A Heuristic Wavelet Based Feature Detection Method for Image Segmentation and Region Growing

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Abstract: The first step in image analysis is image segmentation. Image segmentation decomposes an image to different parts, since image segmentation is used in various applications such as tracking and machine vision. The segmentation accuracy is an important factor of image segmentation. Various Wavelet Transform based on image segmentation methods are introduced to achieve these goals in image segmentation. In this paper a new segmentation method based on wavelet transform for image edge detection and the edge information have been used. This includes seed selection in an image segmentation method based on region growing. In the last step the region merging is used to achieve the higher performance in image segmentation. Proposed simulations result indicate the higher performance compared with other image segmentation methods.

Key words: Image segmentation, Wavelet transform, Region growing, Edge detection

INTRODUCTION

Image segmentation, which is defined as partitioning an image into homogeneous regions, is regarded as an analytic image representation method. It has been very important in many computer-vision and image-processing application (Derakhshan, et al 2007). The example of applications of segmentation can mention to detect of hand writing, detect of face emotion also medical applications such as partitioning various body textures, Computer-Aided Surgery and industrial applications and machine-vision such as farming products capsule, traffic intelligent control and etc.

At present, various techniques and algorithms have been proposed for image segmentation, which can be classed into three categories: thresholding, edge detection and region extraction. Threshhold segmentation techniques, which based on the assumption that adjacent pixels belong to the same region if their value (such as grey value, color value, texture, etc) lie within a certain range (Behrad, et al., 2007). In this technique the action of segmentation is very well, when we have two opposed type. However many relevant improvements to solve the thresholding problem have been developed (Sahoo, et al., 1998; Pal and Pal, 1993) and (Abutaleb, 1989). Edge detection is designed to detect edge boundaries of various regions by normally trying to locate points of abrupt change in intensity values (Palmer, 1996; Wei-Ying Ma and Manjunath, 2000). Since edge authentication is a very important task, a variety of edge operators can be used (e.g. Sobel, Prewitt, Canny, etc). Although, since not all edges produced by these operators are relevant, post processing is still required to identify significant edges (Wenzhan and Kangtai, 2007; Ji wenhua, et al., 2003; Bellon, 1999). Region extraction groups pixels into a set of regions based on similarity. The region growing is one important of this method (Hijjatoleslami and Kittler, 1998). One of the important problem in region growing selected appropriate seed and criteria growing that must be automatic (Adams and Bischof, 1994; Robert et al., 2002). Indeed, most segmentation techniques are based on this three categories.

We can used hybrid approach to improve segmentation. One of the main methods in segmentation are used of edge information and region growing that cased accurate regions in segmentation. The algorithms that presented in this manner differed in seed select and criteria growing and edge detection (Fan et al., 2010; Pavlidis and Liow, 1990; Chu and Aggarwal, 1993). One of the main this algorithms is watershed transform algorithm. That use of gradient of the image the local minimum and image edge to be detect. In this style local minimum points select as seed and growing to edges (Wenzhan and Kangtai, 2007).

As speed and optimisation in image segmentation are very important and above methods cause over-segmentation and high processing and merging time, recently the mentioned multiresolutions by wavelet transform in image segmentation are used (Mallat, 1989; Cao, 2002; Kim, Kim, 2003; Byung-Gyu Kim, 2003).
In this paper, we used hybrid methods for segmentation by edge information and region growing. Also, a main problem in region growing is selection of optimum seed. Bad selection causes over-segmentation. To alleviate this problem and better segmentation edge information can be used. Also in this paper, we present a novel wavelet based edge detection method. Hence, edge information for selecting of optimum seed in region growing is used. The experimental results show that our method is an effective image segmentation algorithm.

This paper is organized as follows: We describe multi-resolution analysis (MRA) and a wavelets transform in section 2. In section 3 explains a novel edge detection of image by wavelet transform. Section 4 deals with using these edge informations to optimum region growing algorithm. Section 5 and 6 are merging algorithm and evaluation criteria. Conclusions are presented in section 6.

Multi-resolution Analysis (MRA) and Wavelets Transform:

Multi-resolution analysis (MRA) is often used for signal representations and signal processing because it can represent signals at the split resolution and scale space. In multi-resolution analysis, a signal is viewed at various levels of approximations or resolutions. A complicated signal is divided into several simpler signals by applying MRA, and each signal is considered separately.

From the viewpoint of signal spaces, the multiresolution spaces can be represented as the following relations:

\[ A_m \cap W_m = \{0\}, \quad m \in \mathbb{Z}, \]  \hspace{1cm} (1)

\[ A_{m+1} \oplus W_{m+1} = A_m \] \hspace{1cm} (2)

where \( m \) denotes the index of scales or resolutions. For each \( m \), \( A_{m+1} \) is a proper subspace of \( A_m \) and there is some space left in \( A_m \) called \( W_{m+1} \), which when combined with \( A_{m+1} \) gives \( A_m \).

