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Segmentation of Images by using Fuzzy k-means clustering with ACO

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Abstract— Super pixels are becoming increasingly popular for use in computer vision applications. Image segmentation is the process of partitioning a digital image into multiple segments (known as super pixels). In this paper, we developed fuzzy k-means clustering with Ant Colony Optimization (ACO). In this propose algorithm the initial assumptions are made in the calculation of the mean value, which are depends on the colors of neighbored pixel in the image. Fuzzy mean is calculated for the whole image, this process having set of rules that rules are applied iteratively which is used to cluster the whole image. Once choosing a neighbor around that the fitness function is calculated in the optimization process. Based on the optimized clusters the image is segmented. By using fuzzy k-means clustering with ACO technique the image segmentation obtain high accuracy and the segmentation time is reduced compared to previous technique that is Lazy random walk (LRW) methodology. This LRW is optimized from Random walk technique.

Index Terms— ACO, Fitness Function, Fuzzy, K-means

1 INTRODUCTION

Computer vision application has several algorithms such as Digital image processing also Digital signal processing. Digital image processing is used to execute on digital images and digital signal processing is used to perform on analog images which have many advantages. It allows a much wider range of algorithms to be applied to the input data and can avoid problems such as the build-up of noise and signal distortion for the period of processing. Digital image processing allows the use of much more complex algorithms, and hence, can offer both more complicated performance of simple tasks, and the implementation methods which would be impossible with analog. Any techniques which are used in digital image processing consist of Pixilation, Linear filtering, Hidden Markov models, anisotropic diffusion, Partial differential equations, Self-organizing maps, neural networks, Wavelets.

The key purpose of segmentation is to change the representation of image that is more significant and easier to analyze. Image segmentation is used to place the objects and boundaries (lines, curves, etc.) in the images. More precisely, the process of image segmentation is to assigning a label to every pixel in image such that pixels with the same label share certain characteristics. The result of image segmentation is covering the entire image, or a set of contours extracted from the image. The same characteristic or computed property of each pixel in a region is similar, such as color, intensity, or texture. Nearby regions are considerably different with respect to the same characteristic (s).

There is an N number of segmentation techniques are offered in the image processing. Clustering having high accuracy compared to other segmentation technique because of the detecting a number of portions high at a single iteration. The basic algorithm of clustering

1. Pick *K* cluster centers, either randomly or based on some heuristic
2. Assign each pixel in the image to the cluster that minimizes the distance between the pixel and the cluster center
3. Re-compute the cluster centers with averaging all of the pixels in the cluster
4. Repeat steps 2 and 3 until convergence is attained (i.e. no pixels change clusters)

The K-means algorithm is an iterative technique that is used to partition an image into *K* clusters. In this case, distance is the squared or absolute difference between a pixel and a cluster center. The difference is typically based on pixel color, intensity, texture, location, or a weighted combination of these factors. *K* can be selected manually, randomly, or with a heuristic. This algorithm is guaranteed to converge, but it may not return the optimal solution. The quality of the solution depends on the initial set of clusters and the value of *K*.

Many difficulties are happen in image processing because the data, tasks, and the results are uncertain. This uncertainty, however, is not always due to the randomness, but to the inherent ambiguity and vagueness of image data. Beside randomness-which can be managed with probability theory-other kinds of imperfection in image processing include grayness ambiguity, geometrical fuzziness, and a vague knowledge of image features.

The idea of fuzzy sets is simple and natural, in classical set theory; a threshold such as the gray level 100 has to be set. But since the darkness of a particular pixel is a matter of degree, a fuzzy set (or subset to be precise) can model this property greatly better. To define this subset, two thresholds, say gray levels 50 and 150 is required. Then all the gray levels that are less than 50 are full members of the set and all gray levels greater than 150 are not members of the set. Gray levels between 50 and 150, however, have a partial membership in the set.

To make image processing using fuzzy logic, three stages must occur. First image fuzzification is used to modify the membership values of a specific data set or image. After the image data are transformed from gray-level plane to the membership plane using fuzzification, appropriate fuzzy techniques modify the membership values. This can be a fuzzy clustering, that is a fuzzy rule-based approach, or a fuzzy integration approach. After this fuzzification process we have to decoding this result, called de-fuzzification, then the results in an output image. "The main power of fuzzy image processing is in the modification of the fuzzy membership values,"

Ant Colony Optimization [7] (ACO) is a paradigm for designing Meta heuristic algorithms in combinatorial optimization problems. The essential feature of ACO algorithms are combination of a priori information about the structure of a promising solution with a posteriori information about the structure of previously obtained good solutions. Meta heuristic algorithms are algorithms which, in order to escape from local optima, drive some basic heuristic: either a constructive heuristic starting from a null solution and adding elements to build a good complete one, or a local search heuristic starting from a complete solution and iteratively modifying some of its elements in order to achieve a enhanced one. The Meta heuristic part permits the low- level heuristic to obtain solutions better than those it could have achieved alone, even if iterated. Usually, the controlling mechanism is achieved either by constraining randomizing the set of local neighbor solutions to consider in local search or by combining elements taken with different solutions (as is the case of evolution strategies and genetic or bionomic algorithms).

