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MULTIPLE FEATURE IMAGE SEGMENTATION ALGORITHM

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Abstract

In this paper we present an algorithm based on the pyramidal approach. For local information we device a new uniformity criterion, *called Fisher criterion,* which utilizes all multiple perceptual impression information. This uniformity criterion for region classification has been formulated recursively for building the pyramid in a bottom up fashion. Each region in the image is extracted individually by first reaching its seed region and then growing its possible neighbouring areas. The statistics of the multiple features used here are derived form the CIE (L*a*b*) system which is assumed possesses uniform characteristics of the colour perception.

Introduction

Achieving an adequate segmentation depends upon devising techniques to detect properties of uniformity among the picture elements, and then isolating the clusters of points which are discovered. Several techniques and operators have been developed to achieve this goal to date. The classical ones are *edge detection, region growing,* and *thresholding* or *clustering.* The former two techniques operate in a local fashion in small areas to the image, while the latter ones selects the whole image and operate in global fashion. The local analysis may generate a great deal of spurious activity, while the global analysis may miss all the local properties. The integration of local processing into globally consistent boundaries and regions is not at all straightforward.

In colour image segmentation a variety of region based segmentation based on the global approaches has been reported, utilizing perceptual attributes of colour or different colour coordinate systems. Ohlander 1978 was probably the first employed global information utilizing multidimensional histogram thresholding scheme. Ali 1977 has performed image segmentation by partitioning the picture into regions according to decision surfaces in a three dimensional normalized colour space. A similar clustering image segmentation technique was used by Schacter 1976. Otha 1980 has suggested three colour features for three orthogonal coordinates. Image segmentation based on a recursive thresholding method for colour images was suggested by Shoji 1986. A colour clustering technique for image segmentation was proposed by celenk 1990. The method operates in a uniform colour coordinage system (L*, a*, b*) defined by the CIE, Wyszeck, et al. 1982. The image cluster is detected in a set of circular-cylindrical decision elements of the colour space. Image segmentation based on a perceptual colour system was performed by Hiroshi 1991. His work used an indoor controlled environment with a uniform white background. Scenes were segmented by using the threshold derived from the chroma histogram.

These classical approaches for colour image segmentation can be considered

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global methods, since they use whole image or a large part of it. They are based on the assumption that different classes, or segments, of an image can be represented by a distinct 'modes' in the distributions of suitably chosen features extracted from the image. For instance, in the case of Ohta, three orthogonal features are used, and in Ohlander's case nine colour features have been chosen for image partition. All these methods employ classical pattern recognition techniques and demand heavy computational cost. Additionally, Most of these technique do not utilize plausible schemes naturally evolved for perceptual colour impressions and also they do not lend themselves very easily to be dedicated for hardware design. We are investigating an algorithm for colour segmentation utilizing all the perceptual parameters employing a local information of the input multiple feature image based on Pyramidal scheme.

Pyramidal Shemes

The image segmentation methods which use pyramidal based approach (Horowitz and Pavlidis 1974, Chen and Pavlidis 1979, Chen and Pavlidis 1980, Burt, Hong, Rosenfeld 1981, Pietikain and Rosenfield 1981, Larkin and Burt 1983, Blanford and Tanimoto' 1988, and Khan and Gillies 1989 and Ismaili and Bukhari 1997 are sometimes justified using the biological evidence that the brain and visual system of higher mammals is a highly parallel system ysing roughly 12 billion neurons, though which volleys of impulses transfer and process information. A parallel set of neurons projects and transforms this information, through several synaptic junctions, into the visual cortex where is it is further transformed and combined by additional layers of synapes-embodied operations (Uhr 1980).

