K-MEANS AUTOMATIC IMAGE SEGMENTATION USING WAVELETS

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ABSTRACT

Model-Based image segmentation plays a dominant role in image analysis and image retrieval. To analyze the features of the image, model based segmentation algorithm will be more efficient compared to non-parametric methods. In this paper proposed K-means Automatic Image Segmentation using Wavelets (KAISWT) to make segmentation fast and simpler. The approximation band of image Discrete Wavelet Transform is considered for segmentation which contains significant information of the input image. Automatic image segmentation using wavelets result is displayed in white and black color, Using k=2 only. The Existing system problem overcomes using K-means clustering technique.The proposed system over the existing system is flexibility of changing the number of segments and this avoids the over segmentation problem. The proposed system requires very less amount of time when compared to existing system

Keywords:

Discrete Wavelets, Image Segmentation, Median Filtering,K-Means Clustering algorithm.

1.INTRODUCTION

In image processing the input is an image and the output is either an image or parameters related to the image is used to solve identification problems, such as forensic medicine or creating weather maps from satellite pictures. Image segmentation is a process of extracting and representing information from an image in order to group pixels together into regions of similarity. Image segmentation is classified into three categories viz., i) Manual i.e., supervised or interactive in which the pixels belonging to the same intensity range pointed out manually and segmented, the disadvantage is that it consumes more time if the image is large. ii) Automatic i.e., unsupervised which is more complex and algorithms need some priori information such as probability of the objects Having a special distribution to carry out the segmentation. iii) Semi-automatic is the combination of manual and automatic segmentation.

The pixel intensity based image segmentation is obtained using Histogram-Based method, Edge-Based method, Region-Based method and Model-Based method. ModelBased segmentation algorithms are more efficient compared to other methods as they are dependent on suitable

probability distribution attributed to the pixel intensities in the entire image. To achieve close approximation to the realistic situations, the pixel intensities in each region follow Generalized Gaussian Distribution (GGD). Some of the practical applications of image segmentation are Medical Imaging to locate tumors and other pathologies, locate objects in satellite images viz., roads, forests, etc., automated-recognition system to inspect the electronic assemblies, biometrics, automatic traffic controlling systems, machine vision, separate and track regions appearing in consequent frames of an image sequence and real time mobile robot applications employing vision systems. Motivation: Image segmentation plays an important role in biometrics as it is the first step in image processing and pattern recognition. Model based algorithms are used for efficient segmentation of images where intensity is the prime feature. The problem of random initialization is overcome by using Histogram based estimation. The Wavelet transform solves the problem of resolution which can indicate the signal without information loss and reduces the complexity. The segmentation is faster since approximation band coefficients of DWT are considered. Contribution: In this paper introduced Wavelet concept for image segmentation which reduces the computation time by considering approximation band of an image which is small in dimensions and contains significant information of original image. The initial parameters and final parameters are obtained by applying segmentation technique where the output of wavelet is given to it this enhance the quality of the segmented output respectively. Finally the out of the segmented image using wavelet is obtained.

2.RELATED WORK

Related Work Sharon et al., [1] introduced fast multi-scale algorithm which uses a process of recursive weighted aggregation to detect the distinctive segments at different scales. It determines an approximate solution to normalized cuts in time domain i.e., linear in the size of image with few operations per pixel. The disadvantage is that the segmented image fails to give smoother boundaries.

Prasad Reddy et al., [2] proposed a color image segmentation method based on Finite Generalized Gaussian Distribution (FGGD). The observed color image is considered as a mixture of multi-variant densities and the initial parameters are estimated using K-Means algorithm. The final parameters are estimated using EM algorithm and the segmentation is obtained by clustering according to the ML estimation of each pixel. However, computational time is more because of complex calculations.

Donnell et al., [3] introduced a phase-based user steered segmentation algorithm using Livewire paradigm that works on the image features. Livewire finds optimal path between users selected image locations thus reducing manual effort of defining the complete boundary. The phase image

gives continuous contours for the livewire to follow. The method is useful in medical image segmentation to define tissue type or anatomical structure.

James et al., [4] proposed color image segmentation for interactive robots based on color thresholding, nearest neighbor classification, color space thresholding and probabilistic methods that are useful in real time mobile robot applications. Each pixel is classified into a full resolution captured color image to merge regions upto 32 colors, the centroid bounding box and area at 30 hertz are then obtained. The method is useful to accelerate low level vision in real time applications.

