A Novel Color Image Segmentation Algorithm Applying Thresholding on Directional Filter Bank Features

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Abstract: Image segmentation has been a challenging issue in the field of computer vision over decades and it plays a critical role for most image analysis tasks such as object recognition and object-based image compression. Our paper is based on segmenting images using Directional Filter Banks (DFB) in conjunction with Peak Finding and Multi-thresholding algorithms. A directional filter is introduced in this paper that retains the ability to handle missing data and is separable, making it computationally efficient. Taking the advantage of DFB, the peak finding and multi-thresholding algorithms are applied to the resultant features of DFB. The new combined algorithm produces very efficient results.

Keywords: Directional filter bank, Image segmentation, Histogram thresholding, Multi-thresholding algorithm, Peak finding algorithm.

I. INTRODUCTION

Of the fundamental steps in image processing techniques image segmentation is one of the most difficult tasks. Segmentation in general refers to the partitioning an image into its constituent parts or objects. Image segmentation partitions an image into non-overlapping regions. Mainly the segmentation is based on color, shape and texture. Image segmentation techniques have been found useful in the analysis and interpretation of radiographic images in medicine, seismic trace images and earth cover images obtained using remote sensing.

A lot of image segmentation methods have been proposed: roughly speaking, these methods can be classified into: (1) Histogram thresholding; (2) Clustering; (3) Region growing; (4) Edge based; (5) Physical-model-based; (6) Fuzzy approaches; (7) Neural network methods. Directional information is important to many multidimensional applications such as image classification, enhancement, denoising, edge detection, segmentation, etc. The directionality provides significant benefits for image and video processing applications. Due to high directional information, curvelet frame provides an optimal approximation of piecewise smooth images.

Curvelets are difficult to implement on discrete images. In order to circumvent this problem, Do and Vetterli introduced contourlets [6] that have the same geometry as curvelets but are directly defined on a discrete lattice. Recently Hong and Smith introduced a directional filter bank that provides a frequency partitioning which is close to curvelets but with no redundancy.

Thresholding techniques are preferable for segmenting images with less computational time. The peak finding and Multithresholding algorithms are applied on Directional Filter Bank features. Peak finding algorithm is employed to identify the most significant peaks of the histogram. The basis of the histogram analysis approach is that the regions of interest tend to form nodes in the corresponding histogram.

An overview of this paper is as follows. In section 2, the analysis of directional filter bank with quincunx sampling is discussed. In section 3, the procedure of image segmentation the peak finding algorithm is discussed. By using the peak finding algorithm the image is segmented. In the same section, the procedure of segmenting the images by means of Multit hresholding algorithm with DFB is also discussed. In section 4, the performance comparison and the resultant images are illustrated. The conclusion is given in section 5.

II. DIRECTIONAL FILTER BANKS

Directional representation that is potentially useful for image processing often with additional properties like exact reconstruction, reduced redundancy, and high computational efficiency. Directional filter banks (DFB) [11] decompose the frequency space into wedge-shaped partitions as illustrated in Fig. 1. In this figure, eight directions are used, where directional sub bands of 1, 2, 3, and 4 represent horizontal directions (directions between -45° and +45°) and the rest stand for the vertical directions (directions between 45° and 135°). The DFB is realized using iterated quincunx filter banks.

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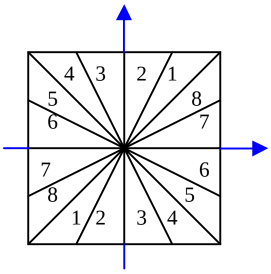


Fig.1 Directional filter bank frequency partitioning using eight directions.

DFB are unique in their ability to decompose a multidimensional signal into direction sub bands that are non-redundant. Moreover, they are capable of representations with high angular resolution, exact reconstruction, and high computational efficiency. The directional sub bands contain the horizontal and vertical frequencies and reject most of the diagonal frequencies. Psychophysics experiments have shown that the human visual system is less sensitive to diagonal high spatial frequencies compared to horizontal and vertical high spatial frequencies.