This over all parallel and serial layered architecture can be represented by pyramids or cones. Thus an N + 1 dimensional pyramid can be thought of as a linked stack of N-dimensional planes or arrays. The links between layers provide an efficient way of implementation of parallel and local operations. The pyramid being a three dimensional structure with two dimensional array layers, gives a logarithmic reduction in size and a logarithmic number of layers. Thus an NxN based pyramid with AxA convergence will have $1+\log_A N$ layers, (for example a pyramid with a 256 x 256 base array and 2 x 2 convergence will have 9 planes or layers). In this architecture, the pyramid's apex, a 1x1 array with one processor links to four child processors arranged in 2x2 array, forming layer 1, and then each of these four processors links as a parent to the four children in a 2x2 sub-array of layer 2 or plane 2. Thus the structure continues until the N x N array at layer log N is reached.

The pyramids having 2x2 convergence can be simulated employing quadtrees on ordinary sequential computes. Correspondingly, image segmentation methods which utilize a structure like a quadtree can be implemented on pyramidal structure computes in parallel. The segmentation algorithm that we describe in this paper is well suited for parallel implementation.

The pyramid which contains a quadtree is made of N+1 planes of dimension $2^n x 2^n$ stacked one upon the other with original image at the base and the root of the tree at the top or apex. For an intermediate plane of size $2^n x 2^n$, the level of the quadtree is given by L = N – n, where N is $\log_2$ of side length of the original image and n is $\log_2$ of side length of the intermediate plane.

For a given level K, the plane, $f_{K+1}(x, y)$ at level K+1 is constructed from $f_K(x, y)$ by

employing one of a number of possible transformations. If f_K (P_1), f_K (P_2), f_K (P_3), f_K (P_4), where $P_n = (x_n, y_n)$, represent colour or an other property of the four children on which the parent node f_{K+1} (P_0) is based, then.

$$f_{K+1}(P_0) = \pi[f_k(P_1), f_k(P_2), f_k(P_3), f_k(P_4)] \quad (1)$$

Where π could be a particular transformation. One of the simplest examples of a transformation is the average which is defined as:

$$\pi_{ave} = [f_k(P_1), f_k(P_2), f_k(P_3), f_k(P_4)]\ /4 \quad (2)$$

this sets f_{K+1} (P_0) to the mean of its four children at level K. Other possible transformation are π_{min} and *maximum* of some property of the four nodes at level K. The typical properties other than minimum and maximum for image analysis could be applied are: standard deviation, variance, skewness, mean, energy, and entropy. Khan and Gillies 1989 have applied mean and variance formulation for image partition using gray level information. Our approach of employing pyramidal based segmentation is close to the approach investigated by Khan and Gillies 1989. However, it also differ in many ways, in their approach only utilizes univariate information of the image, we are using multivariate colour information, requiring use of three perceptual attributes for image analysis and developing a new uniformity criterion, called Fisher's criterion. In the following section we discuss Fisher's criterion and develop a algorithm on this classification method.

Fisher criterion for uniformity

In using a quadtree for image segmentation we build the tree form the pixels upward, and at each stage examine the nodes to see if they conform to some uniformity criterion. Those nodes that are uniform can be marked as belonging to a coherent region that we wish to may identify, and can be used as seeds for a merging process. We now discuss this approach based on the Fisher's criterion and its implementation for multiple image segmentation.

The Fisher distance between the parent node and the children at level k can be computed as:

$$\mathbf{di} = \frac{(\mu_{ki} - \mu_{k+1})^2}{\sigma^2_{ki} + \sigma^2_{k+1}} \quad (3)$$

Where μ_{ki} is mean value of one of the children and μ_{k+1} is mean of parent node, and σ_{ki} and σ_{k+1} are the standard deviations of child and parent node.