Zhixin and Govindaraju [5] proposed hand written image segmentation using a binarization algorithm for camera images of old historical documents. The algorithm uses a linear approximation to determine the flatness of the background. The document image is normalized by adjusting the pixel values relative to the line plane approximation.

Sumengen and Manjunath [6] proposed multi-scale edge detection approach to achieve good localization and good detection of edges. The technique is based on first finding an edge representation at each scale and then combining them using certain heuristics. The objective is to find favour edges that exist at a wide range of scales and localize these edges, which is extended to multi-scale segmentation using anisotropic diffusion scheme.

Jitendra et al., [7] proposed cue integration in image segmentation by using an operational definition of textons, the putative elementary units of texture perception and an algorithm for partitioning the image into disjoint regions of coherent brightness and texture. The method finds boundaries of regions by integrating peaks in contour orientation energy and differences in texton densities across the contour by cue integration.

Felzenswalb and Huttenlocher [8] described image segmentation based on pairwise region comparison. The algorithm makes simple greedy decisions and produces segmentations that obey the global properties of being not too coarse and not too fine according to a particular region comparison function. The method is time linear in the number of graph edges and is fast in practice.

Jianbo and Malik [9] proposed normalized cuts and image segmentation. Normalized cuts measures both the total dissimilarity between the different groups as well as total similarity with in the groups, which is used for segmentation.The method is optimized using generalized eigen value problem.

Wu et al., [10] proposed a color image segmentation method based on Finite Gaussian Mixture (FGM) model. The observed color image is considered as a mixture of multi-variant densities

and the mixture parameters are estimated using the EM algorithm. K-means algorithm is used to initialize the Gaussian mixture parameters. The number of mixture components is automatically determined by implementing the Minimum Message Length (MML) criteria into the EM algorithm. The method is totally unsupervised because it integrates the parameter estimation and model selection in a single algorithm.

Yamazaki [11] introduced a color image segmentation method based on the ML estimation. The EM algorithm is used for calculating the ML estimates and initial parameters for the EM algorithm are estimated by the multi-dimensional histogram and the minimum distance clustering methods. Since no random selection is used for parameter estimation, the method is useful for unsupervised image segmentation applications. Mena and Malpica [12] proposed supervised method for solving automatic extraction problem in segmentation of color images for extracting information from terrestrial, aerial or satellite images. The Dempster-Shafer theory of evidence is applied in order to fuse the information using Texture Progressive Analysis (TPA) so as to obtain the greatest amount of information from the different order statistics.

Sumengen and Manjunath [13] introduced variational segmentation cost functions and associated active contour methods that are based on pairwise similarities or dissimilarities of the pixels. A curve evolution framework known as Graph Partitioning Active Contours is used which is computationally efficient and a good solution for natural images.

Marian [14] used active contours for image segmentation. An active contour is an energy minimizing spline that detects specified features within an image and is a flexibile curve which can be dynamically adapted to required edges or objects in the image by interactive process. The user must suggest an initial contour, which is quite close to the intended shape. The disadvantages are the fact of active contour dependency on the initial points of the contour, type of the picture and computation difficulty.

Geraud et al., [15] proposed segmentation of color images using a classification in the 3-D color space. A classifier that relies on mathematical morphology and more precisely on the Watershed algorithm is used. Since Connected Watershed Algorithm (CWA) is applied in the histogram space, the method contrasts with the "classical" use of the Watershed algorithm in the image space as a segmentation tool. The main drawback is CWA consumes more memory and time.

Wesolkowski et al., [16] introduced color image segmentation algorithm based on shading and highlight invariant transformation. The transformation coupled with the mixture of Principal Components Algorithm is able to cluster colors irrespective of highlights and shading under the

condition of white balancing. The disadvantages are the problems caused by small RGB values and illumination color changes.

Wenchao et al., [17] proposed a hybrid segmentation algorithm that combines prior shape information with normalized cut to correctly segment the target whose boundary may be corrupted by noise. The shape model is used for finding corresponding Eigen Vectors to segment the image.

Leah et al., [18] showed that the segmentation and blind restoration are tightly coupled and can be successfully solved together. Mutual support of the segmentation and blind restoration is processed by a joint variational framework which integrates Mumford-Shah segmentation with parametric blur-kernel recovery and image deconvolution. The function is formulated using the convergence approximation and is iteratively optimized via the alternate minimization method.

Mavrinac [19] proposed a color image segmentation using a competitive learning clustering scheme. Two fundamental improvements are made to increase the speed performance. i) Initialization of the system with two units rather than one ii) Reducing the number of iterations with no adverse effect and random selection among winning vectors in case of a tie. A very high number of clusters lead to over segmentation which is reduced using thresholding and rival penalization.

