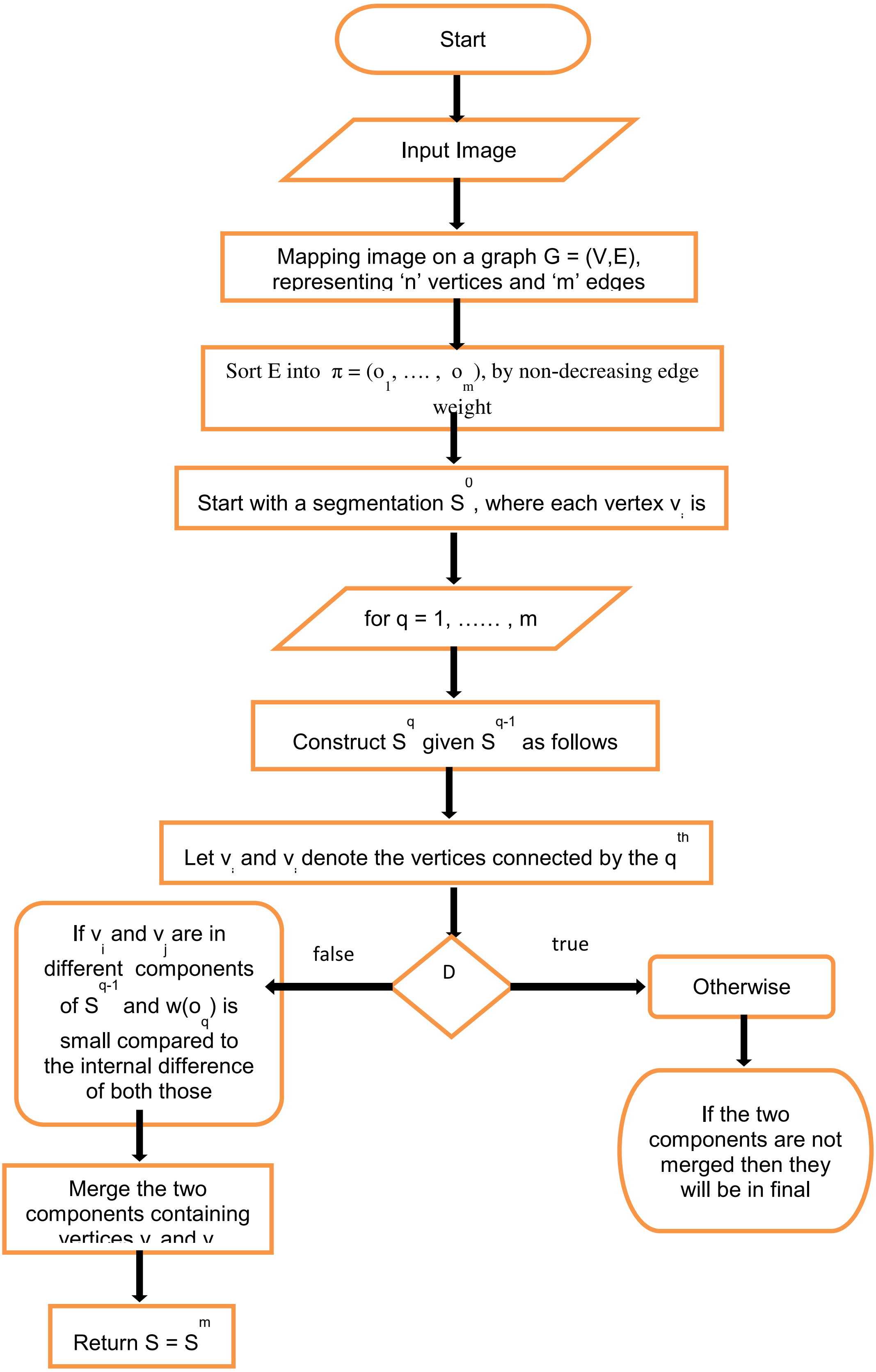


Figure 3: Flowchart, prepared by us, for the graph based segmentation approach

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## IV. WAVELET TRANSFORM

Wavelets have the special ability to examine signals simultaneously in both time and frequency. In the DWT, an image is analyzed by passing it through an analysis filter bank. This process is followed by a decimation operation. This analysis filter bank of a low pass and a high pass filter is commonly used in image compression. A signal is split into two bands when it passes through these filters. The coarse information of the signal is extracted by low pass filter which corresponds to an averaging operation. The high pass filter extracts the detail information of the signal which corresponds to a differencing operation. The output of the filtering operations is then decimated by two.