With the condition Eq. (1), the summation in Eq. (2) is referred as direct sum and decomposition in Eq. (2) as a direct-sum decomposition in (Goswami and Chan, 1999). The following relations satisfied by Eq. (2):

\[ A_{m+1} = A_{m+2} \oplus W_{m+2} = W_{m+2} \oplus W_{m+3} \oplus A_{m+3} \]

\[ = W_{m+2} \oplus W_{m+3} \oplus W_{m+4} \oplus \cdots. \] \hspace{1cm} (3)

Fig. 1 shows a diagram representation of the hierarchical nature of \( A_m \) and \( W_m \) as the above relationships.

![Fig 1: Subspaces in MRA.](image)

In wavelets theory, subspaces \( \{W_m\} \) are generated by \( \psi(t) \in L^2_\mathbb{R} \), called the wavelets. Subspaces \( \{A_m\} \) are
generated by \( \phi(t) \in L^2(R) \), called a scaling function, in the same way. The trend of a given signal is approximated by the scaling function and the detailed fluctuation is extracted by the wavelets signal. Thus, the transformed signals in subspaces \( \{A_m\} \) are approximations of the original and those in \( \{W_m\} \) are the details of that. The transformed signals can be perfectly converted to the original signals. Therefore, with wavelet transform of the original image with low resolution get in LL sub level that they are approximation low frequency image. Figure(2) shows the result of two level wavelet transform on Lena image.

![Figure 2](image)

**Fig 2**: a Original image and b Two level of wavelet transform

**Edge Detection by Wavelet Transform:**

Two dimensional wavelet transform applied on the image causes separate component at frequency image domain. So all the low frequency component will be located at LL band. Although, all the edges that exist in the image are known as low frequency image component. Hence these edges will be located at LL band after giving wavelet transform. Hence these edges will be detected by using this capability.

For detecting edges, first wavelet transform will applied, second all the LL sublevels set zero. Third, upon the result image the inverse wavelet transform will applied. As all the resultant numbers are positive and negative, with calculating absolute of them and transferring numbers from 0 to 255. At the end the thresholding will do to detecting edges in binary format. In fig(3), a sample image with result have been shown.

**Suggest Algorithm:**

Region growing algorithm is supposed that initial seed is known, then algorithm searches the pixels that are adjacent to seed pixel and homogeneous with seed pixel. If adjacent pixel is homogeneous, this pixel becomes the new seed pixel. Then keep searching based on above principle, until it forms a new region. Each pixel is connective at horizontal and vertical and four diagonal directions. We demonstrate the definition of eight connectivity region in figure 4.

If \( f(i,j) \) to be initial seed, eight point near it declare this:

- \( M_u = f(i,j-1) \)
- \( M_r = f(i+1,j) \)
- \( M_d = f(i,j+1) \)
- \( M_l = f(i-1,j) \)
- \( M_{ur} = f(i+1,j-1) \)
- \( M_{rd} = f(i+1,j+1) \)
- \( M_{dl} = f(i-1,j+1) \)
- \( M_{lu} = f(i-1,j-1) \)

Point growing algorithm based on stack, basis flow as follow.

- Set homogeneous characteristics parameter and threshold, set the initial seed;
- Push seed pixel into the stack;
- While the stack is not null, pull a pixel on the top of stack out of stack, at the same time, set this pixel visited; if stack is null, algorithm is over;
- For every pixel that is eight connectivity with current pixel and that has not been visited and that is homogeneous with current pixel, put them into the stack;
- Goto (3);
In this algorithm, we search row by row until that pixels that don’t visit get to next seed. Set \( f(i, j) \) as the grey value of \((i, j)\) point in \(m \times n\) image, there are \(m\) grey level. Suppose value of \(f(i, j)\) between 0 and \(m - 1\).

Thus, the average grey value of image can be defined as:

\[
E(f) = \frac{1}{MN} \sum_{i=0}^{M-1} \sum_{j=0}^{N-1} f(i, j) \tag{4}
\]

The grey variance can be defined as:

\[
D(f) = \frac{1}{MN} \sum_{i=0}^{M-1} \sum_{j=0}^{N-1} \left[ f(i, j) - E(f) \right]^2 \tag{5}
\]

The average grey variance can be defined as:

\[
\sigma = \sqrt{D(f)} \tag{6}
\]
The best amount of threshold using for simulating measure is \( T = \beta \alpha \). Here, we set \( \beta = 0.5 \). If the difference between amount of neighbouring seed became lower than \( T \), we can categories those seed as one area. Actually, the amount of \( M_0 \), \( M_1 \),... have been calculated separately and whether those amount became lower than \( T \), the point will send to stack.

One of the important point in selecting seed is nonlocating seed on edge. If the one of seed locate on any edge of image the segmentation will not be work well, because the measure of evaluation is the amount of \( T \) in the above method. Because of selecting seed randomly, we can select the seeds from all the pixels that is located on edges. So far working this algorithm well, we can use the information that is approached from edges. We can use the point as a seed that are not located on edges also we should check the simulating measure and be careful of crossing edge. Here with having these, the neighbouring point of seeds will be send to the transferring data stack.

