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Research Paper

CADIST: COMPARATIVE ANALYSIS OF DIVERSE IMAGE SEGMENTATION TECHNIQUES

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Image segmentation is the initial step in image analysis and pattern recognition. Several general-purpose algorithms and techniques have been developed for image segmentation. Since there is no general solution to the image segmentation problem, these techniques often have to be combined with domain knowledge in order to effectively solve an image segmentation problem for a problem domain. This paper presents a comparative study of the basic image segmentation techniques, i.e., corner based, fuzzy c-means, Region-Based and neural network techniques using a number of test images. We are planning to test each segmentation method over a representative set of input parameters that fully characterize algorithm performance over the complete image database. Experimental results have demonstrated that the proposed scheme could obtain promising segmentation results compared with other existing segmentation.

Keywords: Color space models, Fuzzy c-mean, Corner based, Region based method, Hybrid color space, Image segmentation, Neural network

INTRODUCTION

Image segmentation is a fundamental process in many image, video, and computer vision applications. It is often used to partition an image into separate regions, which ideally correspond to different real-world objects. It is a critical step towards content analysis and image understanding.

Many segmentation methods (Gonzales *et al.*, 2008; Aksoy, 2012; and Gunturk) have been proposed in the literature. The choice of a segmentation technique over another and the level of segmentation are decided by the particular characteristics of the problem being considered.

IMAGE SEGMENTATION TECHNIQUES

Clustering Methods

Clustering (Aksoy, 2012; Gunturk; and Kettaf *et al.*, 1996) is a process whereby a data sets (pixels) is replaced by cluster; pixels may belong together because of the same color,

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texture, etc. There are two natural algorithms for clustering: divisive Clustering and agglomerative clustering. The difficulty in using either of the methods directly is that there are lots of pixels in an image. Also, the methods are not explicit about the objective function that is being optimized. An alternative approach is to write down an objective function and then build an algorithm.

Thresholding Methods

Thresholding (Aurdal, 2006; Gonzales *et al.*, 2008; Gunturk; and Zhang *et al.*, 2006) is the operation of Converting a multilevel image into a binary image, i.e., it assigns the value of 0 (background) or 1 (objects or foreground) to each pixel of an image based on a comparison with some threshold value *T* (intensity or color value). When *T* is constant, the approach is called global thresholding; otherwise, it is called local thresholding. Global thresholding methods can fail when the background illumination is uneven. Multiple thresholds are used to compensate for uneven illumination. Threshold selection is typically done interactively; however, it is possible to derive automatic threshold selection algorithms.

Edge-Detection Methods

Edge detection methods (Gonzales *et al.*, 2008; and Aksoy, 2012) locate the pixels in the Image that corresponds to the edges often objects seen in the image. The result is a binary image with the detected edge pixels. Common algorithms used are Sobel, Prewitt and Laplacian operators. These algorithms are suitable for images that are simple and noise-free; and will often produce missing edges, or extra edges on complex and noisy images.

Region-Based Methods

The goal of region-based (Chang and Li, 1994; Gevers and Kajcovski, 1994; Gonzales *et al.*, 2008; Gunturk; and Zhang *et al.*, 2006) segmentation is to use image characteristics to map individual pixels in an input image to sets of pixels called regions that might correspond to an object or a meaningful part of one. The various techniques are: Local techniques, Global techniques and Splitting and merging techniques. The effectiveness of region growing algorithms depends on the application area and the input image. If the image is sufficiently simple, simple local techniques can be effective. However, on difficult scenes, even the most sophisticated techniques may not produce a satisfactory segmentation. Over-stringent criteria create fragmentation; lenient ones overlook blurred boundaries and over-merge. Hybrid techniques using a mix of the methods above are also popular.

METHODOLOGY OF PROPOSED WORK

This section we describes an, comparative study of the basic image segmentation techniques, i.e., Corner based, fuzzy c-means, Region-Based techniques, over the proposed method using a number of test images. We are planning to test each segmentation method over a representative set of input parameters that fully characterize algorithm performance over the complete image database.