A. Constructing 2^n-Band DFBs

A simple two-band DFB can be constructed with a modulator, a pair of diamond filters $H_0(\omega)$ and $H_1(\omega)$, and quincunx sampling matrices as shown in Fig 2. The directional frequency components labeled in the figure can be extracted by the two-band DFB structure. The need of the modulator is to rearrange the data into a diamond support shape. The two diamond shaped filters are shown in Figure 3. The two frequency regions are filtered by these diamond shaped filters. We consider the ideal diamond-shaped frequency band filter as

$$\begin{aligned} H_{ideal}(e^{j\omega 1}, e^{j\omega 2}) &= 2 \quad (\omega 1, \omega 2) \in P \\ H_{ideal}(e^{j\omega 1}, e^{j\omega 2}) &= 0 \quad (\omega 1, \omega 2) \in S \end{aligned} \qquad (1)$$

After filtering, the quincunx sampling matrices are used for down-sampling. The down-sampling matrices corresponding to the diamond shaped analysis/synthesis filters are given by

$$Q = \begin{bmatrix} 1 & -1 \\ 1 & 1 \end{bmatrix}$$

A unimodular matrix is a resampling matrix whose determinant is ±1 . Its inverse matrix is also unimodular. For four band decomposition the second stage of the tree structure is identical to the first stage. Due to the geometrical constraints, the filters and the re-sampling matrices for the remaining stages are not the same as the ones for the first two stages. The modulators are used in the first two stages.

This will cause some spatial distortions due to frequency shifting and geometrical distortions. This problem can be solved by some stretching and rotations introduced by decimation process. For that we are using re-sampling matrices. They are also called as diamond conversion matrices.

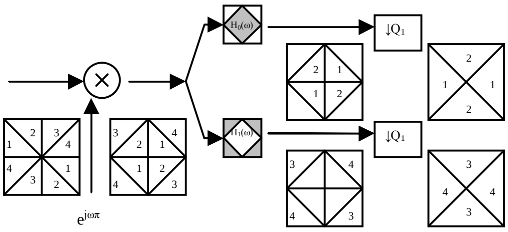


Fig.2 Two band DFB structure

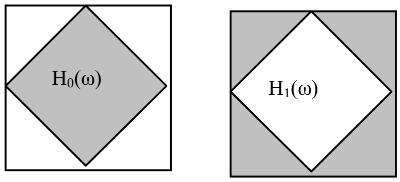


Fig.3 Diamond shaped filters

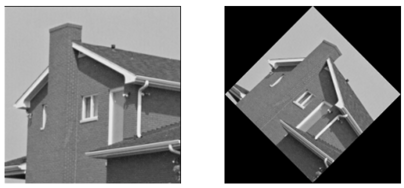


Fig.4 Quincunx down sampling

A diamond-conversion matrix is a n unimodular matrix that can change a filter $H_0(\omega)$ with a diamond shaped pass band into one of the four parallelogram pass bands as depicted in Figure 5. There are four re-sampling matrices, which are having the directional features.

III. SEGMENTATION PROCEDURE

The image is applied to the 3 stage DFB structure in separate RGB planes. As a result eight directional sub bands are available. Out of eight sub bands one sub band is taken which is having the maximum information.

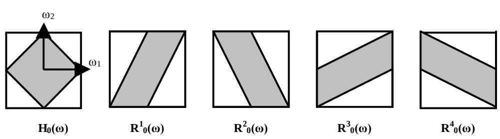


Figure 5. Diamond shaped pass band and four parallelogram pass bands

These sub bands in the separate planes are combined to form one image. Then the Peak finding and Multi-thresholding algorithms are separately applied for segmentation.

A. Peak Finding Algorithm

Peak finding algorithm is an efficient algorithm and it is employed to identify the most significant peaks of the histogram. The basis of histogram analysis approach is that the regions of interest tend to form modes in the corresponding histogram. Histogram thresholding is one of the popular techniques for monochrome image segmentation. This technique considers that an image consists of different regions corresponding to the gray level ranges. The histogram of an image can be separated using peaks (modes) corresponding to the different regions. A threshold value corresponding to the valley between two adjacent peaks can be used to separate these objects.

a. Homogeneity Histogram Analysis

Homogeneity is largely related to the local information extracted from an image and reflects how uniform a region is. It plays an important role in image segmentation since the result of image segmentation would be several homogeneous regions. Homogeneity is defined as a composition of two components: standard deviation and discontinuity of the intensities I=(R+G+B)/2 .Standard deviations describe the contrast within a local region. Discontinuity is a measure of abrupt changes in gray levels and could be obtained by applying edge detectors to the corresponding region.

Suppose g_{ij} is the intensity of a pixel P_{ij} at the location (i,j)in an MxN image, w_{ij} is a size dxd window centered at (i,j) for the computation of variation, wij is a size kxk window centered at (i,j) for the computation of discontinuity, and d and k are odd integers greater than 1. The standard deviation of pixel P_{ij} is calculated as

$$v_{ij} = \sqrt{\frac{1}{d^2} \sum_{p=i-(d-1)/2}^{i+(d-1)/2} \sum_{q=j-(d-1)/2}^{j+(d-1)/2} (g_{pq} - \mu_{ij})} \qquad (2)$$