The following process demonstrated how reconstruction of the image is carried out. Initially, the image is upsampled by a factor of two on all the four subbands at the coarsest scale and filters the subbands in each dimension. Then the four filtered subbands are sum up to reach the low-low subband at the next finer scale. This process is repeated until the image is fully reconstructed.

It means that the visually insignificant regions in an image are merged when wavelet transform is applied to it. This encourages us to use wavelet transform as a preprocessing step before segmenting it. The main advantage of wavelet transform is that it is very fast in practice. Also when graph based segmentation is done after preprocessing it with wavelet transform, it is found that the computational complexity is decreased because the similar regions are merged in the preprocessing step. Hence, the computational time is decreased.

Among the various wavelet transforms, we carried out experimentations by preprocessing the image by using Haar transform, DB2 transform, DB4 transform, DB6 transform and DB8 transform and found that the execution speed is marginally increased and also the visual quality of the segmentation output is maintained and even improved in many cases.

## V. COHERENCE FILTER

In order to compensate for digitization artifacts and removal of the noise inculcated in the images, we used a Coherence filter to smooth the image slightly before computing the edge weights. When the image is passed through a coherence filter, the coherence filter performs Anisotropic Diffusion of the color or grayscale image. This process reduces the noise in an image while preserving the region edges.

Anisotropic diffusion is a technique that aims at reducing image noise while preserving significant parts of the image details like edges, lines or other parameter that are important for the analysis of the image. Anisotropic diffusion successively generates more and more blurred images based on a diffusion process. As a result, the images obtained after filtering preserves linear structures while at the same time smoothing is made along these structures. A generalization of the usual diffusion equation describes both these cases where the diffusion coefficient is a function of image position and assumes a matrix value.

In Anisotropic diffusion each new image in the family is computed by applying the above mentioned generalized equation to the previous image. As a result, anisotropic diffusion is an iterative process where a relatively simple set of computation are used to compute each successive image in the family and this process is continued until a sufficient degree of smoothing is obtained. Due to the above-mentioned advantages, we preprocessed the image by means of the coherence filter.

## VI. WORKING OF THE PROPOSED APPROACH

The process for color image segmentation.is as follows:

- As a preprocessing step discrete wavelet transform is done on the images. In our experimentations we used the single-level discrete 2-D wavelet transform (DWT2) which performs single-level 2-D wavelet decomposition with respect to either a particular wavelet or particular wavelet filters specified. We used the wavelets like Haar, DB2, DB4, DB6 and DB8 for experimentations.
- Before passing the image to the coherence filter, the gray scale component image for each color plane, i.e. red, green and blue colors, is extracted by simple operation.
- The grayscale color plane image is then given to the coherence filter where the noise is removed while preserving the edges.

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- The graph based segmentation is done on this filtered image. For implementation purpose, we have used the C++ code provided by [2] on the URL http://cs.brown.edu/~pff/segment/. We have compiled these codes by Visual Studio complier and then called it in MATLAB. Some input parameters have to be initiated before segmentation is done. These parameters includes
  1. neighbor_radius: the neighborhood radius of each pixel [1 by default]
  2. Coefficient k: segmentation algorithm coefficient (large prefer large segmented component)
  3. min_size: the minimum size allowed for each segment.
- The graph segmentation is then done on the three color planes respectively depending upon the parameters provided.
- As discussed earlier, the boundaries between the two regions are determined based on the definition of predicate.
- Gradient operator help visualize the boundaries between the components. The white color indicates the presence of boundaries. The black color regions are the components separated by the boundaries.
- Morphological operations are done on the gradient image from where the contours are obtained. Finally the contours obtained are more prominent as the insignificant boundaries get eliminated.
- The image is then labeled with random intensity values for each color plane.
- Two neighboring pixels are put in the same component when they appear in the same component in all three of the color plane segmentations.
- The contours obtained from the three color planes are intersected together to form the final contours and the regions are determined based on these contours for color images.
- The regions are finally assigned random colors so that the neighboring regions can be differentiated.