The equation (3) based on the Fisher criterion for separation of two classes can be applied only for univariate distribution. In case of multivaritate distribution (multiple features) it needs to be transformed into univvariate observations as shown in Figure 1. This is based on taking linear combination of **X** to create **Y's** being a function of **X**. It can be seen in Figure 1 that y1 is the mean of y,s obtained form x's observations to class one and y2 is the mean of y's obtained from x's observation to an other class. For separation of these two population the Fisher criterion use the linear combination that maximize the squared distance, equation (3) between y1 and y2 (means) relative to the variability of the derived **Y's**. The means and variance for multivariate observation are alternatively given by the following relations, in that Y has mean

$$\bar{y1} = E(Y/\pi 1) = E(W'X) = W'\mu 1 \quad (4)$$

or

$$\bar{y2} = E(Y/\pi 2) = E(W'X) = W'\mu 2 \quad (5)$$

and its variance

$\sigma^2_Y = Var\,(W'X) = W'Cov\,(X)\,W = W'\Sigma W$ (6)

These results can be shown by considering the linear combination of $w_1X_1 + w_2X_2$, mean and variance are given by

$$E(w_1X_1 + w_2X_2) = w_1E(X_1) + w_2E(X_2) = w_1\mu_1 + w_2\mu_2 \quad (7)$$

$$Var(w_1X_1 + w_2X_2) = E[w_1(X_1 + w_2X_2) - (w_1\mu_1 + w_2\mu_2)]^2 \quad (8)$$

$$= E[w_12(X_1 - \mu_1)^2 + w_2(X_2 - \mu_2)^2 + 2ab\,(X_1 - \mu_1)(X_2 - \mu_2) \quad (9)$$

in equation (9) the first and second terms are variance and the third term is a co-variance, thus we can write

$$= w1^2Var(X_1) + w1^2Var(X_2) + Cov(X_1, X_2) \quad (10)$$

$$= w1^2\,\sigma11 + w_2^2\sigma22 + 2w1w2\sigma12 \quad (11)$$

letting

$W' = [w1\ w2]$, we can write equation (7)

$$[\,w_1\,,\,w_2\,]\begin{bmatrix}\mu1\\ \mu2\end{bmatrix} = W'\mu.$$

Similarly if we let $\Sigma = \begin{bmatrix}\sigma_{11} & \sigma_{12}\\ \sigma_{12} & \sigma_{22}\end{bmatrix}$ (12)

which is a variance-covariance matrix of X, equation (11) can be expressed as

$$Var(w_1X_1 + w_2X_2) = [\,w1\ w2\,]\begin{bmatrix}\sigma11 & \sigma12\\ \sigma12 & \sigma22\end{bmatrix}\begin{bmatrix}wI\\ w2\end{bmatrix} \quad (13)$$

which is

$$Var(w1X1 + w2X2) = Var(W'X) = W'\Sigma W \quad (14)$$

Since, we can write equation (3), Fisher's criterion, for multivariate observation as:

$$d_i = \frac{(W'\mu_{ki} - W'\mu_{k+1})^2}{W'(\Sigma_{ki} + \Sigma_{k+1})W} \quad (15)$$

where vector W is given by

$$W = (\Sigma_{ki} + \Sigma_{k+1})^{-1}(\mu_{ki} - \mu_{k+1}) \quad (16)$$

Thus equation (15) is used here for colour image segmentation based on pyramidal employing quadtree data structure, which is equivalent to equation (3) mentioned earlier.

