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AN IMPROVED ALGORITHM FOR AUTOMATIC COLOR IMAGE SEGMENTATION

A. GOKULANATHAN[a1], R. CHANDRASEKARAN[b] AND C. RAJANANDHINI[c]

[abc]Department of Electronics and Communication Engineering, Periyar Maniammai University, Thanjavur, India

ABSTRACT

This paper presents the new automatic color image segmentation. The input image is converted into LAB color space by color space conversion method. Then an edge-detection algorithm is implemented to produce an edge-map used in the generation of adaptive gradient thresholds, which in turn dynamically select regions of contiguous pixels that display similar gradient and color values, producing an initial segmentation map. A texture characterization channel is created by quantizing the input image, followed by entropy based filtering of the quantized colors of the image. The obtained texture and region growth map combine to perform a unique multiresolution merging procedure to blend regions with similar characteristics.

KEYWORDS: LAB Color Space, Edge Detection, Gradient Threshold, Texture

Image Segmentation

The goal of image segmentation is to cluster pixels into salient image regions that are regions corresponding to individual surfaces, objects, or natural parts of objects. Image segmentation is a process of pixel classification. Segmentation could be used for object recognition, boundary estimation within motion or stereo systems, image compression, image editing, or image database look-up an image is segmented into subsets by assigning individual pixels to classes. Color image segmentation is useful in many applications. From the segmentation results, it is possible to identify regions of interest and objects in the scene, which is very beneficial to the subsequent image analysis or annotation.

Automatic Image Segmentation

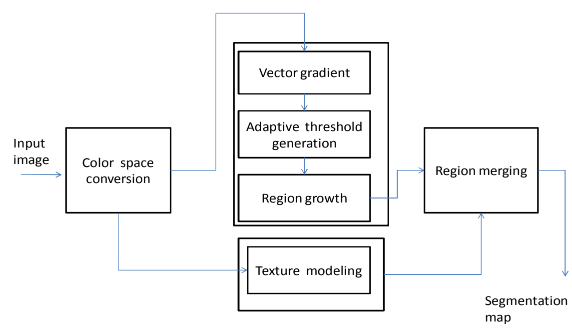
Automatic image segmentation proposes in an image are first obtained automatically by adaptively choosing threshold value and region will growth. Vector gradient approach is proposed to detect boundaries in multidimensional data with multiple attributes. It is used to extend a gradient edge detector to color images. This vector fields to derive similar results and to solve the directional ambiguity. Because noise is the major problem in boundary detection. Vector gradient was highly correlated. The vector gradient approach computes a representation of “distance” that is more natural than that computed by the conventional color edge detectors.

Texture

Texture regions may contain regular patterns such as a brick wall, or irregular patterns such as leopard skins, bushes, and many objects found in nature. The presence of texture in images is so large and descriptive of its objects that ignorance of this important information is not possible and therefore, requires being part of any meaningful segmentation algorithm. A method for obtaining information of patterns within an image is to evaluate the randomness present in various areas of that image. Entropy provides a measure of uncertainty of a random variable. Textured regions contain various colors and shades. Information theory introduces entropy as the quantity which agrees with the intuitive notion of what a measure of information.

AUTOMATIC COLOR IMAGE SEGMENTATION IMPLEMENTATION

The block diagram representation of implementation is given as



Color Spaces

Each color space has an interesting property, which can efficiently be taken into account in order to make more reliable merging procedure. RGB color model is for the sensing, representation, and display of images in electronic systems, such as televisions and computers, though it has also been used in conventional photography. Before the electronic age, the RGB color model already had a solid theory behind it, based in human perception of colors. LAB color is designed to approximate human vision. It aspires to perceptual uniformity, and its L component closely matches human perception of lightness. It can thus be used to make accurate color balance corrections by modifying output curves in a and b components, or to

[1]Corresponding author

adjust the lightness contrast using the L component. In RGB or CMYK spaces, which model the output of physical devices rather than human visual perception, these transformations can only be done with the help of appropriate blend modes in the editing application.LUV uses Judd-type (translational) white point adaptation. This can produce useful results when working with a single illuminant, but can predict imaginary colors.

