IMAGE SEGMENTATION USING MULTIWAVELET TRANSFORM

Manal Fadel Younis Computer Engineering Department Baghdad University

ABSTRACT

This paper presents region growing image segmentation method which unifies region and boundary information. Several studies shown that segmentation based on image features can improve the accuracy of the interpretation. The goal of segmentation is to simplify and/or change the representation of an image into something that is more meaningful and easier to analyze. Image segmentation is typically used to locate objects and boundaries (lines, curves, etc.) in images. More precisely, image segmentation is the process of assigning a label to every pixel in an image such that pixels with the same label share certain visual characteristics.

A problem that frequently arises when an image is segmented is that the number of feature variables or dimensionality is often quite large. It becomes necessary to decrease the number of the variables to manageable size. The other main difficulty of traditional image segmentation is the lack of adequate tools to characterize different scales of image effective. In this paper it proposed three dimension multiwavelet algorithm to overcome this difficulty and then the region growing method is applied to segment this image.

الخلاصه

في هذا البحث تم تقديم طريقة لتقسيم صورة معتمدة على نمو المناطق التي توحد مناطق وحدود المعلومات. حيث هناك در اسات عديدة بينت انه التقسيم الذي يعتمد على خصائص الصورة يستطيع ان يحسن في دقة التفسير. الهدف من التقسيم هو تبسيط و تغيير تمثيل الصورة بشكل اكثر مفيد واسهل بالتحليل. تقسيم الصورة نموذجيا يستخدم في تحديد الأشياء والحدود (الخطوط، المنحنيات،...الخ) في الصور. وبتوضيح أدق، تقسيم الصورة هو عملية تحديد الصفة لكل نقطة في الصورة لذلك النقاط بنفس الصفات تشترك بخصائص محددة و مرئية.

المشكلة التي تظهر دائما عند تقسيم الصورة هي عدد متغيرات الخصائص او الابعاد عادة تكون كبيرة جدا. فمن الضروري تقليل عدد المتغيرات الى حجم معقول. ومشكلة صعبة اخرى هي التقسيم العادي للصورة يحتاج الى ادوات وافية للحاجة لتخصيص مقايسس مختلفة ذات تاثير على الصورة.

في هذا البحث تم اقتراح طريقة متعدد الموجات ذات ثلاثية البعد (3D-Multiwavelet) لتجاوز هذه المشاكل وثم تطبيق طريقة نمو المناطق لتقسيم الصورة.

KEYWORDS: Image Segmentation, 3-D Multiwavelet, Symmetry, Orthogonality, Region growing methods, and Seed point.

INTRODUCTION

Image segmentation is important research area in computer vision. Several segmentation methods are based on two basic properties of the pixels in relation to their local neighborhood: discontinuity and similarity. Method based on pixel discontinuity is called boundary-based methods whereas methods based on pixel similarity are called region-based methods [Pajdla 2004].

Several image segmentation algorithms have been proposed in the last 30 years. In this research related work are listed below:

"Testing of Image Segmentation Methods"

In this paper, an approach is developed which allows quantitative and qualitative estimation of segmentation programs. It consists in modeling both difficult and typical situations in image segmentation tasks using special sets of artificial test images. The description of test images and testing procedures are given [GRIBKOV 2008].

"Multi-class image segmentation using Conditional Random Fields and Global Classification" A key aspect of semantic image segmentation is to integrate local and global features for the prediction of local segment labels. An approach is presented to multi-class segmentation which combines two methods for this integration: a Conditional Random Field (CRF) which couples to local image features and an image classification method which considers global features [Plath 2009].

"VARIATIONAL APPROACH TO IMAGE SEGMENTATION"

This paper focuses on a second order functional depending on free discontinuity and free gradientdiscontinuity, whose minimizers provide a variational solution to contour detection problem in image segmentation [Carriero 2009].

"Optimization-Based Image Segmentation by Genetic Algorithms"

Many works in the literature focus on the definition of evaluation metrics and criteria that enable to quantify the performance of an image processing algorithm. These evaluation criteria can be used to define new image processing algorithms by optimizing them. In this paper, general scheme it proposed to segment images by a genetic algorithm. The developed method uses an evaluation criterion which quantifies the quality of an image segmentation result. The proposed segmentation method can integrate a local ground truth when it is available in order to set the desired level of precision of the final result [Chabrier 2008].

"Image Segmentation by Branch-and-Mincut"

The main contribution of this paper is a new global optimization framework for a wide class of such energies. The framework is built upon two powerful techniques: graph cut and branch-and-bound. These techniques are unified through the derivation of lower bounds on the energies. Being computable via graph cut, these bounds are used to prune branches within a branch-and-bound search [Victor 2008].