Timothee et al., [20] presented a spectral segmentation algorithm based on multiple scales of the image by capturing both coarse and fine level details without iteration. The method focused on the Propagation of local grouping cues that helps in detecting coherent regions with faint boundaries. The multi-scale graph is introduced in parallel so that information propagates from one scale to another. The complexity of the algorithm is linear in the number of pixels. The long-range graph connections significantly improve the running time and quality of segmentation.

3.MODEL

In this section discussed definitions and AISWT model A. Definitions: i. Mean: The average intensity of a region is defined as the mean of the pixel intensities within that region. The mean μz of the intensities over M pixels within a region K is given by Equation (3.1)

$$\mu_z = \frac{1}{M}\sum_{i=1}^{M} x_i$$

Alternatively, we can use formulation based on the normalized intensity histogram p(zi) where i=0, 1,2,…,L-1 and L is the number of possible intensity values as given by Equation (3.2)

$$\mu = \sum_{i=1}^{L} z_i \, p(z_i)$$

ii. Variance: The variance of the intensities within a region K with M pixels is given by Equation (3.3).

$$\sigma_z^2 = \frac{1}{M} \sum_{i=0}^{M} (x_i - \mu_z)^2$$

Using histogram formulation the variance is given by Equation (3.4)

$$\sigma^2 = \sum_{i=0}^{L} (z_i - \mu)^2 \, p(z_i)$$

**iii. Probability Distribution Function (PDF) of the intensities:**

The PDF P(z), is the probability that an intensity chosen from the region is less than or equal to a given intensity value z. As z increases from -∞ to +∞, P (z) increases from 0 to 1. P(z) is monotonic, non-decreasing in z and thus dP/dz ≥ 0.

iv. Shaping parameter P: Shaping parameter defines the peak ness of the distribution which varies from 1 to ∞. The GGD becomes Laplacian Distribution if P = 1, Gaussian Distribution if P=2 and Uniform Distribution if P→ +∞. v. Computational Time: Time required for the Execution of the algorithm B. Block diagram of AISWT The Figure 1 gives the block diagram of AISWT I. Input image: The input images are of different formats, sizes and types. The image pixel intensity in the entire image is a Random Variable and follows a GGD. II. DWT: The Wavelet Transform is created by repeatedly filtering the image coefficients on a row by row and column by column basis. A two-dimensional DWT decomposition of image contains various band information such as low-low frequency approximation band, high-low frequency vertical detail band, low-high frequency horizontal detail band and high-high frequency diagonal detail band. We assume each coefficient of approximation band is a Random Variable z and also follow GGD. The approximation band is used for the segmentation purpose, which is quarter the size and has significant information of the original image. Hence the computation time required reduces. III. Initial parameters Estimation: Initial parameters like mean μ, variance σ and mixing parameter α are determined using Histogram based initial estimation which is a clustering algorithm. The initial parameters are calculated in two steps:
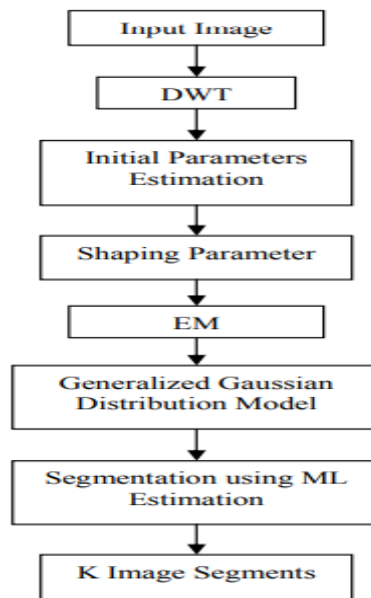
Fig 3.1 EXISTING SYSTEM
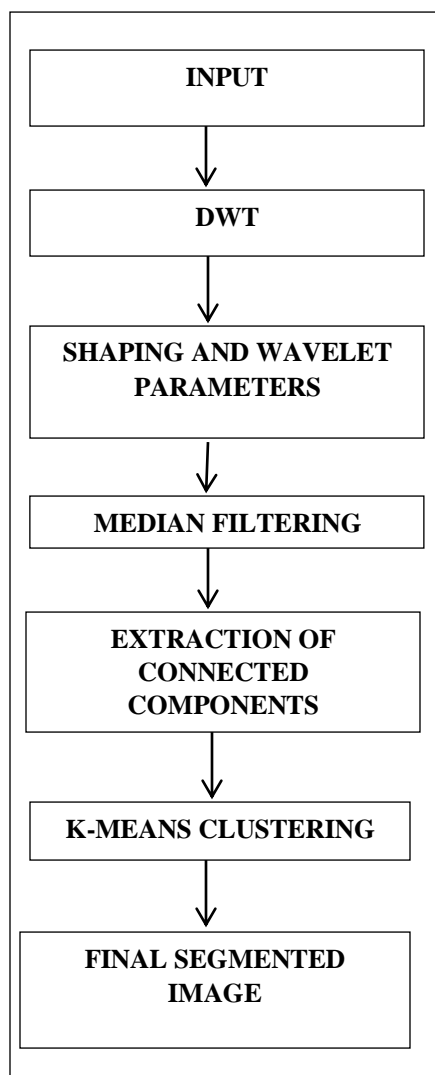
PROPOSED SYSTEM OF K-MEANS AUTOMATIC SEGMENTATION USING WAVELETS