Color Space Conversion

The task of segmenting images in perceptually uniform color spaces is an ongoing area of research in image processing. The work showed that uniform/approximately uniform spaces such as LAB, LUV and HSV, possess a performance advantage over RGB, a non uniform space traditionally used for color representation. The use of these spaces was found to be well suited for the calculation of color difference using the Euclidean distance, employed in many segmentation algorithms.

The advantage of quantizing the LAB information rather than RGB information is that, if approximately uniform LAB is uniformly quantized a constant distance between and any two quantization levels will result in small variation of perceptual color difference.

Edge Detection

The proposed algorithm uses an edge-detection algorithm that provides the intensity of edges present in an image. These help to detect the individual regions into which an image is segmented and the direction in which the region growth procedure takes place. The detected areas with no edges inside them are the initial clusters or seeds selected to initiate the segmentation of the image. Image is a function f(x,y), the gradient can be defined as its first derivative

$$\nabla f = [(\frac{\delta f}{\delta x}); (\frac{\delta f}{\delta y})]$$

Choosing the magnitude of the gradient provides a rotational invariant value of the edges. The gradient vector

$$D(x) = \begin{bmatrix} D_1 f_1(x) & \cdots & D_n f_1(x) \\ \vdots & \ddots & \vdots \\ D_1 f_m(x) & \cdots & D_n f_m(x) \end{bmatrix}$$

Where D_j f_k is the first partial derivative of the k^{th} component of f with respect to the j^{th} component of x.

The vector maximizing this distance is the eigenvector of the matrix D^t D that corresponds to its largest eigen value. In the special case of a three-channel color image, the gradient can be computed in the following manner, let u,v,w denote each color channel and x,y denote the spatial coordinates for a pixel.

Defining the following variables to simplify the expression of the final solution:

$$q = \left(\frac{du}{dx}\right)^2 + \left(\frac{dv}{dx}\right)^2 + \left(\frac{dw}{dx}\right)^2$$

$$t = \left(\frac{du}{dx}\frac{du}{dy}\right) + \left(\frac{dv}{dx}\frac{dv}{dy}\right) + \left(\frac{dw}{dx}\frac{dw}{dy}\right)$$

$$h = \left(\frac{du}{dy}\right)^2 + \left(\frac{dv}{dy}\right)^2 + \left(\frac{dw}{dy}\right)^2$$

The vector maximizing this distance is the eigenvector of the matrix D^T D becomes

$$D^T D = \begin{bmatrix} q & t \\ t & h \end{bmatrix}$$

Largest eigen value λ is

$$\lambda = \frac{1}{2}\left(q + h + \sqrt{(q+h)^2 - 4(qh - t^2)}\right)$$

The corresponding gradient at each location is defined as,

$$G = \sqrt{\lambda}$$

Adaptive Threshold Generation

The GSEG algorithm is initiated with a color space conversion of the input image from RGB to LAB. This step is vital, because the latter is a better model for the human visual perception, justified by the fact that given two colors, the magnitude difference of the numerical values between them is proportional to the perceived difference as seen by the human eye, a property that cannot be associated with the RGB space. Using the acquired data, the magnitude of the gradient of the color image field is calculated. The histogram of this gradient map is utilized to determine the seed addition levels employed for dynamic seed addition.

Initially, the objective is to select a threshold for the initiation of the seed generation process. Ideally, a threshold value could be selected to provide the most edges, while ignoring the noise present in images. The problem is that the nature of images does not allow for this disposition. A single threshold that may correctly delineate the boundary of a given region may allow other regions to merge incorrectly.

Due to this factor, we propose choosing one of two empirically determined threshold values for initiating the seed generation process, by validating how far apart the low and high gradient content in the image are, in its corresponding histogram. The idea is that a high initial threshold be used for images in which a large percentage of gradient values spread over a narrow range and a low initial threshold value be used for images in which a large percentage of gradient values spread over a wide range, in comparison to the span of the histogram. The choice of made in such a manner ensures that all significant low gradient regions are acquired as initial seeds.

From a practical implementation standpoint, we made this decision of selecting the initial threshold by obtaining the percentage ratio of the gradient values corresponding to 80% and 100% area under the histogram curve. If 80% area under the histogram curve corresponds to a gradient value that is less than 10% of the maximum gradient value in the input image, a high threshold value is chosen, else a low initial threshold value is chosen. Keeping in view the problems posed by over and under-segmentation, the low and high threshold values were empirically chosen to be 5 and 10, respectively.