"Image Segmentation Method Using Thresholds Automatically Determined from Picture Contents"

This work develops an image segmentation method based on the modified edge-following scheme where different thresholds are automatically determined according to areas with varied contents in a picture, thus yielding suitable segmentation results in different areas [Yuan 2009].

"Non-Parametric Probabilistic Image Segmentation"

The proposed model is principled, provides both hard and probabilistic cluster assignments, as well as the ability to naturally incorporate prior knowledge. While previous probabilistic approaches are restricted to parametric models of clusters (e.g., Gaussians) it eliminates this limitation. The suggested approach does not make heavy assumptions on the shape of the clusters and can thus handle complex structures. Our experiments show that the suggested approach outperforms previous work on a variety of image segmentation tasks [Andreetto 2007].

"Semi-automatic Handwritten Word Segmentation Based on Character Width via Maximum Likelihood Method and Model" Approximation Regression This paper presents a method of word image segmentation into images of individual characters. The method is semi-automatic; because it requires that the character sequence constituting the word on the image is know. It is assumed that widths of the characters in the alphabet are random variables and that the parameters of probability distribution are specific for each character [Springer 2008].

"Unsupervised Segmentation of Natural Images via Lossy Data Compression"

We cast natural-image segmentation as a problem of clustering texture features as multivariate mixed data. We model the distribution of the texture features using a mixture of Gaussian distributions. Unlike most existing clustering methods, we allow the mixture components to be degenerate or nearly-degenerate. We contend that this assumption is particularly important for midlevel image segmentation, where degeneracy is typically introduced by using a common feature representation for different textures in an image. We show that such a mixture distribution can be effectively segmented by a simple agglomerative clustering algorithm derived from a lossy data compression approach. Using either 2D texture filter banks or simple fixed-size windows as texture features, the algorithm effectively segments an image by minimizing the overall coding length of the feature vectors. We conduct comprehensive experiments to measure the performance of the algorithm in terms of visual evaluation and a variety of quantitative indices for image segmentation. The algorithm compares favorably against other well-known image segmentation methods on the Berkeley image database [Hong 2007].

"A Variational Level Set Approach to Segmentation and Bias Correction of Images with Intensity In homogeneity"

This paper presents a variational level set approach to joint segmentation and bias correction of images with intensity inhomogeneity. Our method is based on an observation that intensities in a relatively small local region are separable, despite of the inseparability of the intensities in the whole image caused by the intensity in homogeneity [Chunming 2008].

THE PROPOSED METHOD OF SEGMENTATION:

Image segmentation is a set of segments that collectively cover the entire image, or a set of contours extracted from the image. Each of the pixels in a region is similar with respect to some characteristic or computed property, such as color, intensity, or texture. Adjacent regions are significantly different with respect to the same characteristic(s) [Linda 2001].

Applications some of the practical applications of image segmentation are [Wikipedia 2009]:

- Medical Imaging
 - Locate tumors and other pathologies
 - Measure tissue volumes
 - Computer-guided surgery
 - Diagnosis
 - Treatment planning
 - Study of anatomical structure
- Locate objects in satellite images (roads, forests, etc.)
- Face recognition
- Fingerprint recognition
- Traffic control systems
- Brake light detection
- Machine vision

The proposed image segmentation is shown below in fig. (1):



Fig. (1): The diagram of the proposed method

<u>3-D Multiwavelet Transform:</u>

In this paper, the proposed an approach is 3-D multiwavelet transformation as an image extraction tool for segmenting images.

The general form for the procedure of 3-D FDMWT [Hadeel 2005]:-

The algorithm is initially run in x-direction, row by row for all slices. The algorithm splits the volume into two halves, the left half representing the low-frequency coefficients while the right half represents the detail coefficients. In the second stage of the algorithm, the entire volume is then again transformed in y-direction splitting the volume into four quadrants. For the final run, the volume is transformed in z-direction splitting the volume into eight octants. The upper left front octant contains the low-frequency coefficients that are initially transmitted over the network.

3 Dimensional Multiwavelet Computations

1-	Let

								_					3	2	1	5
	10				1	2	0	1	1 2	1 1	0 1	1 0	2	1	4	1
X =	16 5	2 11 7	3 10 6	13 8 12	1 3	1 0	2	0 1	0 3	2 0	1 1	1 2	3	1	0	1
	9 4	7 14	6 15	1	2	1	1	0								
									-							

2- Apply 2-D DMWT to each NXN input matrix, which result in a 2NX2NXM matrix.