## VII. EXPERIMENTAL RESULTS AND DISCUSSIONS

The approach is implemented using (MATLAB 8.1.0.604) (R2013a). The experimentations are carried out on Intel (R) Core (TM) 2 Duo T6570, 2.10 GHz processor. The RAM of the system used is 3GB and ROM is 300GB. The operating system is 32-bit and the processor is x64 installed on Windows 8 platform.

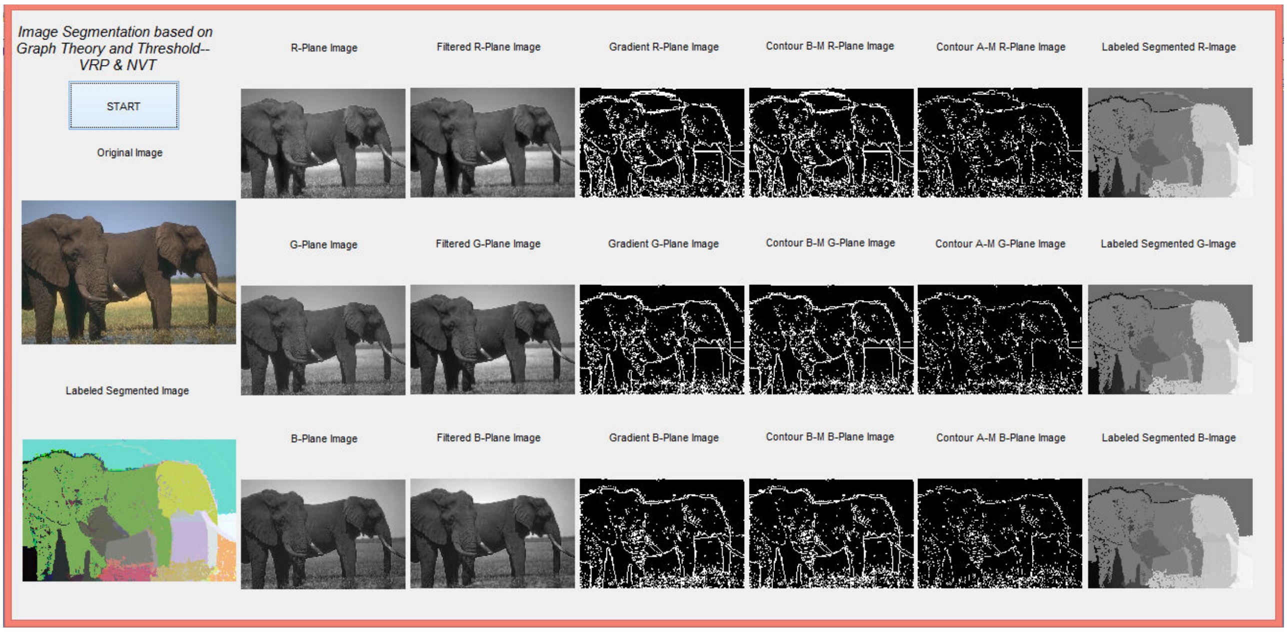


Figure 4: Screenshot of GUI showing the stepwise obtained results for each color plane along with the input image as well as the labeled segmented image when the image is not preprocessed by any wavelet transform.