Threshold for initiating the segmentation process is determined; we proceed to calculate thresholds intervals for the dynamic seed addition portion of the region growth procedure.

Generating the threshold values in such a manner always ensures that:

1) They are adjusted to account for the exponential decay of gradient values.

2) Regions of significant size are added to the segmentation map at each interval.

3) They lie within the span of the histogram, avoiding the possibility of wasted computational efficiency.

Initial Seed Generation

Initial seeds are generated by detecting all the regions in the image whose gradient value fall below the initial thresholds, λ and λ+5 .If no region exists under this threshold, the edge value is increased until regions are detected.

1. The first requirement is to enforce that seeds be larger than 0.5% of the image when searching for regions with a threshold value lower than λ.

2. The second requirement is to enforce seeds to be larger than 0.25% of the image in the range λ to λ+5.

The labelling Procedure, 1) Run-length encoding of the input image, 2) Scan the runs and assign preliminary labels and recording label equivalences in a local equivalence table, 3) Resolve the equivalence classes and 4) Relabel the runs based on the resolved equivalence classes.

Dynamic Seed Generation

The parent seeds are created in the initial seed generation, the regions represented by these seeds are characterized by areas of the image that have no texture. Regions that are not attached to any parent seeds and are larger than the minimum seed size are added to the PS map. For the addition of new seeds that share borders with existent seeds, it is required for them to meet two qualifications: 1.A group must be large enough to be considered as an independent entity and 2.The color differences between a region and its neighbours must be greater than the maximum color difference allowed.

Region Growth

The existent parent seeds grow by increasing the threshold a single unit at a time. After each increment, detection of new regions or child seeds that fall below the new threshold occurs. These child seeds need to be classified into adjacent-to-existent or nonadjacent seeds. The filter operates on the pixels of a 3 X 3 neighbourhood, and its output is assigned to the center pixel of the neighbourhood. The filter is defined as follows:

$$F(i,j) = \begin{cases} 0, & if\ PS(i,j) > 0 \\ 0, & if \sum_{(i,j)\in\beta} PS(i,j) = 0 \\ 1, & otherwise \end{cases}$$

The detected and labeled child seeds form a child seeds map. Performing an element-by-element multiplication of the child seeds map with the PS borders mask, results in a matrix containing the labels of the adjacent child seeds. Asking all the pixels in the child seed map that matches these labels generates the adjacent child seeds map. For proper addition of the adjacent child seeds, it is necessary to compare their individual color differences to their parents to assure a homogeneous segmentation. The child seed sizes are computed utilizing sparse matrix storage techniques to allow for the creation of large matrices with low memory costs.

Seed Growth Tracking

Region growth without growth rate feedback of each seed may cause parent seeds to overflow into regions of similar colors but different textures. Implementation of seed growth tracking helps maintain homogeneity through the segmented regions. At each dynamic seed-addition interval, the number of pixels per parent seed is calculated and stored. When the algorithm has reached the next interval, calculation of the seed-size percentage increment, using the stored size and the current size, detects regions that have slow is growth rate. The border delimited by these seeds, often correspond to boundaries of image elements that display low levels of texture. The growth rate determined empirically to detect this behaviour, is any size increment equal to or below 5%. The seeds detected by this process are temporarily replaced from the PS map into a grown seed map. This is the same as continuing the growing procedure, but inhibiting only these regions to grow any more. After the last dynamic seed generation, no additional seeds will be generated. All seeds, both in the PS map and the grown seed map are placed together into one segmentation map. At this point all remaining pixels that do not belong to this map are the edges of the segmented regions. Continuing the region growth on the new segmentation map, until all pixels in the image has a label assigned to them, generates the Region Growth Segmentation (RGS) map.

Texture Channel Generation

Texture regions may contain regular patterns such as a brick wall, or irregular patterns such as leopard skins, bushes, and many objects found in nature. The presence of texture in images is so large and descriptive of its objects that ignorance of this important information is not possible and, therefore, requires being part of any meaningful segmentation algorithm.

