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A Brief Review: Super-Pixel Based Image Segmentation Methods

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Abstract: *In this paper image segmentation techniques have been explored which uses super pixel as intermediate step along with fuzzy clustering methods. Superpixel segmentation is the process of partitioning an image into multiple segments called superpixels, which are homogeneous as in pixels inside every portion are comparable concerning certain attributes, for example, shading and surface. In spite of the fact that superpixel segmentation as a rule yields over-sectioned results instead of item level fragments, it radically diminishes the quantity of picture primitives with insignificant loss of data and offers a simple approach to separate the probably picture objects with as few portions as could be expected under the circumstances. Likewise, since superpixel segmentation gives a more characteristic and perceptually significant representation of the info picture, it is more helpful and powerful to concentrate area based visual elements utilizing superpixels. In order to get better segmentation the FCM use the GLCM features of turbo pixels instead of intensity values of pixels and hence help in decision making to put a particular turbo-pixel into different fcm clusters. In the proposed work, we will explore these techniques in order to get better segmentation of different sections of the input images.*

Keywords: Super-pixels, Segmentation, FCM,DWT, GLCM

1.1 Image segmentation

The image segmentation aims to divide an image into several disjoint regions with uniform and homogeneous attributes. Many different segmentation methods have been explored and proposed **[1].** Clustering based method for image segmentation is an important method. fuzzy c-means (FCM) clustering method has been widely studied and successfully applied in image segmentation. The conventional FCM method is able to effectively segment noise-free images. However, this method does not incorporate any spatial information, so that the segmentation result is sensitive to noise [2]. Therefore, spatial constraint is imposed in fuzzy clustering [3]. By modifying the objective function, the methods of enhancing the robustness of FCM to noise are proposed [2] In the aforementioned algorithm, the state of each pixel is determined by the membership of neighboring pixels. Due to these techniques are computationally intensive, applying them directly to the pixels in an image usually leads to long computation times. So we use super pixel to reduce complex computations. Superpixels are the result of perceptual grouping of pixels, and the result of an image over segmentation. Super pixels carry more information than pixels and align better with image edges than rectangular image patches. The proposed method is based on superpixels, and the superpixels are extracted based on multi-scale spatial features. The influence of neighboring and similar superpixels is incorporated into FCM and the influential degree is optimized to improve segmentation performance [4].

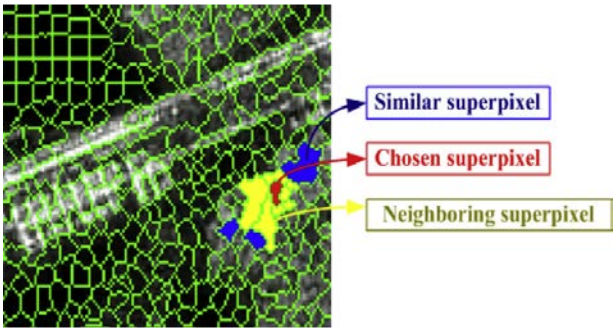

Figure 1.1: Selecting superpixel [5]

1.2 Super pixels

Image representation is fundamental to image analysis. Superpixels aim to resolve this by representing the image in a more logical manner, grouping pixels based on homogeneity criteria and restoring the object boundaries. This provides a differing representation of each image, where the boundaries are irregular and the superpixels are of different size. This is achieved by image over-segmentation, the process of reducing an image into a number of regions, by covering images in such a way as to create non-overlapping regions of homogeneous colour. A superpixel can be defined as a spatially coherent homogeneous structure.

1.3 Superpixel extraction

Figure 1.2 shows an image represented using the basic approach to superpixel generation. Each superpixel contains a small number of colours, yet the area or shape of each superpixel can be allowed vary. Therefore, the careful choice of the superpixel method and its parameters for the particular application are crucial. We use Turbo Pixels to extract superpixels from an image, in which one superpixel is roughly uniform in texture and gray, so that the boundaries of regions are preserved. In order to encode gray, texture and spatial information into superpixels, we describe each superpixel j by a 7-dimensional wavelet feature vector Fj = (f1, f2, . . . , f7), in which Fj is the average wavelet value of all pixels in superpixel j across 3 layers. This feature is represented as F. Spj is the average location of all pixels in superpixel [5] The primary use of superpixels is to significantly reduce the number of pixel regions, typically by two orders of magnitude. This reduction in pixels naturally leads to faster implementation of further image processing algorithms [6]