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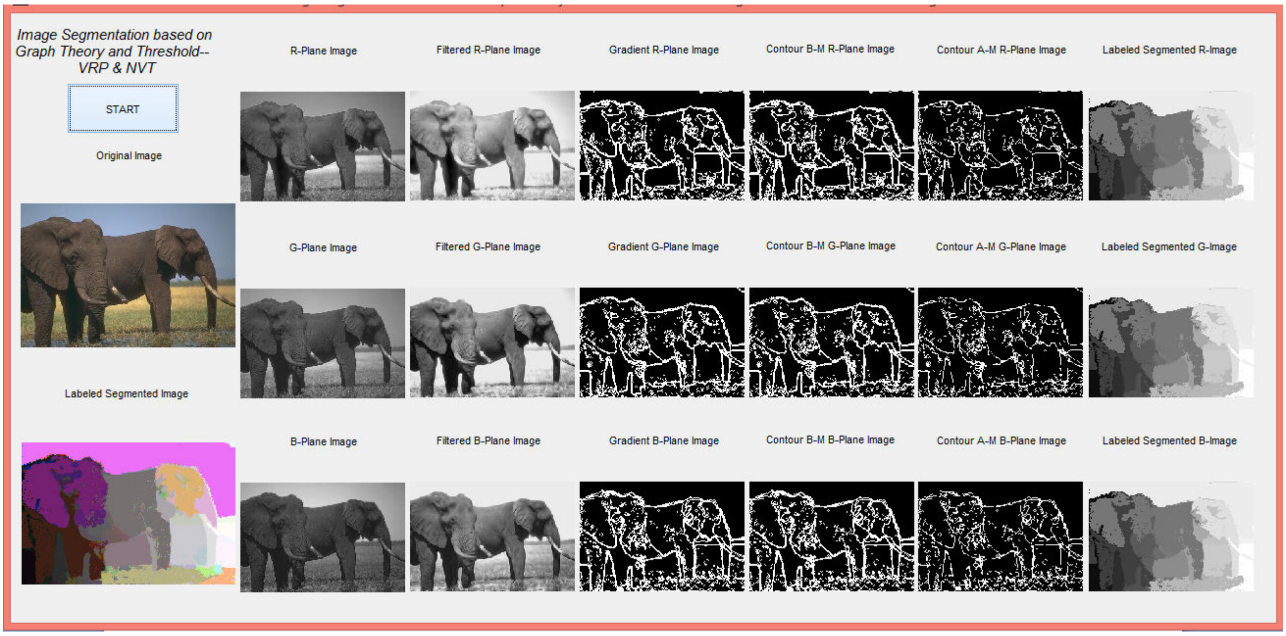
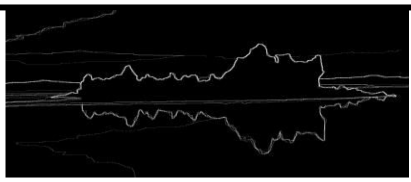
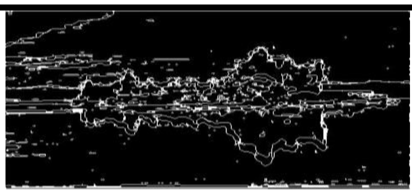
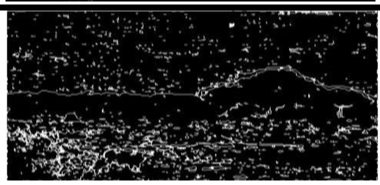
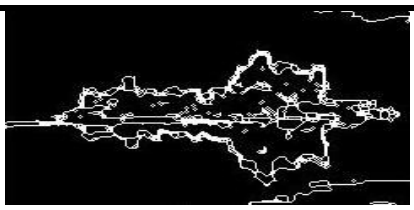



Figure 5: Screenshot of GUI showing the stepwise obtained results for each color plane along with the input image as well as the labeled segmented image when the image is preprocessed by discrete wavelet transform by Wavelet

Table 5.9: Demonstration of Contour Images obtained for given images.

| Image name | '143090.jpg' | '296007.jpg' |
|---|---|---|
| Image |  |  |
| Ground Truth Data for Edge Detection |  |  |
| Contours obtained without preprocessing by any Wavelet Transform |  |  |
| Contours obtained after DWT2 using Haar Wavelet |  |  |