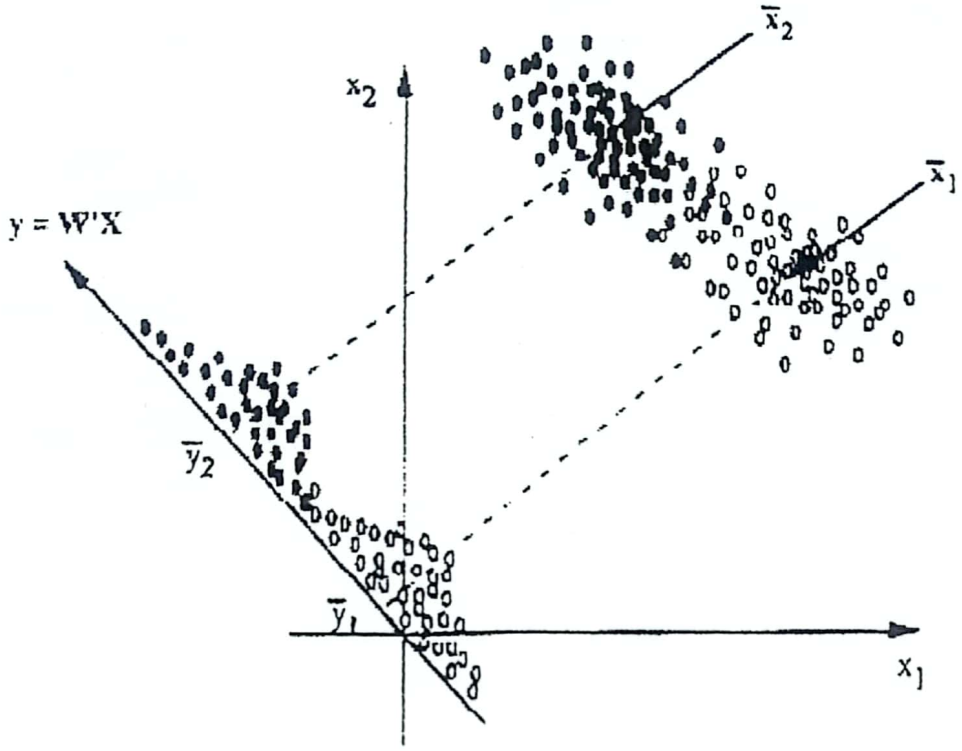


Figure 1. Classification representation of Fisher's procedure for two observation. The feature vectors are projected on to vector **W** using Fisher's linear discriminant function as shown in this diagram. To classify two population one can apply threshold at the valley between two modes.

4. Algorithm Implementation

The algorithm based on the Fisher's distance criterion has been developed from the previous work (Khan and Gillies [1989] and Ismaili and Gillies [1993, 1994]). The following distinct steps are to be employed for colour image segmentation utilizing hue, saturation and lightness of CIL Lab as feature space.

Colour transformation: The digitized full colour image is represented by the value of R, G, and b system in MxN rectangular image grid which can be expressed as a composite signal by the following expression as:

$$I(i, j) : i = 1, 2,....M : j= 1, 2, ..., N$$

Where $I(i,j) = \{ R(i.j), G(i, j), B(i, j) \}$ is a colour vector of image components located at the ith row and jth column. This colour image is transformed into the psychometric parameter 'hue, saturation and Lightness for L*a*b* colour system.

Extraction of seed regions: A pyramid image representation employing a quadtree is constructed starting from the second lowest level of the tree .Thus making the image of half resolution. For each square region, which is a group of four pixels, Fishers distance criterion as shown equation (15) is to be computed and the information whether corresponding node is uniform or not is determined and stored . The Fisher distance criterion for each parent node at level k+1 is calculated using

recursive formulation of mean, variance and co-variance matrix of colour features from child nodes at level k . This is done by taking the following steps, let us consider first recursive formulation for co-variance . Starting with the definition of co-variance as:

$$\sigma_H{}^{O}{}_{C}{}^{*} = \frac{\sum_{ij=0}^{n} f(H_i^{o}, C_j^{*})\, H_i^{o} C_j^{*}}{\sum_{ij=0}^{n} f(H_i^{o}, C_j^{*})} - \frac{\sum_{i=0}^{n} f(H_i^{o}) H_i^{o}}{\sum_{i=0}^{n} f(H_i^{o})} * \frac{\sum_{i=0}^{n} f(C_i^{*}) C_i^{*}\, s}{\sum_{i=0}^{n} f(C_i^{*})} \tag{17}$$