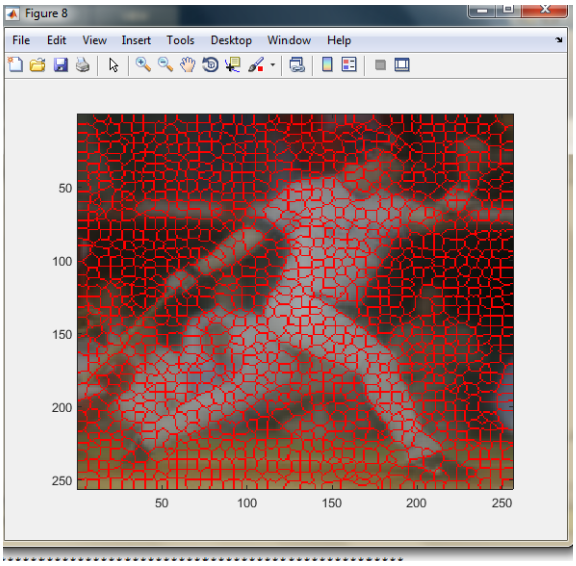

Figure 1.2: A superpixel representation of a simple image [7]

1.4 Selecting the neighboring and similar superpixels

To reduce the computational complexity, we extract superpixels from an image. Given a chosen superpixel shown in red color in Fig. 1.1, the neighboring superpixels are all adjacent superpixels of the chosen superpixel, which are shown in yellow color in Fig. 1.1 The similar superpixels are outside of the neighboring superpixels and near the chosen superpixel, which are shown in blue color in Fig. 1.1 The selection of the similar superpixels actually is to search a certain number of the most similar superpixels. The searching procedure is achieved by a similarity metric between the chosen superpixel and a nearby superpixel. We use a hierarchical histogram difference kernel [8] as the similarity metric. Accordingly, in constructing the objective function of FCM, the relative distance and the feature difference between the chosen superpixel and neighboring and similar superpixels are considered as spatial weighting information of the chosen superpixel to modify the FCM clustering (see Section 3.3.2).

1.5 Techniques used

1.5.1 Discrete wavelet transforms (DWT)

The Discrete Wavelet Transform (DWT) is used in a variety of signal processing applications, such as video compression, Internet communications compression, object recognition, and numerical analysis. It can efficiently represent some signals, especially ones that have localized changes. Consider the example of representing a unit impulse function with the Fourier transform, which needs an infinite amount of terms because we are trying to represent a single quick change with a sum of sinusoids. However, the wavelet transform can represent this short term signal with only a few terms. This transform came about from different fields, including mathematics, physics, and image processing.

1.5.2 Gray level co-occurrence matrix (GLCM)

Gray level co-occurrence matrix transforms an image into a matrix which correspond to the relationship of pixels in the original image. It calculates the mutual occurrence of pixel pairs for a specific distance and in a particular direction. An example of GLCM calculation is shown in Fig. 3. In Fig. 3, first matrix is image matrix and second matrix is the gray level co-occurrence matrix. Pixel pair of (2, 2) with distance '1' and angle 0° is denoted by red arrow in the first matrix and this pixel pair is occurring three times in the original matrix, and accordingly in the GLCM at position (2, 2) a number '3' is occurring. Similarly, for other pixel pairs, GLCM is calculated [9].

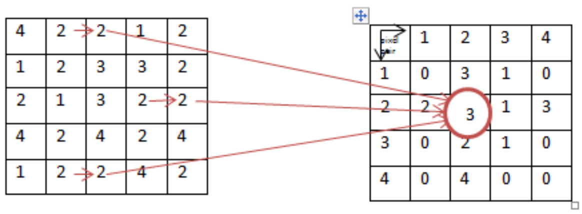

Fig.3 gray level co-occurrence matrix

1.5.3 Modified Superpixel-based FCM

1.5.4 Superpixel based FCM

For superpixel-based FCM method, we attempt to partition a finite collection of superpixels into a collection of C number of fuzzy clusters with respect to some given criteria [10].Mathematically, the superpixel-based FCM objective function of partitioning a superpixel dataset $\left\{F_i\right\}_{j=1}^{N}$ into C clusters is given by

$$J(U,V) = \sum_{i=1}^{C}\sum_{j=1}^{N} u_{ij}^{m} d_{ij}^{2} \qquad (1)$$

where u_{ij} is membership between 0 and 1; V = {v1, v2, . . ., vi, . . ., vC} is the centroids of cluster, d_{ij} is the Euclidean distance between the i-th centroids and the j-th superpixel $m \in [1, \infty]$ determines the level of cluster fuzziness. Fuzzy portioning of known superpixel sample is carried out through an iterative optimization of the objective function:

$$u_{ij} = \frac{1}{\sum_{k=1}^{C}\left(\frac{d_{ij}}{d_{kj}}\right)^{\frac{2}{m=1}}}, v_i = \frac{\sum_{j=1}^{N} u_{ij}^{m} F_j}{\sum_{j=1}^{N} u_{ij}^{m}} \qquad (2)$$

The traditional FCM method functions well on segmenting most noise-free images, however, it is not able to segment images corrupted by noise, imaging artifacts, and intensity inhomogeneity, which will lead to its non-robust results. The main reasons are due to the non-robust Euclidean distance, and the disregard of spatial contextual information in image. To deal with these problems, we propose robust distance measures by incorporating neighboring and similar superpixel into traditional FCM objective function.