Mean of the gray level within the window w_{ij} is calculated as

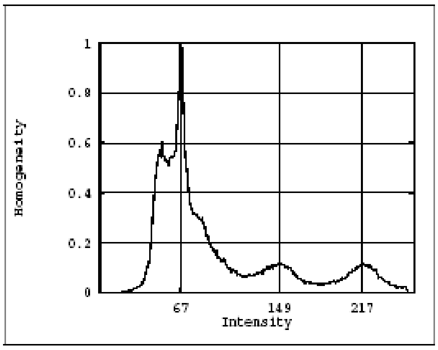
$$\mu_{ij} = \frac{1}{d^2} \sum_{p=i=(d-1)/2}^{i+(d-1)/2} \sum_{q=j-(d-1)/2}^{j+(d-1)/2} g_{pq} \qquad (3)$$

The homogeneity is represented as

$$H(g_{ij}, w_{ij}^{(1)}, w_{ij}^{(2)}) = 1 - E(g_{ij}, w_{ij}^{(1)}) x V(g_{ij}, w_{ij}^{(2)}) \qquad (4)$$

The homogeneity histogram gives us a global description of the distribution of the uniform regions across intensity levels. Each peak in this histogram represents a uniform region. Suppose a homogeneity histogram of an image is represented by a function h(i), where i is an integer between 0 to 255. A typical image segmentation approach based on histogram analysis generally carries out three steps:

1. Find the set of points corresponding to the local maximums of the histogram.
2. Find significant peaks*:* The points in set P_0 form a new curve. On this new curve, repeat the operation of step1.The result forms set P_1:
3. Thresholding



This peak finding algorithm locates the globally significant peaks of the histogram. After the peaks are selected, the minimum values between any adjacent peaks are identified as valleys. Finally, valleys between peaks are noted and the image is divided into several segments, and each segment represents a region that is similar in color. After all the uniform regions are processed and all the regions are obtained, the average color of each region is calculated and assigned to each pixel of the region.

B. Multithresholding Algorithm

Multithresholding algorithm is used to cluster the image into several objects based on clustering analysis. The clustering analysis is an unsupervised method for automatically separating image objects. The pixels of an original image will be classified into different clusters. Each cluster contains one object with similar gray values.

a. Clustering Based Thresholding Algorithm

The mean value m, and the standard deviation σ, of the input image x, where x(i,j) denote the pixel located at (i,j) coordinate. Then x(i,j) is split according to mean and standard deviation of the processed sub-block image. Two centers C1 and C2 are defined by,

$$C1 = m + 0.5 * \sigma$$

$$C2 = m - 0.5 * \sigma \qquad (5)$$

The Euclidean distance from each pixel x(i,j) to C1 and C2 is calculated by,

$$D_{ij,1} = |x(i,j) - C1|$$

$$D_{ij,2} = |x(i,j) - C2| \qquad (6)$$

Initially two clusters are created and if $D_{ij,1}<D_{ij,2}$, x(i,j) will be placed in first cluster. Otherwise it will be placed in the second cluster. The maximum value of the first cluster or the minimum value of the second cluster is chosen as the threshold. Two classes are formed with all gray level values till the threshold in one class and the remaining values in the other class. To compute the seperability factor among k existing clusters, the computation of cluster probabilities w_n, cluster means μ_n, of each cluster ψ_n, can be calculated as,

$$\mu_n = \sum a(i) * p(i) \tag{7}$$

Where a(i) is the intensity value within the class,

P(i) is the probability of occurrence of the intensity value.

The within class variance (V_{WC}) of each class is calculated by,

$$V_{WC} = \sum \left\{ p(i) * (a(i) - \mu_c)^2 \right\} \tag{8}$$

Where μ_c is the mean of all intensity values in the cluster.

The seperability factor SF is calculated for the existing classes can be calculated as,

$$SF = V_{WC} / V_t \tag{9}$$

Where V_t is the total variance.

The class with maximum within class variance is further separated based on the Euclidean distance. The steps are repeated until the desired SF value is reached. SF values of 0.92 to 0.95 will yield satisfactory thresholding.

IV. Experimental Results

The peak finding and multithresholding algorithm using DFB structures are applied. Natural, texture and multispectral images are taken for comparison.

A. Performance Evaluation

The criteria of a good segmentation are,

- Regions should be homogeneous.
- Regions should be simple and without many holes inside.
- Adjacent regions should be significantly different.
- Boundaries should be smoothed.

To incorporate these requirements, a novel evaluation function is used.