The characteristic of ACO algorithms are their explicit use of elements of previous solutions. In fact, they drive a constructive low-level solution, as GRASP does, but including it in a population framework and randomizing the construction in a Monte Carlo way. A Monte Carlo combination of different solution elements is suggested also by Genetic Algorithms, but in the case of ACO the probability distribution is explicitly defined with previously obtained solution components. A set of computational concurrent and asynchronous agents (a colony of ants) moves through the states of the problem corresponding to partial solutions of the problem to solve.

2 LRW FOR SUPERPIXEL SEGMENTATION

Superpixel is combining more number of pixels, which is grouping regular pixels in the image, which is used in many computer vision applications such as image segmentation and object recognition. Our LRW algorithm with self-loops efficiently solves the segmentation difficulty in weak boundary and complex texture regions. On the other hand, the LRW based superpixel algorithm may experience from the sensitiveness of the initial seed positions. In order to overcome these limitations and get better performances, we further build up a new superpixel optimization [7] approach by introducing an energy optimization framework. Our superpixel optimization strategy is basically a compactness constraint, which ensures the resulting superpixel to distribute uniformly with the homogeneous size through relocation and splitting mechanism.

Our energy function is composed of two items, the first data item adaptively optimizes the positions of seed points to make the superpixel boundaries stick to the object boundaries well, and the second smooth item adaptively divides the large superpixel into small ones to make the superpixel more homogeneous. According to these relocated seed positions and newly created seeds with the splitting scheme, our LRW algorithm is executed again to optimize the initial superpixel, which makes the boundaries of final superpixel adhere to object boundaries incredibly fit.

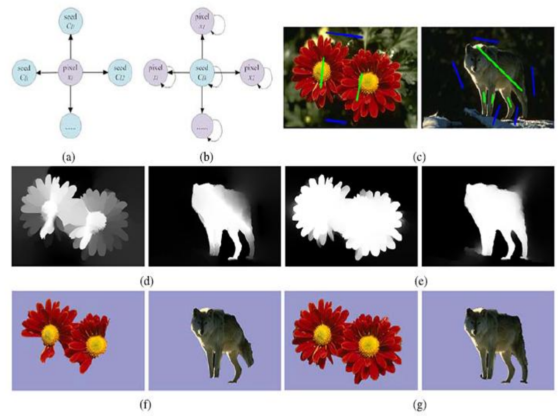

Fig.1 Illustrates the structure of RW and LRW algorithms with their comparison results.

(a)usual RW method without self-loops; (b)our LRW algorithm with self-loops; (c)input images with user seeds (scribbles); (d)and (e)are the probability maps by RW and LRW algorithms; (f)and (g)are the segmentation results by RW and our LRW method. Image segmentation result of our LRW algorithm has better performances than the classic RW method with the same user scribbles (green for foreground and blue for the background), especially in the leg regions of wolves and the flower parts.

Lazy Random Walk [6] is a twofold algorithm that is shown in bellow figure 2. First one self-loop is added to the vertex to ensure the boundary constrains. Since a vertex with a heavy self-loop is more likely to absorb its neighboring pixels than the one with light self-loops, which makes the vertex to absorb and capture both the weak boundary and texture information with self-loops.

On the other hand, instead of starting from the pixels to the seed points as the original RW algorithm does, our LRW algorithm computes the commute time from the seed points to other pixels. The probability maps with our LRW approach gives more confident separation than the ones by RW method. Thus, our LRW algorithm significantly outperforms the original RW algorithm of the test images with the same the background and the foreground seed scribbles.

3 SUPERPIXEL INITIALIZATION

Our aim is to make super pixel [1] spread over the input image as much as possible. LRW methods begin with initial superpixel seeds on the input image. We first place K circular seeds in a lattice formation along with the distance between lattice neighbors are equal to $\sqrt{N/K}$ where N is the total number of pixels in the image. This strategy ensures that the superpixels [1] will be evenly distributed on the whole image.

However, this placement approach may cause some seeds too irregularly close to a strong edge because these images are not completely uniform distribution. Hence, the initial seed position is perturbed by moving it along its gradient direction according to the seed density.