$\begin{array}{c ccccccccccccccccccccccccccccccccccc$	$d_{1,7}$ $d_{2,7}$ $d_{3,7}$ $d_{4,7}$
$\begin{array}{c ccccccccccccccccccccccccccccccccccc$	$d_{2,7}$ $d_{3,7}$ $d_{4,7}$
$\begin{array}{c ccccccccccccccccccccccccccccccccccc$	$d_{3,7}$ $d_{4,7}$
$d_{4,5}$ $d_{4,6}$	$d_{4,7}$
	,
$C_{0,0}$ $C_{0,1}$ $C_{0,2}$ $C_{0,3}$ $C_{0,4}$ $C_{0,5}$ $C_{0,6}$ $C_{0,7}$ $d_{5,5}$ $d_{5,6}$	$d_{5,7}$
$c_{1,0}$ $c_{1,1}$ $c_{1,2}$ $c_{1,3}$ $c_{1,4}$ $c_{1,5}$ $c_{1,6}$ $c_{1,7}$ $d_{6,5}$ $d_{6,6}$	d _{6,7}
$c_{2,0}$ $c_{2,1}$ $c_{2,2}$ $c_{2,3}$ $c_{2,4}$ $c_{2,5}$ $c_{2,6}$ $c_{2,7}$ $d_{7,5}$ $d_{7,6}$	$d_{7,7}$
$c_{3,0}$ $c_{3,1}$ $c_{3,2}$ $c_{3,3}$ $c_{3,4}$ $c_{3,5}$ $c_{3,6}$ $c_{3,7}$	
$\mathbf{V}_{-} \qquad \qquad b_{0,0} b_{0,1} b_{0,2} b_{0,3} b_{0,4} b_{0,5} b_{0,6} b_{0,7} c_{4,5} c_{4,6} c_{4,7}$	
$\mathbf{I} = \begin{bmatrix} b_{1,0} & b_{1,1} & b_{1,2} & b_{1,3} & b_{1,4} & b_{1,5} & b_{1,6} & b_{1,7} \\ c_{5,5} & c_{5,6} & c_{5,7} \end{bmatrix}$	
$b_{2,0}$ $b_{2,1}$ $b_{2,2}$ $b_{2,3}$ $b_{2,4}$ $b_{2,5}$ $b_{2,6}$ $b_{2,7}$ $c_{6,5}$ $c_{6,6}$ $c_{6,7}$	
$ \begin{array}{c ccccccccccccccccccccccccccccccccccc$	
$a_{0,0} a_{0,1} a_{0,2} a_{0,3} a_{0,4} a_{0,5} a_{0,6} a_{0,7}$ $b_{A5} b_{A6} b_{A7}$	
$a_{1,0} a_{1,1} a_{1,2} a_{1,3} a_{1,4} a_{1,5} a_{1,6} a_{1,7} b_{1,7} b_{2,7} b_{2$	
$a_{2,0} a_{2,1} a_{2,2} a_{2,3} a_{2,4} a_{2,5} a_{2,6} a_{2,7} b_{5,5} b_{5,6} b_{5,7} b_{5$	
$a_{3,0}$ $a_{3,1}$ $a_{3,2}$ $a_{3,3}$ $a_{3,4}$ $a_{3,5}$ $a_{3,6}$ $a_{3,7}$ $b_{6,5}$ $b_{6,6}$ $b_{6,7}$	
$a_{4,0} a_{4,1} a_{4,2} a_{4,3} a_{4,4} a_{4,5} a_{4,6} a_{4,7} b_{7,5} b_{7,6} b_{7,7}$	
$a_{5,0} a_{5,1} a_{5,2} a_{5,3} a_{5,4} a_{5,5} a_{5,6} a_{5,7}$ 5243	
$a_{6,0}$ $a_{6,1}$ $a_{6,2}$ $a_{6,3}$ $a_{6,4}$ $a_{6,5}$ $a_{6,6}$ $a_{6,7}$	
$a_{7,0}$ $a_{7,1}$ $a_{7,2}$ $a_{7,3}$ $a_{7,4}$ $a_{7,5}$ $a_{7,6}$ $a_{7,7}$	

3- Apply 1-D DMWT algorithm to each 2Nx2N (64 element) in all M matrices in z-direction. This can be done as follows:

a. For each i,j construct the Mx1 input vector $Y(i, j) = \begin{bmatrix} a_{i,j} & b_{i,j} & c_{i,j} & d_{i,j} \end{bmatrix}_{1 \times M}^{T}$ where $i, j = 0, 1, 2, \dots, N$

b. Preprocessing the input vector by repeating the input stream.