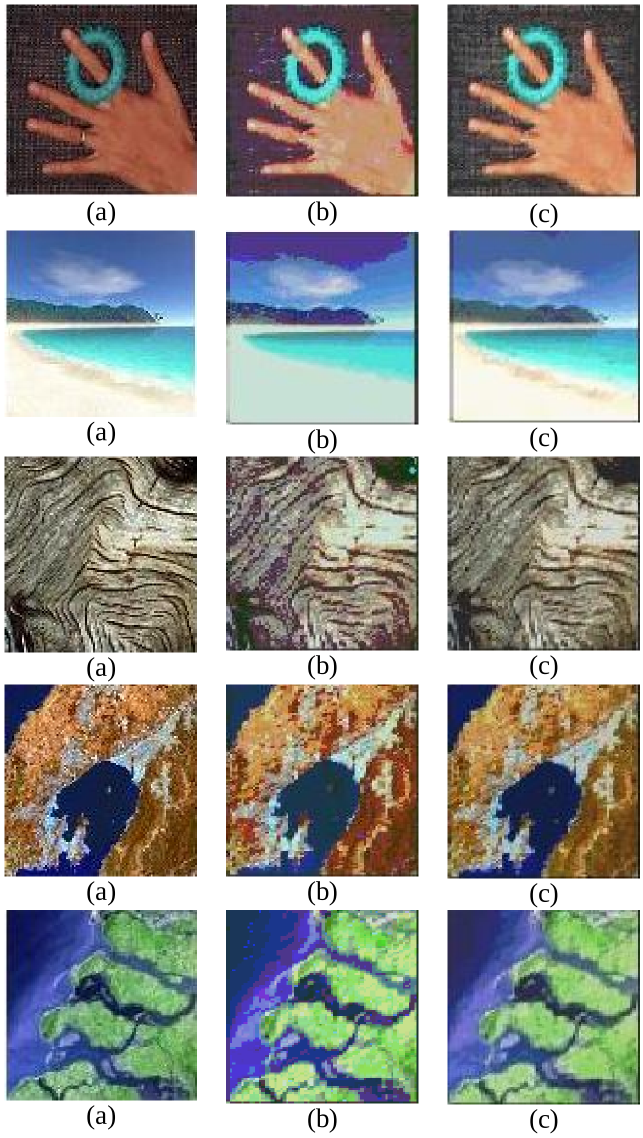


Fig 8. Experimental Results (a) Input image (b) Peak finding algorithm output (c) Multithresholding output

Table 1. Performance evaluation

Images	Peak Finding algorithm with DFB						Multithresholding with DFB					
	F measure			Color error			F measure			Color error		
	RGB	XYZ	LUV	RGB	XYZ	LUV	RGB	XYZ	LUV	RGB	XYZ	LUV
Natural Images												
original	10.67	7.90	5.86	7.76	26.93	106.26	0.63	0.72	5.84	0.01	18.61	106
Gallery Thumb	1.58	3.76	6.92	3.02	5.41	115.43	0.70	0.66	6.90	0.01	16.33	115
Multispectral images												
tn_farewell	0.42	1.20	1.93	1.55	0.62	61.09	0.19	0.21	1.93	0.008	9.18	60.9
tn_neth-dikes	0.51	1.16	2.81	1.70	0.62	73.57	0.35	0.50	2.80	0.01	14.49	73.4
Texture Images												
blue_red	0.30	1.50	2.90	1.31	0.82	74.77	2.43	2.34	2.89	0.02	30.06	68.1

Fabric.0013	6.74	6.80	1.97	6.16	16.34	61.71	1.33	1.25	1.97	0.02	23.54	60.0
g_tex2	9.81	7.43	1.02	7.44	27.84	44.41	1.09	1.25	1.02	0.02	21.36	58.1

The evaluation measure is defined as

$$F(I) = \sqrt{R} * \sum_{i=1}^{R} \frac{e_i^2}{\sqrt{A_i}} \qquad (10)$$

where 'I' is the image to be segmented, 'R' the number of regions in the segmented image, 'A_i' the area and 'e_i' the color error of region i. Table.1 provides a comparison of evaluation measure and color error for segmented images.

From Table 1, it is clear that that, the multithresholding algorithm offers good segmentation results when compared to the peak finding method, as both the value of evaluation function and color error is small. For some images although the color error is small as the number of regions is large and hence the evaluation function is high. Even though the color error is slightly increased for some images due to more number of regions, the segmentation is very good.

V. Conclusion

This paper presents a novel approach for segmentation of color images by peak finding and multithresholding algorithm using directional filter bank structure. The directional filter bank structure adds the important feature of directionality, and non-redundant in nature and also the computational efficiency is high. The peak finding technique takes only very few seconds to determine the homogeneity histogram and it is more accurate. The multithresholding algorithm is extremely powerful compared to the existing ones. It gives better segmentation results. The effect of this segmentation algorithm can also be studied for recently generated wavelet transforms.

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