SEGMENTATION THROUGH DWT AND ADAPTIVE MORPHOLOGICAL CLOSING

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ABSTRACT

Object segmentation is an essential task in computer vision and object recognitions. In this paper, we present an image segmentation technique that extract edge information from wavelet coefficients and uses mathematical morphology to segment the image. We threshold the image to get its binary version and get a high-pass image by the inverse DWT of its high frequency subbands from the wavelet domain. This is followed by an *adaptive* morphological closing operation that dynamically adjusts the structuring element according to the local orientation of edges. The ensued holes are, subsequently, filled by a morphological fill operation. For comparison, we are relying on the well-established Canny's method and show that, for images with low-textured background, our method performs better.

1. INTRODUCTION

Image segmentation is the process of partitioning a digital image into multiple regions or sets of pixels [11]. These partitions represent different objects in the image, usually having the same texture or color. Segmentation is quintessential to image feature extraction and subsequent classification of the resultant features. As a central step in computer vision and image understanding, image segmentation has been extensively investigated in the literature. We have different categories of image segmentation techniques like amplitude thresholding, component labeling, boundary based segmentation, template matching and texture segmentation. Image segmentation also involves techniques like image enhancement, restoration and simple representation of data. However, we still lack reliable ways in performance evaluation for quantitatively positioning the state of the art of image segmentation.

The edges are normally concentrated in the high frequency components of the image. Thus if we can extract high frequencies from the image then we can get edge information of that image. Wavelet domain provides frequency information that is mappable in localization in the corresponding spatial domain, leading us to believe that high frequency details pertain to high pass information. In this paper, we extract the edge details of an image by employing the discrete wavelet transform (DWT). This is followed by the application of adaptive morphological closing that adjusts the structuring element according to the local orientation of edges in the image.

The rest of the paper is arranged as follows. Section 2 briefly describes the state of of the art. We elaborate our method in Section 3 followed by the analysis of results in Section 4. The paper is concluded in Section 5.

2. RELATED WORK

Most of the contemporary works are focused on finding the methods to measure the accuracy/error of the segmentation. Some of them do not require the ground truth image segmentation and in these methods, the segmentation performance is usually measured by some contextual and perceptual properties, such as homogeneity within the resulting segments and the heterogeneity across neighboring segments. Image segmentation and grouping have always been great challenging problems in computer vision. It has been known that perceptual grouping plays a powerful role in human visual perception. A wide range of computational vision problems could, in principle, make good use of segmented images, were such segmentations reliably and efficiently computable.

Currently, powerful segmentation techniques are available in the literature. In [1, 10] several techniques are cited for edge detection and segmentation. These include spatial domain filters like Sobel, Prewitt, Kiresh, Laplacian, Canny, Roberts and Edge Maximization (EMT) which have been extensively employed for edge detection and image segmentation. During segmentation, sometimes, the image is subdivided to read the objects from background and for this purpose two techniques are mainly employed, namely the discontinuity detection technique and the similarity detection technique. In the first technique, the image is partitioned on the basis of abrupt changes in gray level, whereas the second technique is based on thresholding and region growing [11, 1]. In [3], image segmentation is performed through mathematical morphology. The segmentation is based on the watershed transformation followed by region merging with the procedure being formalized as basin morphology, where regions are eroded, in order to form greater catchment basins. An automated color segmentation procedure, designed for polar color spaces based on morphological operators is also given. In [5], a predicate for measuring the evidence for a boundary between two regions, using a graph-based representation of the image, is defined. The authors have developed a greedy image segmentation algorithm wherein decisions are made using two different kinds of local neighborhoods in constructing the underlying graph. This method has the ability to preserve the details in low variability image regions and ignores the detail of high variability regions.

Pun and Zhu [7] propose an approach for image segmentation that uses adaptive tree-structured wavelet transform for texture analysis. They first split the input image into $N \times N$ blocks and then calculate the distances between neighboring blocks by the energy signatures of the coefficients of the adaptive tree-structured wavelet transform of each block. Thereafter, they merge blocks with smallest distances to form larger regions. The process is repeated till the desired number of regions are extracted. An objective evaluation of two popular segmentation techniques, viz. water-shed segmentation and mean-shift segmentation, has been carried out in [9]. They used a hybrid variant that combines these algorithms. They have analyzed the correctness and consistency of these techniques with wide range of parameters and images. A computational efficient approach is proposed, in [8], on the basis of texture analysis wherein a 2D discrete cosine transform (DCT) is utilized to extract texture features in each image block. They first split the input image into $M \times N$ blocks, and then the distance between neighboring blocks is calculated by using a set of largest energy signatures from DCT for each block. These blocks are thereafter merged with smallest distance to form a large region. The process is repeated until the desired number of regions are obtained. In [9] a watershed transform computes the catchments basins and ridge lines, with the former corresponding to image regions while the latter relating to region boundaries.