Corner Based Segmentation Method

Traditional single-scale algorithms detect corners by considering their local properties (Ahmed Talib *et al.*, 2013), and either miss fine features or detect noise as false corners. In our proposed method we utilize global and local curvature properties, and balance their influence when extracting corners. With this philosophy and the problems of traditional corner detectors in mind, a new corner detector is proposed as follows:

1. Detect edges using the likes of a Canny edge detector to obtain a binary edge map.
2. Extract contours as in the CSS method.
3. After contour extraction, compute the curvature at a fixed low scale for each contour to retain the true corners, and regard the local maxima of absolute curvature as corner candidates.
4. Compute a threshold adaptively according to the mean curvature within a region of support. Round corners are removed by comparing the curvature of corner candidates with the adaptive threshold.
5. Based on a dynamically recalculated region of support, evaluate the angles of the remaining corner candidates to eliminate any false corners.
6. Finally, consider the end points of open contours, and mark them as corners unless they are very close to another corner. Open and closed contours are defined.

$$A_j = P_{1j}, P_{2j}, ..., P_{Nj}$$

where $P_{ij} = x_{ij}, y_{ij}$ are pixels on the contour, N is the number of pixels on the contour, and x_{ij}, y_{ij} are the coordinates of the i^{th} pixel on the j^{th} contour. We further define the contour as closed if the distance between its end points is small enough, and otherwise open:

$$A_j \text{ is } \begin{matrix} \textit{closed if } \left\| P_1^j \ P_N^j \right\| < T \\ \textit{open if } \left\| P_1^j \ P_N^j \right\| > T \end{matrix}$$

Gradient Based Segmentation Method

Gradient is the first derivative for image $f(x, y)$, when there is abrupt change in intensity near edge and there is little image noise, gradient based method works well. We convolve gradient operators with the image. High value of the gradient magnitude is possible place of rapid transition between two different regions (Charless Fowlkes *et al.*, 2003). These are edge pixels, they have to be linked to form closed boundaries of the regions. Common edge detection operators used in gradient based method canny operator, canny is most promising one, but takes more time as compared to Sobel operator. The result of 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 are similar with respect to some characteristic or computed property, such as color, intensity, or texture. Gradient is applied for different sigma values (Aksoy, 2012; Chang and Li, 1994; Kettaf *et al.*, 1996; and Gonzales *et al.*, 2008). We get the following images for different sigma values. After gradient has been applied for the image, ground truth image is compared with the proposed method, In order compare, both the images should of same order, since ground truth is in binary, and we should make gradient image as binary.

Fuzzy c-Means Clustering Based Segmentation Method

Clustering is an unsupervised learning task, where one needs to identify a finite set of categories known as clusters to classify pixels (Bezdek and Pal, 1992). Clustering use no training stages rather train themselves using available data. The FCM is the most accepted method since it can preserve much more information than other approaches. FCM assign pixels to each class by means of membership function.

Let us suppose $X = (x_1, x_2, x_3, \ldots, x_n)$ Denotes an image with N pixels which is to be divided into C clusters, FCM follows an iterative process which minimize following objective function.

$$J = \sum_{j=0}^{N} \sum_{i=0}^{n} uijm \left\| Xj - vi \right\| \quad ...(1)$$

where, $ujim$ = membership function of pixel Xj in i^{th} cluster vi is the centre pixel of i^{th} cluster m is the fuzzifier that controls the fuzziness of resulting clusters and lies between $1 < m \le \infty$.

The membership function and cluster centers are updated, the cluster centers can either be initialized randomly or by an approximation method.

Color Spaces

Color space is a geometrical representation defined by means of three components in a space, numerical values of which define a specific color. Earlier color of human perception was considered to be color spaces, later according to trichromatic theory, three primary color known as Red (R), Green (G) and Blue (B) are necessary and sufficient to match any color by mixture in primary spaces. Given an input image and it is transformed into different color spaces like Y'CbCr, YUV, Y'PbPr, Y'CbCr, Y'DbDr, Y'UV, Y'IQ, HSI, XYZ, CIE XYZ, CIE L*a*b*, L*u*v*, and L*C*H*. All these color space adopt nonlinear transformation in order to use Euclidian distance to compare color in different spaces. After the transformation process, we considered only single plane (e.g., Y component from Y'CbCr color space) and later two significant planes from different color spaces (e.g., HCbCr) were taken to generate hybrid color space and were analyzed using fuzzy c-means. Here in this study, we choose fuzzy c-means = 3 due to the property of discriminating the foreground pixels from background very effectively.