After we have finished the seed initialization stage, we then use the LRW algorithm to compute the boundaries of super pixels.

4 SUPERPIXEL OPTIMIZATION

This optimization should contain that the superpixel boundaries stick well to image intensity boundaries and also make with regular uniform size in complicated texture regions. The optimization new energy function has data item and smooth item.

$$E = \sum (\text{Area } (S_l)\text{-Area } (\hat{s}))^2 + \sum \hat{w}_x CT\,(c_l^n,x)^2$$

The data item makes the texture information of image to be distributed uniformly in the superpixels, which produces more homogeneous superpixels. The smooth item makes the boundaries of superpixels to be more consistent with the object boundaries in the image. Area (Sl) is the area of super pixel and Area (¯S) defines the average area of super pixels.

5 MODULES

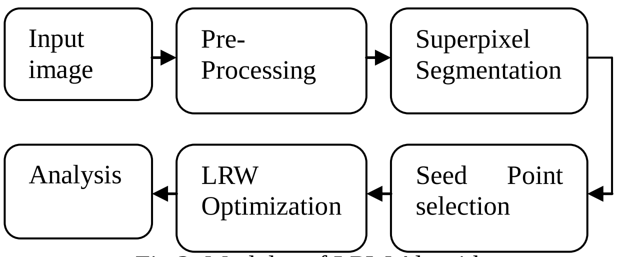

Fig 2: Modules of LRW Algorithm

5.1 Pre Processing

Initially the input images are pre-processed which is used to improve the quality of the images. For pre-processing stage normally some filtering operations are used. Here Median filter is used for filtering which consider each pixel in the image in turn and looks at its nearby neighbors to decide whether or not it is representative of its surroundings.

5.2 Seed Selection

Seed selection has numerous desired properties, that is computationally efficient, representationally efficient, percetually meaningful.computationally efficient reduces the complexity of images from hundreds of thousands of pixels to just a few hundred superpixels.Representationally efficient which provides pairwise constraints among units, whereas adjacent pixels on the pixel-grid, can currently model much longer-range relations between superpixels.Percetually meaningful produce each superpixel is a perceptually consistent unit, i.e. every part of pixels in a superpixel is most likely uniform in, say, color and texture.

5.3 Superpixel Segmentation

Superpixel segmentation is an important element for several computer vision applications such as object recognition, image segmentation and single view 3D reconstruction. A superpixel is commonly defined as a perceptually identical region in the image. A superpixel representation greatly reduces the number of image primitives compared to the pixel representation. The preferred properties of superpixel segmentation depends on the application of interest. At this point listed some common properties required with various vision applications: Each superpixel should be related with only one object. The set of superpixel boundaries should be a superset of object boundaries.

5.4 LRW Optimization

It will be sometime suitable to consider a slight variation of the random walk, in which each step, with probability 1= 2, Staying of the current vertex and only with probability 1 = 2. Its make the usual step of random walk. This variation is called lazy random walk and it can be viewed as a vanilla version of random walk[6] in a graph in which we added d (u)self-loops to every vertex u. Our LRW algorithm with self loops effectively solves the segmentation problem in weak boundary and complex texture regions. Further, the LRW based superpixel algorithm may suffer from the sensitiveness of the initial seed positions.

Performances analysis

Accuracy and Error rate are the best in proposed approach compared with prior work. The simplicity, efficiency and the performances of the algorithm is faster and more practical for real-time systems than other the existing superpixel segmentation methods. A Segmentation performance that context-aware approach of motivated us to pursue a training method for a superpixel classifier with even some of the examples while retaining the accuracy of that learned on complete groundtruth.

5.5 Quantitative Comparison Results with Other Algorithms

There are three commonly used evaluation measures to evaluate the performances of superpixel algorithms. These measures include the under segmentation error (UE), the boundary recall (BR), and the achievable segmentation accuracy (ASA).