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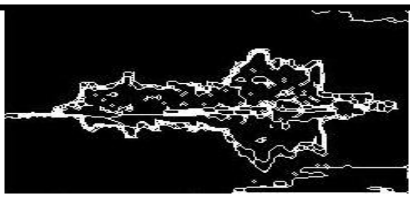
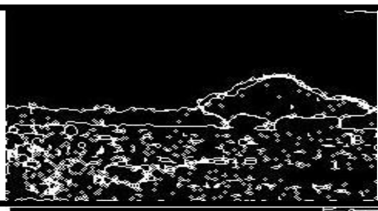
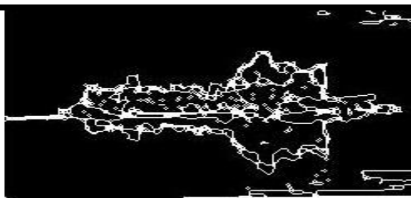
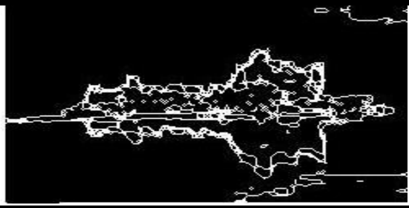
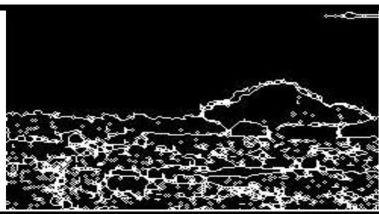
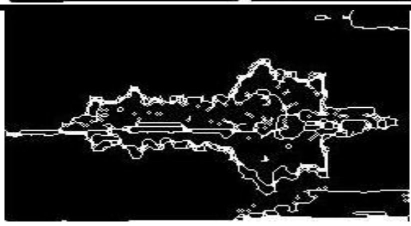
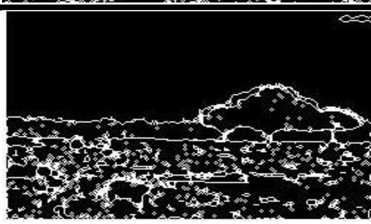
| | | |
|---|---|---|
| **Contours obtained after DWT2 using DB2 Wavelet** |  |  |
| **Contours obtained after DWT2 using DB4 Wavelet** |  |  |
| **Contours obtained after DWT2 using DB6 Wavelet** |  |  |
| **Contours obtained after DWT2 using DB8 Wavelet** |  |  |

## VIII. EVALUATION AND COMPARISON OF OBTAINED EXPERIMENTAL RESULTS

We, here, used the following parameters used for evaluations of our results.

1. Time Required for Graph Based Segmentation
2. Peak Signal to Noise ratio (PSNR)
3. Performance Ratio (PR)
4. Precision and Recall.

Table 1: Time required for segmentation of natural gray images in seconds

| Input Image | Haar | DB2 | DB4 | DB6 | DB8 |
|---|---|---|---|---|---|
| **‘45096.jpg’** | 0.46 | 0.46 | 0.48 | 0.48 | 0.49 |
| **‘65019.jpg’** | 0.47 | 0.46 | 0.47 | 0.48 | 0.49 |
| **‘113044.jpg’** | 0.47 | 0.47 | 0.48 | 0.48 | 0.50 |
| **‘135069.jpg’** | 0.40 | 0.41 | 0.42 | 0.42 | 0.44 |
| **‘143090.jpg’** | 0.42 | 0.43 | 0.44 | 0.45 | 0.45 |
| **‘296007.jpg’** | 0.43 | 0.44 | 0.45 | 0.46 | 0.48 |
| **‘296059.jpg’** | 0.46 | 0.46 | 0.46 | 0.48 | 0.49 |
| **‘306005.jpg’** | 0.46 | 0.47 | 0.47 | 0.48 | 0.50 |
| **‘beach.jpg’** | 0.24 | 0.25 | 0.25 | 0.24 | 0.25 |
| **‘rice.jpg’** | 0.51 | 0.65 | 0.50 | 0.53 | 0.52 |

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Table 2: Performance Ratio of the Segmented Results

| Input Image | HAAR | DB2 | DB4 | DB6 | DB8 |
|---|---|---|---|---|---|
| **‘45096.jpg’** | 0.0022 | 0.0020 | 0.0023 | 0.0035 | 0.0019 |
| **‘65019.jpg’** | 0.0024 | 0.0024 | 0.0017 | 0.0018 | 0.0016 |
| **‘113044.jpg’** | 0.0009 | 0.0007 | 0.0010 | 0.0011 | 0.0007 |
| **‘135069.jpg’** | 0.0026 | 0.0025 | 0.0012 | 0.0025 | 0.0028 |
| **‘143090.jpg’** | 0.0035 | 0.0031 | 0.0030 | 0.0019 | 0.0026 |
| **‘296007.jpg’** | 0.0038 | 0.0041 | 0.0047 | 0.0021 | 0.0025 |
| **‘296059.jpg’** | 0.0026 | 0.0027 | 0.0030 | 0.0024 | 0.0042 |
| **‘306005.jpg’** | 0.0014 | 0.0015 | 0.0019 | 0.0013 | 0.0015 |