Complex Hybrid Color Space Model

Instead of searching the best classical color space for segmentation, we propose an original approach 'pixel classification' in order to improve the results of image segmentation. In this we introduce a complex hybrid color space model by choosing color components belonging to classical color spaces. The proposed model is derived by considering prominent components from the early described different color space models. In this method, chrominance and human color vision perception components are extracted, which is crucial and found to be very effective for image segmentation. Algorithm of the derived complex hybrid color space model is as shown in Table 1. The derived color spaces have neither psycho-visual nor physical color significance, named hybrid color spaces in the proposed work. In this, pixels are discriminated between the pixel classes in the hybrid color space for better classification. The resultant space is called the complex hybrid color space, built by means of a sequential supervised feature selection scheme.

Neural Network Based Segmentation Method

The neuron is the basic information processing unit of a NN. It consists of:

Table 1: Proposed Algorithm

Algorithm: Proposed complex hybrid color space model
Input: RGB color image
Output: Segmented image
Method
Step 1: Transform RGB image into Y'CbCr and HSI Color spaces.
Step 2: Consider CbCr of Y'CbCr and H of HSI.
Step 3: Compute high dimensional hybrid HCbCr three 2-D matrices.
Step 4: Transform hybrid HCbCr to LUV color space.
Step 5: Apply fuzzy c-means (c-means = 3) for U and V components.
Step 6: End
Method ends

1. A set of links, describing the neuron inputs, with weights $W_1, W_2, \ldots, W_m$
2. An adder function (linear combiner) for computing the weighted sum of the inputs:

   (real numbers)

$$U = \sum_{j=1}^{m} W_j X_j \quad \ldots(2)$$

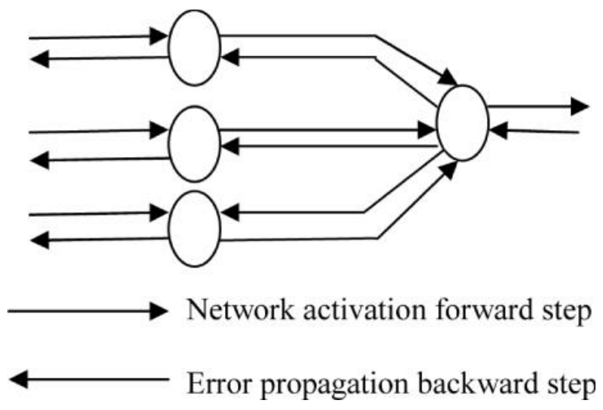
3 Activation function w, for limiting the amplitude of the neuron output. Here '*b*' denotes bias.

$$Y = \ddot{\ } (u + b) \quad \ldots(3)$$

Back Propagation Algorithm

- Back propagation adjusts the weights of the NN in order to minimize the network total mean squared error.
- Consider a network of three layers.
- Let us use *i* to represent nodes in input layer, *j* to represent nodes in hidden layer and *k* represent nodes in output layer.
- w_{ij} refers to weight of connection between a node in input layer and node in hidden layer.

Figure 1: Back Propagation Network



- The following equation is used to derive the output value Y_j of node *j*.

$$Y_j = \frac{1}{1 + e^{-X_j}} \quad \ldots(4)$$

where, $X_j = \Sigma x_i.w_{ij} - \bar{\ }_j$, $1 \leq i \leq n$; *n* is the number of inputs to node *j*, and $\bar{\ }_j$ is threshold for node *j*.

In this project proposing a Image segmentation algorithm using back propagation neural network. Initially algorithms selects seeded pixel with predefined threshold, then applying 8-connectivity at that pixel and selecting linked pixels. In next step compute a mean feature vector for each group of linked pixels as follows.

$$\pm_i^g = 1/M \sum_{j=1}^{M} x_{ij}^g \quad \ldots(5)$$

where *g* is the group index, *j* is the pixel index, and *M* is the total number of pixels in the group. Considering the regions obtained in last step. Adjacent regions will be merged if they fulfill the size. Here, three sub steps of region merging will be performed, where each sub step has a pair of thresholds for segment size and color distance. A region will be merged to one of its adjacent regions if it satisfies the thresholds. The algorithm, the resultant segments are grouped under simple geometric constraints such as area constraints, elongation constraints, and separation constraints. In each step of the algorithm, new groups are established using the largest area segment as its root, which is actually the largest area segment excluding its predecessors. In this segmented region extracting mean features. The resultant regions are used to back propagation neural network for Image segmentation finally.