The well-known Canny's algorithm [4] uses two thresholds to minimize the error rate by a process popularly known as hysteresis. But before that, it smoothens the image, and uses the gradiant and local angles to get the preliminary edge details [11, 1]. Shape based object segmentation has been cited in [6] where Bayesian model is used to estimate the object shape on the basis of prior knowledge about the shape and thus provides a methodology that uses some prior knowledge about the shape. In the method cited in [12], the image is divided into two regions on the basis of focus values - focused area is considered to be the object and defocused part is taken as the background.

None of the segmentation techniques, discussed in the literature, can be generalized to applicable to any type of segmentation problem. A given technique may be suited for some scenarios but may tend to over- or under-segment in many others. Specially, when it comes to images with low-textured background, even powerful techniques, like Canny, may under-segment on objects' outer boundaries and may well over-segment on boundaries interior to objects. The next section attempt to deal with such low-textured images.

3. THE PROPOSED METHOD

The edges normally concentrate in the high frequency components of the image. Hence if we can extract high frequencies from the image then we can get its edge information. Wavelet domain provides frequency information that is mappable in localization in the corresponding spatial domain, leading us to believe that high frequency details pertain to high pass information. Our proposed method extracts edge information using the DWT and performs the following steps to segment the image, as illustrated in the form of the diagram shown in Fig. 1:

1. The input image is first preprocessed by using level setting and normalize the image by using 10% black and 90% white on the basis of expansion limit of 130 gray value in order to highlight the edge information in the image.
2. A high-pass image, extracted from the wavelet domain, has low signal to noise ratio and only strong edges may be extractable leading to high probability of broken edges. To extract a good subset of edges, we first convert the image into its binary form by using a threshold T.

```
Input: High pass connected M × N binary image (I)
Output: An image (I′) with minimum boundary
        distortion in objects
begin
  initialize SE ⟵ {H,V,I,D,F} /* The four
      SE's given in Fig. 2 plus a
      flat SE, F, with all 1's      */
  for i ← 2 to M − l do
    for j ← 2 to N − l do
      if I[i+1,j+1] = 1 and I[i-1,j-1] = 1 then
        se ⟵ H

      else if I[i-1,j+1]=1 and I[i+1,j-1]=1 then
        se ⟵ V

      else if I[i+1,j] = 1 and I[i-1,j] = 1 then
        se ⟵ I

      else if I[i,j+1] = 1 and I[i,j-1] = 1 then
        se ⟵ D

      else
        se ⟵ F
      end
      apply morphological close at I[i,j] with se
    end
  end
end
```

Algorithm 1: adaptive_close

3. The image is decomposed into wavelet domain by using DWT in order to extract the edge information contained in the original image.
4. The wavelet decomposed image is subjected to inverse DWT after setting the approximation coefficients, i.e. the lowest energy subband, to zero. The resultant image may contain a good deal of the edge information of the input image.
5. The edges obtained after the preceding step may still have gaps corresponding to the original. In this step**,** we try to complete these edges on the basis of 8-connected neighbors.
6. To remove the boundary distortion, a morphological close operation is applied, as elaborated in Algorithm 1. The process is *adaptive* in the sense that the structuring element (SE) is adjusted dynamically according to the situation. The SE's, as shown in Fig. 2 8-neighbor case, are adapted on the basis of direction of the edges corresponding to a in 3×3 window. When all the elements are 1's in 3×3 one of the given SE's is adapted but if there is conflict between vertical , horizontal or two diagonal SE's then the adaptation is carried out on the basis of 16-connected neighbors in order to remove the ambiguity of the edge direction.
7. Use of adaptive morphological closing operation enables us to extract the object boundaries with least distortion. To extract the object, a morphological filling operation is performed to fill holes in the image.
8. In the last step, the objects' boundaries are extracted by using morphological boundary extraction operation.

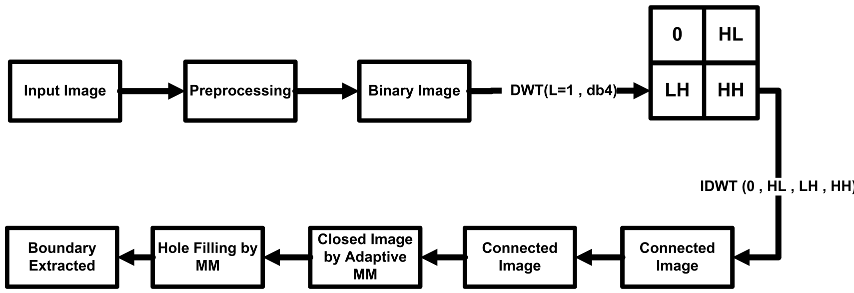


Figure 1: **Overview of the** Proposed Method.

$$\begin{bmatrix}0&0&0\\1&1&1\\0&0&0\end{bmatrix} \quad \begin{bmatrix}0&1&0\\0&1&0\\0&1&0\end{bmatrix} \quad \begin{bmatrix}1&0&0\\0&1&0\\0&0&1\end{bmatrix} \quad \begin{bmatrix}0&0&1\\0&1&0\\1&0&0\end{bmatrix}$$

(a) H (b) V (c) I (d) D

Figure 2: Structuring Elements used.