Table 3: PSNR of the Segmented Results in decibels

| Input Image | Haar | DB2 | DB4 | DB6 | DB8 |
|---|---|---|---|---|---|
| **‘45096.jpg’** | 12.2143 | 11.4409 | 12.5631 | 12.7120 | 12.2341 |
| **‘65019.jpg’** | 9.6443 | 9.5434 | 9.1652 | 9.0504 | 9.101 |
| **‘113044.jpg’** | 8.6669 | 8.8337 | 8.4517 | 8.5042 | 8.5383 |
| **‘135069.jpg’** | 17.721 | 17.6791 | 16.8576 | 16.4634 | 16.7061 |
| **‘143090.jpg’** | 12.7865 | 12.2663 | 12.0917 | 12.6261 | 12.3636 |
| **‘296007.jpg’** | 12.0733 | 12.3503 | 12.2443 | 10.9233 | 11.7055 |
| **‘296059.jpg’** | 10.6418 | 11.089 | 10.7377 | 10.9542 | 10.3224 |
| **‘306005.jpg’** | 10.0494 | 10.3964 | 10.0695 | 9.6637 | 9.6162 |

Table 4: Precision of the Segmented Results

| Input Image | Haar | DB2 | DB4 | DB6 | DB8 |
|---|---|---|---|---|---|
| **‘45096.jpg’** | 46.7611 | 50.0392 | 49.1753 | 51.2983 | 43.1365 |
| **‘65019.jpg’** | 70.7948 | 71.9072 | 70.4551 | 70.5546 | 67.2279 |
| **‘113044.jpg’** | 34.9189 | 35.0555 | 34.3365 | 35.1997 | 33.7685 |
| **‘135069.jpg’** | 41.6328 | 42.4072 | 38.3769 | 42.1317 | 33.0302 |
| **‘143090.jpg’** | 44.1998 | 45.2006 | 43.4386 | 42.8078 | 41.0001 |
| **‘296007.jpg’** | 58.5074 | 59.4026 | 57.2390 | 59.1842 | 58.3477 |
| **‘296059.jpg’** | 59.3160 | 61.5131 | 59.6177 | 60.2192 | 59.5920 |
| **‘306005.jpg’** | 60.0831 | 61.6381 | 58.8643 | 56.7069 | 57.6688 |

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Table 5: Recall of the Segmented Results

| Input Image | HAAR | DB2 | DB4 | DB6 | DB8 |
|---|---|---|---|---|---|
| **‘45096.jpg’** | 0.0499 | 0.0420 | 0.0472 | 0.0682 | 0.0446 |
| **‘65019.jpg’** | 0.0428 | 0.0428 | 0.0308 | 0.0317 | 0.0300 |
| **‘113044.jpg’** | 0.0248 | 0.0189 | 0.0272 | 0.0295 | 0.0189 |
| **‘135069.jpg’** | 0.0610 | 0.0563 | 0.0282 | 0.0563 | 0.0751 |
| **‘143090.jpg’** | 0.0449 | 0.0402 | 0.0393 | 0.0234 | 0.0327 |
| **‘296007.jpg’** | 0.0337 | 0.0360 | 0.0422 | 0.0186 | 0.0219 |
| **‘296059.jpg’** | 0.0404 | 0.0404 | 0.0461 | 0.0362 | 0.0643 |
| **‘306005.jpg’** | 0.0274 | 0.0283 | 0.0365 | 0.0256 | 0.0292 |

## IX. CONCLUSION

Based on the experimental results and discussion, the following conclusions are drawn:

- The contours obtained from graph segmentation are relevant to the true edges of the image.
- The algorithm captures perceptually important regions. In our approach, we’vecomparedthe segmented results are with the input image as well as ground truth data.
- The execution time after the image is preprocessed by the respective wavelets. From the table it is very tough to suggest which of the approaches is more preferable as the time differences is only of a few milliseconds. However, it is found that time taken for graph segmentation after DWT2 using Haar wavelets required less time for almost all the mentioned images.
- The comparative study from the Table 2 shows that all the wavelet images performed in nearly an equal conduct as long as PR is concerned. The PR of DB2 is, however, found to be better when the comparison is done based on the bar graphs and is closely followed by DB6.
- The precision and recall of each wavelet are calculated and presented in the Table 4 and Table 5. By observing the results, we found that precision of DB2 and Haar wavelets are comparatively higher. The recall of DB6 is minimum, closely followed by DB4 and DB2.