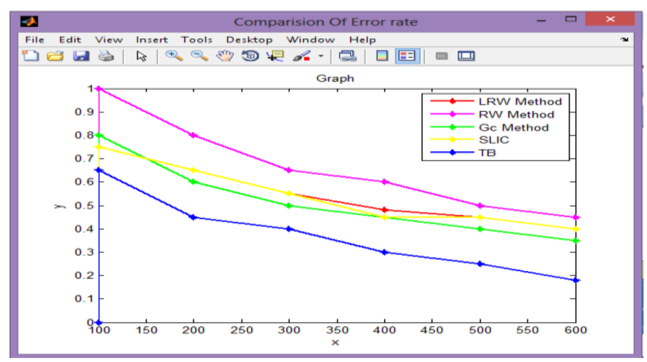

Fig 3. comparison of error rate

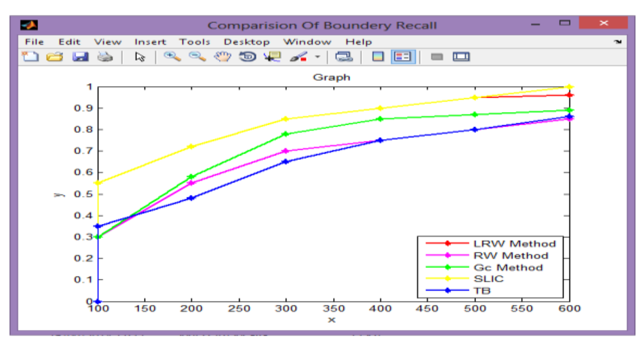

Fig 4. Comparison of Boundary Recall

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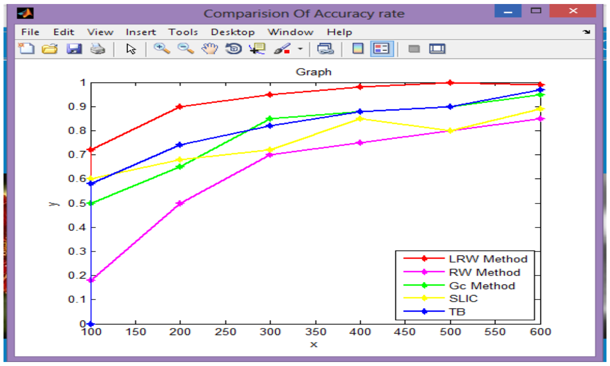

Fig 5. Comparison of accurate rate

6 MODULE DESCRIPTIONS FOR FUZZY K-MEANS CLUSTERING

The proposed system that is Fuzzy k-means clustering with ACO technique gives high accuracy in image segmentation and segmentation time is reduced compared to previous technique that is Lazy random walk methodology. In figure 4 defined how the segmentation and optimization process is done via using Fuzzy k-means clustering with ACO technique.

6.1 Pre- Processing

Initially the input images are preprocessed; in order to enhance the quality of the images we normally employ various filtering operations in that Median filter is used for filtering it considers each pixel in the image in turn and looks at its nearby neighbors to decide whether or not it is representative of its surroundings. In place of minimally replacing the pixel value with the median of neighboring pixel values. The median is calculated by means of first sorting all the pixel values from the surrounding neighborhood in numerical order along with replacing the pixel being considered with the middle pixel value.

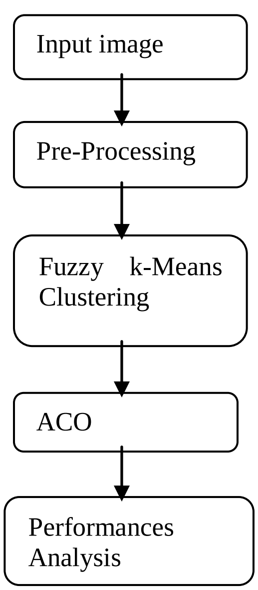

Fig 3: Module description for Fuzzy K-means clustering with ACO

6.2 Fuzzy k-means clustering

The K-means algorithm is an iterative technique that is used to partition an image into *K* clusters. In this case, distance is the squared or absolute difference among a pixel and a clusters center. When the image is clustered into a number of clusters defined. Due to improper separation fuzzy rule is used. The K-means clustering is a distance based clustering technique. Then the fuzzy rule is applied to the clustered image in that rule fixing some threshold value according to rules clustered image is again re-cluster.

6.3 Ant Colony Optimization

This algorithm is a member in swarm intelligence methods, and it constitutes some Meta heuristic optimizations. Optimization technique is mostly used to obtain the suboptimal solution in many opportunities. While using fuzzy k-means clustering the required object boundary will be detected with relevant background boundaries. While increasing the levels of ant colony optimization we can reduce background boundaries.

7 CONCLUSION

We have presented a novel image superpixel approach using the Fuzzy k-Means Clustering and Ant colony optimization algorithm. In this paper, we developed fuzzy k-means clustering with Ant Colony Optimization (ACO). In this proposed algorithm the primary assumptions are made in the calculation of the mean value, which is depending on the colors of neighbored pixel in the image. Fuzzy mean is calculated for the whole image, this process having set of rules that rule is applied iteratively and the whole image is clustered. From this method the segmentation accuracy is high and iteration is reduced compared to the existing system.

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