By applying the above procedure, we believe, a good deal of segmentation can be realized. This may specially be beneficial in those cases where established methods, like Canny's, may have a tendency of over-segmentation.

4. EXPERIMENTAL RESULTS

We have applied our method to a number of images, from an online database [2], with varying object sizes and shapes in mind. Due to space limitation we are dwelling on few of these examples with the detailed discussion being focused on the input image given in Fig. 3(a). The said image results, by our method of segmentation, in the image given in Fig. 3(b). We compare our results with the results obtained from the Canny's method, as illustrated in Fig. 3(c). A comparison of Fig. 3(b) and (c) suggests that in the latter the edges are incomplete. These incomplete portions are highlighted by the red circles drawn in the figure. Our proposed method results in a more complete edge information, as shown in Fig. 3(b). Fig. 4 illustrates the stepwise application of our method to Fig. 3(a) wherein the input image is preprocessed to highlight the object. The preprocessed image is converted into its binary form by setting a certain threshold T that will remove the irrelevant details from the preprocessed image leading to the highlighting of boundaries. The binary image is shown in Fig. 4(b). Afterwards, the high frequency details of the image are filtered out in the wavelet domain resulting in the image shown in Fig.Fig:proposed(c). Fig.Fig:proposed(d) shows the image after connecting the broken edges by using 8-connected neighbors. Some distortion on the boundary is seen due to this operation. To remove the artifacts generated by the aforementioned 8-connected neighbor operation, we use adaptive morphological closing and the resultant image is shown in Fig. 4(e). As the image shown in Fig. 4(e) has complete edges and the holes are present in the image interior, a morphological hole filling is applied to get the image shown in Fig. 4(f). The object in the image can be identified exclusively by the pixels set to 1 and the background has the reset pixels, i.e. binary zeros. Subsequent application of morphological boundary extraction yields what is shown in Fig. 3(b).

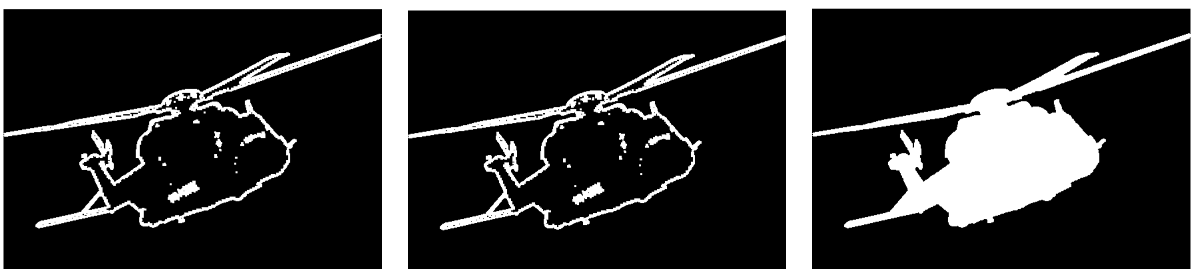
It is pertinent to note that, without adaptation of the SE, our technique may not fair badly for larger objects and for objects with low background texture. Partitioning the image by a grid, to extract the local structure, works well for large segments but tiny sized objects may not be optimally segmented, especially for overlapped objects. To avoid this we extract the local structure at a 3×3 window, using an adaptive SE, to improve the segmentation results for smaller objects. An adaptive SE, thus, depends on the size of the cell in the grid. For the image, shown in Fig. 3(a), we have an object large enough to allow the grid to partition the image into small portions and thus provide better adaptability of the SE. Note that a 3×3 SE is the smallest optimal grid cell size that can work well for almost all object sizes. Another problem may arise with the images having objects with complex background, which may cause the DWT to interpret, as edge, erroneous information from the background and thus disturb the actual object segmentation. Another example is taken in Fig. 5, where Fig. 5(a) illustrates the original. For the sake of comparison we are zooming in one of the object. In Fig. 5(b) it is seen that our method provides better recognition description than produced by Canny's method in Fig. 5(c). In the said example, the object is an aeroplane and the Canny's method gives an *occluded* object data and it is a well-established fact that occlusion reduces the recognition capability. On the other hand, our method provides better information and good image descriptor information. It can be readily seen from Fig. 5(b) and Fig. 5(c), especially in those parts which are marked with red circles; these are the boundary points where image descriptors are clearly defined by our method. With the example, given in Fig. 6, our results are a bit dilated but we believe that the center of gravities of the objects are intact.