- c. Constructing a 2Mx2M transformation matrix using GHM low and high pass filters.
- d. Apply matrix multiplication to the 2Mx2M constructed transformation matrix by the 2Mx1 preprocessing input vector.
- e. Permute the resulting 2Mx1 matrix

4- Repeat step 3 for all i, j.

5- Finally, a 2Nx2Nx2M DMW matrix results from the NxNxM original matrix using repeated row preprocessing.

Advantages of Multiwavelet:

Some reasons for choosing multiwavelets can be shown as follows [Hadeel 2005]:

- 3-D FDMWT decreases the number of variables to manageable size, at the same time, retaining as much discriminatory information as possible.
- Multiwavelets can be used to reduce restrictions on the filter properties. But a scalar wavelet cannot simultaneously have both orthogonality and a symmetric impulse response that has length greater than 2. Symmetric filters are necessary for symmetric signal extension, while orthogonality makes the transform easier to design and implement.
- The length and the number of vanishing moments are directly linked to the filter length for scalar wavelets.
- Multiwavelets are able to possess the best of all these properties simultaneously. For example, the GHM multiwavelet is orthogonal, has second order of approximation, has symmetric scaling and wavelet functions (and thus symmetric filters), and has short support for both of its scaling functions. But scalar wavelet impossible support for these properties.
- Multiwavelets better than scalar wavelet because they can give performance comparable to scalar wavelets with shorter filters of the length of half. Thus for the same quality of decomposed levels multiwavelets require about half the number of operations.

Region Growing Method

The first region growing method was the seeded region growing method. This method takes a set of seeds as input along with the image. The seeds mark each of the objects to be segmented. The regions are iteratively grown by comparing all unallocated neighboring pixels to the regions. The difference between a pixel's intensity value and the region's mean, δ , is used as a measure of similarity. The pixel with the smallest difference measured this way is allocated to the respective region. This process continues until all pixels are allocated to a region [Dzung 2000].

Seeded region growing requires seeds as additional input. The segmentation results are dependent on the choice of seeds. Noise in the image can cause the seeds to be poorly placed. Unseeded region growing is a modified algorithm that doesn't require explicit seeds. It starts off with a single region A_1 – the pixel chosen here does not significantly influence final segmentation. At each iteration it considers the neighboring pixels in the same way as seeded region growing. It differs from seeded region growing in that if the minimum δ is less than a predefined threshold T then it is added to the respective region A_j . If not, then the pixel is considered significantly different from all current regions A_i and a new region A_{n+1} is created with this pixel [Dzung 2000].

Basic Concept of Seed Point

First of all, it chooses a set of seed points. And the initial region now is the exact location of these seeds [Wikipedia 2009].

Then the regions are grown from these seed points to adjacent points depending on a threshold or criteria we make. The threshold could be made by user. It could be intensity, gray level texture, or color [Wikipedia 2009].

There are several important issues about region growing [Wikipedia 2009]:

- b. The suitable selection of seed points is important: The selection of seed points is depending on the users. For example, in a gray-level lightning image, it segments the lightning from the background.
- c. More information of the image is better: The connectivity or pixel adjacent information is helpful for us to determine the threshold and seed points.
- d. The value, "minimum area threshold": No region in region growing method result will be smaller than this threshold in the segmented image.
- e. The value, "Similarity threshold value": If the difference of pixel-value or the difference value of average gray level of a set of pixels less than "Similarity threshold value", the regions will be considered as a same region. The criteria of similarities or so called homogeneity that it chooses are also important. It usually depends on the original image and the segmentation result it want.

Region Growing Algorithm:

- 1. Select seed pixels within the image.
- 2. From each seed pixel grow a region.
 - 2.1. Set the region prototype to be the seed pixel.
 - 2.2. Calculate the similarity between the region prototype and the candidate pixel;
 - 2.3. Calculate the similarity between the candidate and its nearest neighbour in the region;
 - 2.4. Include the candidate pixel if both similarity measures are higher than experimentally-set thresholds;
 - 2.5. Update the region prototype by calculating the new principal component;
 - 2.6. Go to the next pixel to be examined.

Examples of region growing shown in fig. (2) and fig. (3):

 \Rightarrow Starts with a set of seeds (starting pixels)

- Predefined seeds
- All pixels as seeds
- Randomly chosen seeds

 \Rightarrow Region growing steps (bottom-up method)

- Find starting points
- Include neighboring pixels with similar features (grey-level, texture, color), a similarity measure must be selected.
- Continue until all pixels have been included with one of the starting points.





Fig. (2) and Fig. (3): Region growing examples

RESULTS AND DISCUSSIONS

In this paper an image of size (512 X 512) pixels divided into four parts of size (256 X 256) pixels, and then applied 3D-multiwavelete for each part in Matlab V.2008a, as shown below in fig. (5).