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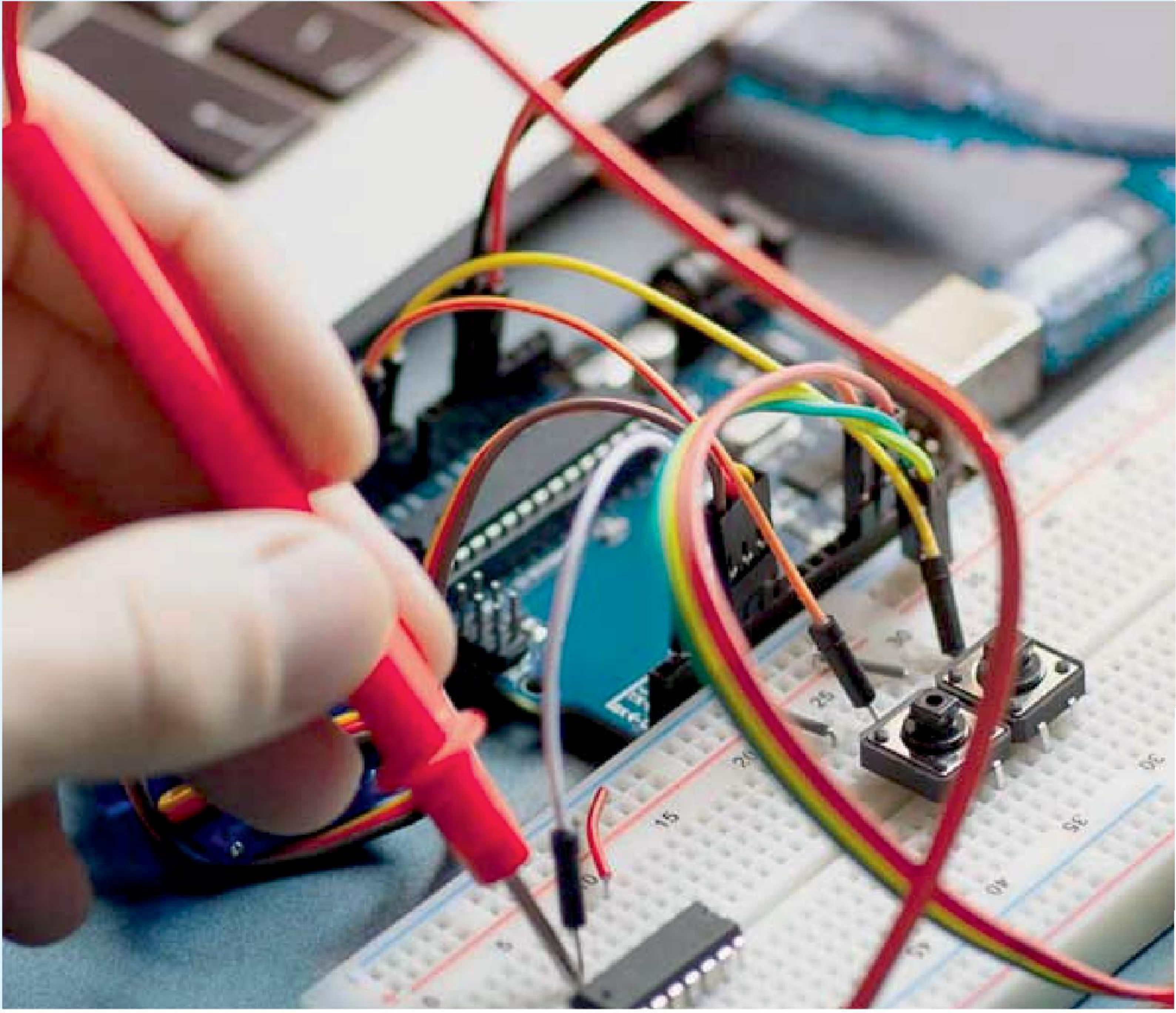


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