In section three detecting the location of edges has been described and in fig(5) the result of segmentation for three sample image have been shown.

**Region Merging:**

Generally, when an image is degraded by noise, it becomes over-segmented. Therefore, over-segmented images may require further merging of some regions. The region merging process is formulated as a graph-based clustering problem. A graph \( G \) is used to represent the information upon which the region merging process is based. In Fig. 6, each node in \( G \) represents one of the segmented regions in the set \( I = \{ R_1, R_2, ..., R_K \} \). Each edge of \( G \) corresponds to a sum of the moment values (mv), which can be used to compare the mv of adjacent regions. Our decision on which regions to merge is determined through homogeneity and similarity criteria based on the wavelet coefficients. Each of the segmented regions will have mean, second- and third-order central moment values of the wavelet coefficients calculated. All the features are computed on a LL decomposed subband of a wavelet transform. For each region \( R_i \) of the segmented image \( S_i(k) \) of the image segmentation phase, we calculate the mean \( (M) \), second- \( (\mu_2) \) and third-order \( (\mu_3) \) central moments of the region as (Kim et al., 2001).

![Fig. 5: results of the image segmentation. a the original image, b region growing and c suggested algorithm.](image-url)
Fig. 6: Region adjacency graph: a segmented regions have a similar value, b segmented region adjacency graph.

\[
M = \frac{1}{\text{num}(R_i)} \sum \sum R_i(x,y) \quad \forall x, y \in R_i
\]

\[
\mu_2 = \frac{1}{\text{num}(R_i)} \sum \sum (R_i(x,y) - M)^2
\]

\[
\mu_3 = \frac{1}{\text{num}(R_i)} \sum \sum (R_i(x,y) - M)^3
\]

(7)

where \(\text{num}(R_i)\) is the number of pixels of segmented region \(i\). To merge the segmented regions using similarity criteria \((d)\), we can use the following equation:

\[
\text{mv}_i = \frac{1}{N} (R(M_i) + R(\mu_{s_i}) + R(\mu_{s_j}))
\]

\[
d(R_i, R_j) = (\text{mv}_i - \text{mv}_j)^2
\]

\(\forall i, j \in \{1, \ldots, N, \text{for } i \neq j\}\)

(8)

where \(\text{mv}_i\) is the similarity value of segmented region \(i\) and \(N\) is the number of segmented regions \(R(m)\), \(R(\mu_s)\) and \(R(\mu_t)\) are the mean, second- and third-order moment values of the segmented region, respectively.

If the \(\text{mv}\) values of the adjacent regions satisfy a specified value, two adjacent regions will be merged. The specified values are found by the experiment.

**Evaluation of objective segmentation performance:**

We evaluated the segmentation results of the presented method. We used two common objective measurements: the number of segmented regions and Goodness. The Goodness function \(F\) is defined by (Liu and Yang, 1994)
\[ F(I) = \sqrt{M} \times \sum_{i=1}^{M} \frac{e_i^2}{\sqrt{A_i}} \] (9)

where I is the image to be segmented, M is the number of regions in the segmented image, \( A_i \) is the area or ith region number of pixels and \( e_i \) is the sum of the Euclidean distance of the color vectors between the original image and the segmented image of each pixel in the region. Eq. (6) is composed of two terms: the first term, \( \sqrt{M} \), penalizes segmentation that forms too many regions; the second penalizes segmentations containing nonhomogeneous regions. A larger value of \( e_i \) indicates that the feature of the region was not well segmented during the image segmentation process.

Table 1 shows the segmentation results of a number of segmented regions, Goodness (F) for two styles segmentation (region growing and suggested algorithm). In first column show results of a number of segmented regions and second column the Goodness(f). the test images are images of fig5. Observed from result that our algorithm segment an image to a lower regions and in a some state the value of Goodness is lower that this indicate our algorithm segment an image to a very better.

<table>
<thead>
<tr>
<th>Goodness</th>
<th>Number of region</th>
<th>The test images</th>
</tr>
</thead>
<tbody>
<tr>
<td>2225-1</td>
<td>240-1</td>
<td>a</td>
</tr>
<tr>
<td>765-2</td>
<td>125-2</td>
<td></td>
</tr>
<tr>
<td>1965-1</td>
<td>257-1</td>
<td>b</td>
</tr>
<tr>
<td>857-2</td>
<td>143-2</td>
<td></td>
</tr>
<tr>
<td>1950-1</td>
<td>209-1</td>
<td>c</td>
</tr>
<tr>
<td>831-2</td>
<td>108-2</td>
<td></td>
</tr>
</tbody>
</table>

Conclusions:
In this paper, we described a novel edge detection by wavelet transform and then we used the edge information in order to select the optimum seed and growing criteria for region growing. In the algorithm the region merging is used to achieve the higher performance in image segmentation. Proposed simulations result indicate the higher performance compared with other image segmentation methods. The experimental results show that our algorithm is better in segmentation.

REFERENCES