Fig. (4): Original image



Fig. (5): After apply 3D Multiwavelet of the second part

After that Sobel filter used to detect the edge of the LH band for the second part. The gradient of the Sobel filter is high at the borders of objects and low inside the objects. As shown in fig. (7):



Fig. (6): The LH band of the second part



Fig. (7): After apply Sobel Filter to the LH band

The resulting image of Sobel filter show the intensity gradients for each pixel in the LH band, then the final step of this work is implement the region growing method to this result by taking seed point and for each seed pixel grow a region by adding neighboring pixels that have properties similar intensity to seed. The region grows based on similarity criteria and stops growth when no more neighboring pixels satisfy this criterion, for this algorithm a threshold of 0.2 value can be used for stopping, when the intensity difference for all neighboring pixels is above this threshold, growth the region stops. The value of threshold is taken from several experiments of this algorithm. Thus the result is As shown in fig. (8).



Fig. (8): After apply region growing method of the result of Sobel filter

This application differs from other related work in applying 3D multiwavelet before image segmented for many reasons are referred to in this paper.

CONCLUSION

In this paper a discrete multiwavelet technique is used for the image features extraction. Multiwavelet offers the advantages of combining symmetry, orthogonality which can not be achieved by scalar two-channel wavelet systems of the same time. Then, this output is segmented in region-growing method.

Because this method presents several advantages over other color image segmentation algorithms. First, it is based on the concept of color vector angle; the vector angle is a shadinginvariant color similarity measure, implying that intensity variations will be discounted in the region growing process, which is clearly not the case when using the Euclidean distance. Secondly, since spatial information is taken into account, regions having a slightly different color, but still spatially distinct, should appear as separate regions due to the region growing process.

REFERENCES

- Carriero M., Leaci A., Tomarelli. F., "VARIATIONAL APPROACH TO IMAGE SEGMENTATION", 2009.
- Chunming Li1, RuiHuang2, Zhaohua Ding, Chris Gatenby1, Dimitris Metaxas, and John Gore1, "A Variational Level Set Approach to Segmentation and Bias Correction of Images with Intensity Inhomogeneity, 2008.
- Dzung L. Pham, Chenyang Xu, and Jerry L. ,"Current Methods in Medical Image Segmentation", 2000.
- http://www.en.wikipedia.org/.../Segmentation_(image_processing), 2009.
- Hadeel Nasrat Al-Taai, "Optical Flow Estimation Using DSP Techniques", 2005.
- I.V.GRIBKOV, P.P.KOLTSOV, N.V.KOTOVICH, A.A. KRAVCHENKO, A.S.KOUTSAEV, A.S. OSIPOV, A.V. ZAKHAROV, "Testing of Image Segmentation Methods", Scientific Research Institute for System Studies, Russian Academy of Sciences (NIISI RAN), Nakhimovskii pr. 36-1, Moscow, 117218 RUSSIAN FEDERATION, vokbirg@yauza.ru, koltsov@niisi.msk.ru, Issue 8, Volume 4, August 2008.
- Linda G. Shapiro and George C. Stockman, "Computer Vision", pp 279-325, New Jersey, Prentice-Hall, ISBN 0-13-030796-3,2001.
- [8] M. Andreetto, L. Zelnik-Manor, and P. Perona, "Non-Parametric Probabilistic Image Segmentation", ICCV 2007.
- Plath, Nils and Toussaint, Marc and Nakajima, Shinichi,"Multi-class image segmentation using Conditional Random Fields and Global Classification ", 2009.
- S. Chabrier, C. Rosenberger, B. Emile, and H. Laurent, "Optimization-Based Image Segmentation by Genetic Algorithms", 8 February 2008
- Springer Berlin, "Semi-automatic Handwritten Word Segmentation Based on Character Width Approximation Via Maximum Likelihood Method and Regression Model", 2008.
- T. Pajdla and J. Matas, pp. 250-261, C_Springer_Verlag Berlin Heidelberg 2004.
- Yuan Been Chen and Oscal T.-C. Chen, "Image Segmentation Method Using Thresholds Automatically Determined from Picture Contents", Accepted 28 January 2009.
- Victor Lempitsky, Andrew Blake and Carsten Rother, "Image Segmentation by Branch-and-Mincut", 2008.
- Wei Hong, John Wright, and Allen Y. Yang, "Unsupervised Segmentation of Natural Images via Lossy Data Compression" (c) Copyright. University of California, Berkeley. 2007, yang@eecs.berkeley.edu.