4.ALGORITHM:

Problem: The *K* segmented regions are obtained and for K=2, the image is segmented into foreground and background. Displaying the colors are white and black only.

Step 1: initially we should consider an input image.

Step 2: now apply discrete wavelet transform at 2 stages. where the enhanced output image is obtained.

Step 3: the shaping and wavelet parameters are extracted.

Step 4: the use of median filter removes the noise parameters form the image.

Step 5: Here the extraction of connected components was extracted by using the ROI.

Step 6: finally the segmented image is obtained with more flexibility with K.

Input : Image of variable size • Output : Segmented regions 1 DWT is applied on an image and approximation band is considered.

Image segmentation is the classification of an image into different groups. Many kinds of research have been done in the area of image segmentation using clustering. There are different methods and one of the most popular methods is **K-Means clustering algorithm**.

k-means clustering is a method of vector quantization, originally from signal processing, that aims to partition n observations into k clusters in which each observation belongs to the cluster with the nearest mean (cluster centers or cluster centroid), serving as a prototype of the cluster. This results in a partitioning of the data space into Voronoi cells. It is popular for cluster   analysis in data   mining. k-means   clustering   minimizes   within-cluster   variances (squared Euclidean distances), but not regular Euclidean distances, which would be the more difficult Weber problem: the mean optimizes squared errors, whereas only the geometric median minimizes Euclidean distances. For instance, better Euclidean solutions can be found using k-medians and k-medoids.

The   problem   is   computationally   difficult   (NP-hard);   however,   efficient heuristic algorithms converge quickly to a local optimum. These are usually similar to the expectation-maximization   algorithm for mixtures of Gaussian   distributions via   an   iterative   refinement approach employed by both k-means and Gaussian mixture modeling. They both use cluster centers to model the data; however, k-means clustering tends to find clusters of comparable spatial extent, while the expectation-maximization mechanism allows clusters to have different shapes.

The algorithm has a loose relationship to the k-nearest neighbor classifier, a popular machine learning technique for classification that is often confused with k-means due to the name. Applying the 1-nearest neighbor classifier to the cluster centers obtained by k-means classifies new data into the existing clusters. This is known as nearest centroid classifier.

$$\underset{\mathbf{S}}{\arg\min} \sum_{i=1}^{k} \sum_{\mathbf{x} \in S_i} \|\mathbf{x} - \boldsymbol{\mu}_i\|^2 = \underset{\mathbf{S}}{\arg\min} \sum_{i=1}^{k} |S_i| \operatorname{Var} S_i$$

where $\boldsymbol{\mu}_i$ is the mean of points in S_i. This is equivalent to minimizing the pairwise squared deviations of points in the same cluster:

$$\underset{\mathbf{S}}{\arg\min} \sum_{i=1}^{k} \frac{1}{2|S_i|} \sum_{\mathbf{x},\mathbf{y} \in S_i} \|\mathbf{x} - \mathbf{y}\|^2$$

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 characteristics.

have never thought otherwise.

***K*-Means clustering** algorithm is an unsupervised algorithm and it is used to segment the interest area from the background. It clusters, or partitions the given data into K-clusters or parts based on the K-centroids.

The algorithm is used when you have unlabeled data(i.e. data without defined categories or groups). The goal is to find certain groups based on some kind of similarity in the data with the number of groups represented by K.