A method for obtaining information of patterns within an image is to evaluate the randomness present in various areas of that image. Entropy provides a measure of uncertainty of a random variable. Textured regions contain various colors and shades. Information theory introduces entropy as the quantity which agrees with the intuitive notion of what a measure of information.

$$I(a_j) = \log \frac{1}{P(a_j)} = -\log P(a_j)$$

$I(a_j)$ is self information of a_j, $p(a_j)$ is probability for a specific value a_j, average self information obtained from outputs is

$$-kP(a_1)\log Pa_1 - \cdots - kP(a_j)\log a_j$$

Average information per sample is,

$$H(s) = -\sum_{j=1}^{j} P(a_j)\log P(a_j)$$

This quantization can be done by uniformly dividing the 8-bit cube into small boxes, and mapping all information that fall within each box to the respective channel values at the center of that box. To create a texture channel, the local entropy is computed in a 9 X 9 neighbourhood around each pixel of the indexed image, and the resulting value is assigned to the center pixel of the neighbourhood.

Region Merging

The objective of one-way variance is to find the optimal coefficients of the vector, which will yield the largest differences across groups and minimize the distances of elements within a group. The between-groups sum-of-squares and products matrix B_0 and the within-groups sum-of-squares and products matrix W_0 are defined by

$$B_0 = \sum_{i-1}^{g} n_i(\overline{x}_i - \overline{x})(\overline{x}_i - \overline{x})^T$$

$$W_0 = \sum_{i=1}^{g}\sum_{j=1}^{n_i}(x_{ij} - \overline{x}_i)(x_{ij} - \overline{x}_i)^T$$

g is an number of groups.It can be verified that the sum of between-groups and within-groups components becomes,

$$SSB(a) = a^T B_0 a$$

$$SSB(a) = a^T W_0 a$$

The Mahalanobis-squared distance between i^{th} and j^{th} group is given by

$$D^2 = (\overline{y}_i - \overline{y}_j)^T W^{-1}(\overline{y}_i - \overline{y}_j)$$

Multiresolution Merging

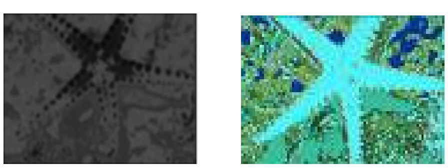
Using a multivariate analysis approach of all independent regions, the resultant Mahalanobis distances between groups is used to merge similar regions. The algorithm uses these distances to locate and merge similar groups. Once a group has been merged, its similarity to the others is unknown but required if the new group needs to be merged to other similar groups. To prevent the need to re-evaluate the Mahalanobisdistances for various groups after each stage of the region merging procedure, an alternate approach is introduced. Having the distances between groups, the smallest distance value is found, corresponding to a single pair of groups. Therefore, we increase the similarity value until a larger set of group pairs is obtained. We begin by merging the smallest group in this set and then continue to merge the next larger group. After the first merge, a check is performed to see if one of the groups being merged is now part of a larger group. In this case all the pair combinations of the groups should belong to the pairs selected initially in the set to be merged together. Once all the pairs of the set have been processed, the Mahalanobis distance is recomputed for the new segmentation map, and the process is repeated until either a desired number of groups is achieved or the smallest distance between groups is larger than a minimum acceptable similarity value between two arbitrary groups. The first criterion aids in achieving a workable number of groups in order to do further processing, and the second criterion assures that all images display a similar level of segmentation.

RESULTS

The input image is converted into LAB color space by color conversion method. Then produce an edge-map used in the generation of adaptive gradient thresholds, which in turn dynamically select regions of contiguous pixels that display similar gradient and color values, producing an initial segmentation map. A texture characterization channel is created by quantizing the input image, followed by entropy based filtering of the quantized colors of the image. Finally, the initial segmentation map and the texture channel are used to obtain the final segmentation map.

Input Image LAB Conversion Gradient Generation

Initial Seed Region Growth Texture Channel



Texture Information Region Merging

CONCLUSIONS

This work presents a computationally efficient method designed for automatic segmentation of color images with varied complexities. The GSEG algorithm is primarily based on color-edge detection, dynamic region growth, and culminates in a unique multi-resolution region merging procedure. The algorithm has been tested on a large database of images including the publicly available Berkeley database, and the quality of results show that our algorithm is robust to various image scenarios and is superior to the results obtained on the same image when segmented by other methods, as can been seen in the results displayed.

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