EXPERIMENTAL RESULTS

Four image segmentation techniques, namely, fuzzy c-means clustering, corner Detection, region based and neural network segmentation techniques have been studied and implemented using a number of test images. The image segmentation results are shown in Figure 2. The regions smaller than a threshold were removed for better visualization. This method has been used to segment an image into distinct color-textured regions on the Berkeley segmentation database. The proposed algorithm was applied to all 110 images and the output was compared to human perceptual ground truth.

Performance Analysis

The metrics used for the quantitative evaluation of the proposed algorithm were the following:

Mean Square Error (MSE): The simplest of image quality measurement is Mean Square Error (MSE). The large value of MSE means that image is poor quality. For a video 16 sequence of frames each having x pixels with -bit depth, first the Mean Square Error (MSE) is calculated using Equation (6).

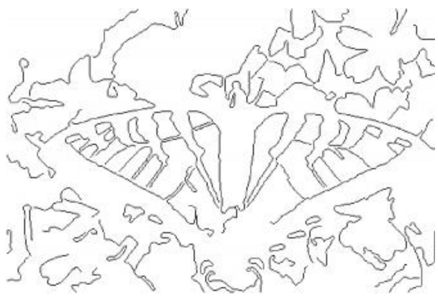
Figure 2: Segmented Output

Fuzzy c-Means

Gradient Magnitude

Neural Network

Corner Detection



$$MSE = \frac{\sum\left(\sum f(u,v) - f'(u,v)\right)^2}{m * n} \quad \text{...(6)}$$

Peak Signal to Noise Ratio (PSNR): The most commonly used objective quality metric is the Peak Signal to Noise Ratio (PSNR) in Decibels. The PSNR is only meaningful for data encoded in terms of bits per sample, or bits per pixel. For example, an image with 8 bits per pixel contains integers from 0 to 255.The PSNR can be calculated using Equation (7).

$$PSNR = !0 \log\left(\frac{255 - 255}{MSE}\right) \quad \text{...(7)}$$

Average Difference (AD): Average Difference (AD) is given by Equation (8)

$$AD = \frac{ABS\left(\sum\sum\left(f(u,v) - f(u,v)\right)\right)}{m * n} \quad \text{...(8)}$$

Jaccard: It measures the interaction over the union of labeled segments for each class and reports the average. One limitation is that it evaluates the amount of pixels correctly labeled, but not necessarily how accurate the segmentation boundaries are. Therefore it is sufficient to compare the different segmentation methods.

$$J = \frac{1}{L}\sum_{i=1}^{L}\frac{cii}{Gi + Pi - cii} \quad \text{...(9)}$$

Maximum Error: The large value of Maximum Difference (MD) means that image is poor quality. MD is given by Equation (10):

$$ME = \left(\max\left(\left(f(u,v) - (u,v)\right)\right)\right) \quad \text{...(10)}$$

We then implemented each of the segmentation algorithms using the same combinations of parameters described above. Experiment is repeated for different segmentation algorithm and the values are recorded that is shown in the following section.

Table 2: Parameter Evaluation

Methods	PSNR	MSE	AD	RMSE	Max Error
Gradient magnitude-canny for sigma = 2	56.9093	0.13248	0.10334	0.36397	1.0000
Fuzzy c-means	60.7480	0.054736	0.02898	0.23395	1.08345
Corner detection	62.9495	0.03297	0.00728	0.18157	1.07956
Neural network	63.49711	0.029065	0.002675	0.17048	1.07000

Table 3: Parameter Evaluation

Methods	dH	Jaccard	Dice	Correlation
Gradient magnitude-canny for sigma = 2	10	0.0155	0.030615	0.0022
Fuzzy c-means	10.559	0.044515	0.20434	0.00646
Corner detection	5.5540	0.0455	0.27299	0.03431
Neural network	13.1928	0.029051	0.195250	0.018726

In the table different segmentation method results for figure above are compared. Settings of algorithms are equitably selected equal. From the above table Results demonstrate, in most cases neural network leads to better results comparing to other methods and had better image segmentation than all methods.

CONCLUSION

Although extensive efforts have been made to develop image segmentation algorithms, much less attention has been paid to evaluating the performance of image segmentation algorithms. In this paper we present a novel framework for quantitatively evaluating the performance of image segmentations. we compare the input segmentation with the ground truth segmentations, the proposed method adaptively constructs a new ground truth from the available ground truths according to the given segmentation. The experiment is conducted for the different images from BDS with different parameters. Experimental results prove that proposed method achieves promising state-of art classification on image datasets. In near future, we would like to examine more effective segmentation techniques with the impact of different parameters for conventional classifiers.

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