Where f is the frequency so $f(H_i^{o}, C_j^{*})$ is the number of pixels with $H= H_i^{o}$ and $C^* = C_j^{*}$
By Manipulating equation (17)

$$\sigma_H{}^{O}{}_{C}{}^{*} + \mu H^{o} \mu c^{*} = \frac{\sum_{ij=0}^{n} f(H_i^{o}, C_i^{*})\, H_i^{o} C_i^{*}}{\sum_{ij=0}^{n} f(H_i^{o}, C_j^{*})} \tag{18}$$

and with a constraint that a t each subtree in the pyramid there are $(2^K)^2$ number of pixels, we can write above equation as:

$$\sigma_H{}^{O}{}_{C}{}^{*}{}_{kn} + \mu_H{}^{o}{}_{kn} \mu c^{*}{}_{kn} = \frac{\sum_{ij=0}^{n} f(H_i^{o}, Cj^{*})\, H_i^{o} C_j^{*}}{(2^k)^2} \tag{19}$$

where n = 1,....4

For the co- variance at level k+l, we can write equation (19) in four terms as:

$$\sigma_H{}^{o}{}_{C}{}^{*}{}_{k+1} = \frac{\sum_{i\ j\ \text{subtree}\ k1} f(H_i^{o}, C_j^{*})\, H_i^{o}\, C_j^{*}}{(2^k)^2} + \frac{\sum_{i\ j\ \text{subtree}\ k2} f(H_i^{o}, C_j^{*})\, H_i^{o}\, C_j^{*}}{(2^k)^2} +$$

$$\frac{\sum_{i\ j\ \text{subtree}\ k1} f(H_i^{o}, C_j^{*})\, H_i^{o}\, C_j^{*}}{(2k)^2} + \frac{\sum_{i\ j\ \text{subtree}\ k1} f(H_i^{o}, C_j^{*})\, H_i^{o}\, C_j^{*}}{(2k)^2} \Big/ 4 - \mu_H{}^{o}{}_{k+1}\, \mu_C{}^{*}{}_{k+1}$$

By substituting left term of equation (19) in the above one we get co-variance of hue and saturation at level k+1

$$\sigma_H{}^{o}{}_{C}{}^{*}{}_{k+1} = \frac{\sigma_H{}^{o}{}_{C}{}^{*}{}_{k1} + \sigma_H{}^{o}{}_{C}{}^{*}{}_{k2} + \sigma_H{}^{o}{}_{C}{}^{*}{}_{k3} + \sigma_H{}^{o}{}_{C}{}^{*}{}_{k4}}{4} +$$

$$\frac{\mu_H{}^{o}{}_{k1}\mu_C{}^{*}{}_{k1} + \mu_H{}^{o}{}_{k2}\mu_C{}^{*}{}_{k2} + \mu_H{}^{o}{}_{k3}C{}^{*}{}_{k3} + \mu_H{}^{o}{}_{k4}\mu_C{}^{*}{}_{k4}}{4} - \mu_H{}^{o}{}_{k+1}\mu_C{}^{*}{}_{k+1}$$

$$= \frac{\sum_{i=1}^{4} \sigma_H{}^{o}{}_{C}{}^{*}{}_{k} + \sum_{i=1}^{4} \mu_H{}^{o}{}_{ki}\mu_C{}^{*}{}_{ki}}{4} - \mu_H{}^{o}{}_{k+1}\mu_C{}^{*}{}_{k+1} \qquad (20)$$

Where $\mu_H{}^{o}{}_{k+1}$ and $\mu_C{}^{*}{}_{k+1}$ are the mean values at level k+1, and given by

$$\mu_{jk+1} = \frac{\mu_j k + \mu_j k + \mu_j k + \mu_j k}{4}, \text{ where } j = H^{o},\ C^{*} \qquad (21)$$

The co-variance of hue, lightness and saturation can be computed similarly as shown in equation (20).