Steps in K-Means algorithm:

1. Choose the number of clusters K.
2. Select at random K points, the centroids(not necessarily from your dataset).
3. Assign each data point to the closest centroid → that forms K clusters.
4. Compute and place the new centroid of each cluster.
5. Reassign each data point to the new closest centroid. If any reassignment . took place, go to step 4, otherwise, the model is ready.

Advantage:

The major advantage of the proposed system over the existing system is flexibility of changing the number of segments and this avoids the over segmentation problem. The proposed system requires very less amount of time when compared to existing system.

RESULT ANALYSIS

Here considered an images lizard, parashot etc.. where the input image is enhanced using DWT-1 and the number of segmented is given by using K. If the number of segments are selected as two i.e., K=2 foreground and background can be differentiated in an image. Figures 3, 4, 5 and 6 gives the segmentation results of lizaed, parashut in which the original image is given. and enhanced image is given. It is observed that as dimension of the image increases, the computational time increases. The existing algorithms FGM, FGGD and AISWT require more time compared to the proposed algorithm. Our proposed technique requires 30% less time compared to AISWT.
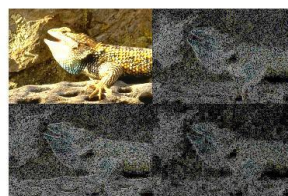
number of segments = 8

number of clusters =2,4,8…

Original Image   Enhanced image of dwt stage 1

OUTPUT OF DWT STAGE 1

Enhanced image of dwt stage 2

OUTPUT OF DWT STAGE 2

Filtered image

segmented image at K=2(black and white)

k means segmented image using k=8

CONCLUSION

In this paper, proposed fast segmentation algorithm of K-Means automatic segmentation of color image using wavelet transform. The approximation band of an image DWT is considered as a mixture of K-Component. The initial parameters are estimated using DWT. Through K-means clustering technique, the final output segmented image is obtained. The segmentation is done by filtering image with clustering segmentation. The AISWT algorithm is computationally efficient for segmentation of large images and performs much superior to the earlier image segmentation methods FGM and FGGD in terms of computation time and image quality index. Here flexibility of providing the number of segments of each input image gives more suitable results.

REFERENCES

[1] E. Sharon, A. Brandt and R. Basri, "Fast Multi-Scale Image Segmentation," Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition, vol. 1, pp. 70-77, 2000

[2] P. V. G. D. Prasad Reddy, K. Srinivas Rao and S. Yarramalle, "Unsupervised Image Segmentation Method based on Finite Generalized Gaussian Distribution with EM and K-Means Algorithm," Proceedings of International Journal of Computer Science and Network Security, vol.7, no. 4, pp. 317-321, April 2007.

[3] L. O. Donnell, C. F. Westin, W. E. L. Grimson, J. R. Alzola, M. E. Shenton and R. Kikinis, "Phase-Based user Steered Image Segmentation," Proceedings of the Fourth International Conference on Medical Image Computing and Computer-Assisted Intervention, pp. 1022-1030, 2001

[4] J. Bruce, T. Balch and M. Veloso, "Fast and Inexpensive Color Image Segmentation for Interactive Robots," Proceedings of the IEEE International Conference on Intelligent Robots and Systems, vol. 3, pp. 2061-2066, 2000.

[5] Z. Shi and V. Govindaraju, "Historical Handwritten Document Image Segmentation using Background Light Intensity Normalization," SPIE Proceedings on Center of Excellence for Document Analysis and Recognition, Document Recognition and Retrieval, vol. 5676, pp. 167-174, January 2005.

[6] B. Sumengen and B. S. Manjunath, "Multi-Scale Edge Detection and Image Segmentation," Proceedings of European Signal Processing Conference, September 2005.

[7] J. Malik, S. Belongie, J. Shi and T. Leung, "Textons, Contours and Regions: Cue Integration in Image Segmentation," Proceedings of Seventh International Conference on Computer Vision, pp. 918-925, September 1999.

[8] P. F. Felzenswalb and D. P. Huttenlocher, "Efficient GraphBased Image Segmentation," Proceedings of International Journal of Computer Vision, vol. 59, no. 2, pp. 167-181, 2004.

[9] J. Shi and J. Malik, "Normalized Cuts and Image Segmentation," IEEE Transactions on Pattern Analysis and Machine Intelligence, vol. 22, no. 8, pp. 888-905, 2000.

[10] Y. Wu, X. Yang and K. L. Chan, "Unsupervised Color Image Segmentation based on Gaussian Mixture Models," Proceedings of Fourth International Joint Conference on Information, Communications and Signal Processing, vol.1, no. 15, pp. 541-544, December 2003.