We are taking a case of two objects, as given in Fig. 7, from the online database [2]. The resultant segmented image, by our method, is shown in Fig. 7(b). The tendency of Canny's method to over-segment is observable in Fig. 7 (c), where the smaller object has many unnecessary details. Our method, in contrast, avoid any such tendency. For the sake of comparison, we are also including, from the said database, three instances of segmentation based on manual inspection by three different humans. When these three manually segmented images were multiplied with our resultant image of Fig. 7(b), we got the results shown in Fig. 7(d-f). Multiplication was carried out to check the deviation of edges by our method and the results were very interesting as compared to

(a) Input image (b) **Segmentation** by our proposed method (c) **Segmentation** by Canny method

Figure 3: Helicopter image.

(a) Image after Preprocessing (b) Binary image (c) High Pass Image



(d) Connected image (e) Image after applying adaptive MM closing (f) Image after hole filling

Figure 4: Example Stepwise Application of the Proposed Algorithm.

(a) Input image (b) By our Proposed method (c) By Canny method

Figure 5: Two object image

other state of the art segmentation methods.

5. CONCLUSIONS

We presented an image segmentation technique that extracts edge information from wavelet coefficients and uses mathematical morphology to segment the image. The method is intelligent in the sense that the SE selection is adaptive. The results have been interesting and it can be observed that with our method one may get a more complete and closed boundary as compared to the Canny's method. Although Canny's method is well-established, it usually ignores weak edges that may play an important role in some object segmentation scenarios. We have not paid much attention to images with complex backgrounds in this present work but our future work focuses in this direction.

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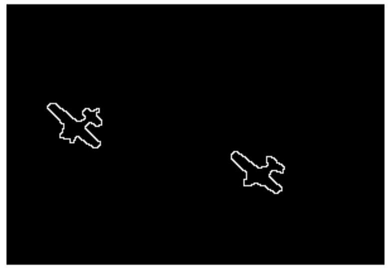
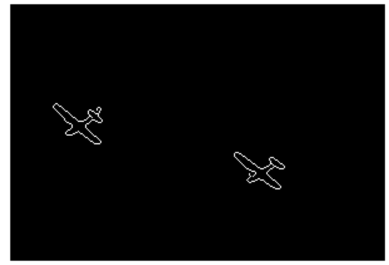
(a) Input image

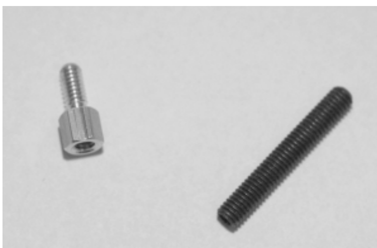


(b) Segmented image

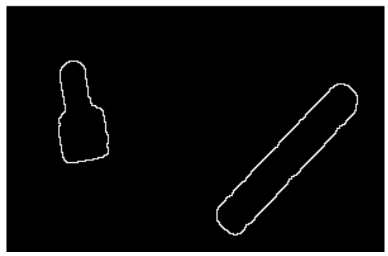


(c) By Canny method

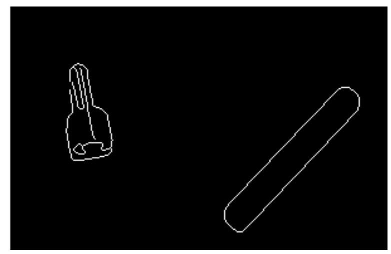
Figure 6: Two planes image.



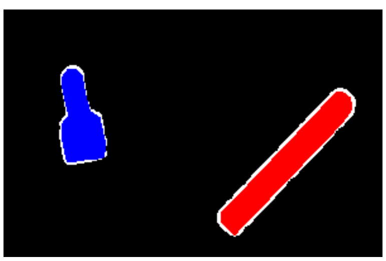
(a) Input image



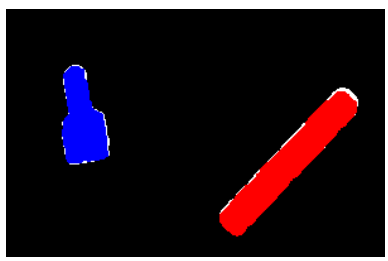
(b) By our Proposed method



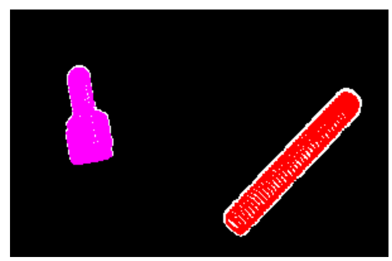
(c) By Canny method



(d) Segmentation by subject 1



(e) Segmentation by subject 2



(f) Segmentation by subject 3

Figure 7: Screws image

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