The variance is defined as follows here it is for hue of the image,

$$\sigma_H^{\,o} = \frac{\sum_{i=0}^{n} f(H_i^o)\,(H_i^o)^2}{\sum_{i=0}^{n} f(H_i^o)} - \frac{\sum_{i=0}^{n} f(H_i^o)H_i^o}{\sum_{i=0}^{n} f(H_i^o)} \qquad (22)$$

Similarly the recursive formulation of variance for hue saturation and lightnes parameters at level k+1 can be derived using the same notation applied for co-variance:

$$\sigma_{ik+1} = \frac{\sigma_{jk1} + \sigma_{jk2} + \sigma_{jk3} + \sigma_{jk4} + \mu^2_{jk1} + \mu^2_{jk2} + \mu^2_{jk3} + \mu^2_{jk4}}{4} - \mu^2_{j\,k+1}$$

$$= \frac{\sum_{i=1}^{4} \sigma_{jki} + \sum_{i=1}^{4} (\mu_{jki})^2}{4} - (\mu_{jki})^2 \qquad (23)$$

where $\mu_{jk+1} = (\mu_{jk+1} + \mu_{jk+2} + \mu_{jk+3} + \mu_{jk+4})/4$ and $j = H^o$, C*, and L*, which stand for hue, saturation and lightness of the colour . thus mean and variance for Fisher distance criterion is to be set for each node as shown in equations (12) and (14).and **W** is determined using equation(16). The process of calculating these particular property recursively continues until the root is reached (L=N).

Merging neighboring regions criteria: Three different measures can be adopted to determine the uniformity :

(i) Merging neighboring areas based on hue average difference from the seed region and uniformity threshold .

(ii) Merging neighboring areas using hues average interval and uniformity variance threshold..

(iii) Merging neighboring areas by scaling the ratio of variance and square of mean.

The first measure of uniformity, used by khan and Gillies(1989),examines whether the average hue of the neighboring areas is equal to the hue of seed or within some tolerance M_{thr} and its variance is below the variance threshold vthr. The M_{thr} is to be adapted from a user

supplied threshold, M_{user}, depending on the uniformity of merged region. The M_{thr} or tolerance within the seed decreases with the decrease in uniformity indicated by an increase in the ratio, which is,

$$M_{thr} = [\ 1 - W' \Sigma_k W / W'_{\mu k})^2\ ]\ M_{user} \qquad (24)$$

The higher the value of M_{user} the less uniform the region in its adopted feature, and *vice versa*. Thus when growing the regions less or more uniformity depends on the constant threshold supplied by the user.

In the second measure, uniformity can be established if the average value of the neighboring areas lies within the hue average interval and its variance is below a uniformity threshold, Vthr that is,

$$\text{Uniform if} \quad W'\mu_L \le W'\mu k \le W'\mu_U \text{and}$$
$$W'\ W'\Sigma_k W_k < v_{thr} \qquad (25)$$
$$\text{Non – uniform otherwise}$$

The third measure was used by Levine and Shaheen (1981) in their region growing method, and is similar to the first one equation(24).The uniformity by scaling the ration of variance and the square of the mean value.

$$\text{Unformaity} = (1 - (W'\Sigma_k W / W'_{\mu k})^2)\ S_{user}) \qquad (26)$$

A higher value of S_{user} means that the region is more uniform in the adopted feature, and vice versa. This is the opposite to the measure of uniformity given in equation(24) and the merging process does not employ the average tolerance between the seed and the region to be merged but it depends on the ratio $[W'\Sigma_k W / W'_{\mu k})^2\ ]$ and the user supplied threshold S_{user}.

5. Conclusion

In this paper we have presented a novel algorithm for colour image segmentation . To date work in this area has been reported using global approaches, which utilize conventional pattern recognition techniques.

We have made pyramidal based approach and investigated a approach how to use all colour perceptual impressions. In this way we have applied contextual approach to multiple feature image analysis which are believed to be more successful, because local information of the image is used in these methods reinforces a classification decision.

In addition to the main advantages of our approach to image segmentation is that real time results can be obtained by implementing it on small pyramidal architecture.

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