1.5.5 Modified superpixel-based FCM

In this neighboring and similar superpixel are introduced into d_{ij}^2. Previous similarly measure d_{ij}^2 in which cluster centers were used. Now similarly measure depends upon membership u_{ij} and influential degree establish in this model.

$$\begin{cases} D_{ij}^2 = d_{ij}^2 \left(1-\alpha_1 \frac{\sum_{k=1}^{S} u_{ik} t_{jk}^2}{\sum_{k=1}^{S} t_{jk}^2}\right)\left(1-\alpha_2 \frac{\sum_{k=1}^{S} u_{ik} r_{jk}}{\sum_{k=1}^{S} r_{jk}}\right) \\ \alpha_1 + \alpha_2 \le 1 \end{cases} \qquad (3)$$

Where t_{jk}^2 is the relative distance between superpixel j and superpixel k, $\| \mathrm{Sp}_j - Sp_k \|$ and α_1 is influential degree; r_{jk} is the spatial feature distance between superpixel j and k, $r_{jk} = \| \mathrm{F}_j - \mathrm{F}_k \|$ and α_2 is its influential degree.
Now equation for FCM is

$$J(U,V) = \sum_{i=1}^{C}\sum_{j=1}^{N} u_{ij}^{m} D_{ij}^{2}$$

(4)

The iterative optimization of the objective function is similar to Eq. (2), where the d_{ij}^2 is replaced by D_{ij}^2

$$u_{ij} = \frac{1}{\sum_{k=1}^{C}\left(\frac{D_{ij}}{D_{kj}}\right)^{\frac{2}{m=1}}}, v_i = \frac{\sum_{j=1}^{N} u_{ij}^{m} F_j}{\sum_{j=1}^{N} u_{ij}^{m}} \qquad (5)$$

1.6 Optimizing influential degree

1.6.1 Particle Swarm Optimization (PSO)

Particle Swarm Optimization (PSO) is an algorithm for finding optimal regions of complex search space through interaction of individuals in a population of particles. The particles evaluate their positions relative to a global fitness at every iteration, and companion particles share memories of their best positions, and then use those memories to adjust their own velocities and positions. At each generation, the velocity of each particle is updated, being pulled in the direction of its own previous best solution (local) and the best of all positions (global). Computation of optimal threshold is handled here with Particle Swarm Optimization (PSO). Implementation of PSO algorithm analyzed here to find out the optimal threshold for segmentation. The population size of particles refers the number of particles in iterative process, thus denoting components in the image here.

A population of particles is initialized with random positions and velocities in d-dimensional space. A fitness function, f is evaluated, using the particle's positional coordinates as input values. Positions and velocities are adjusted, and the function is evaluated with the new coordinates at each time-step. [5]

Steps for proposed method

Step 1: Perform wavelet transform on input image, and the wavelet feature F of each superpixel is obtained.

Step 2: Get the superpixels of the image by over-segmentation using TurboPixels.

Step 3: Search neighboring superpixels for each superpixel (see Section 3.2.2).

Step 4: According to Eqns.(4) and (5), iteratively updating the cluster centers and the membership for each superpixel.

Step 5: Optimize the influential degree, α_1 and α_2 , by PSO method.

1.7 Related work

In this section of this review paper the previous work which has been done on the superpixel is described.

Liu et al. [11] present a color topographic map segmentation method based on super pixel to overcome these problems. Firstly, the finest partition is obtained based on double color-opponent boundary detection method and watershed approach. Then, a strict region merging method is introduced to prevent mis merging while super pixels generated. This merging method could make the super pixel partition accurately adherent the boundary between different geographic elements. Finally, luminosity, color and texture information are combinative applied to classify the super pixel into different layers based on support vector machine.

Xu et al. [12] propose an infrared thermal image processing framework based on super pixel algorithm to accomplish crack detection automatically. Two popular super pixel algorithms are compared and one of them is selected to generate super pixels in this application. Experimental results show that the proposed framework can recognize cracks on metal surface through infrared thermal image automatically.

Buyssen et al. [13] describe a semi-supervised organ segmentation method for Computed Tomography images. The proposed super pixel algorithm performs state-of-the-art algorithms on classical metrics

Tasli et al. [14] propose a method to explore the conventional feature extraction techniques in the image classification.Experimental evaluations on image classification and retrieval tasks are performed in order to validate the proposed hypothesis. They observed a consistent performance increase in terms of Mean Average Precision (MAP) score for different experimental scenarios and image categories

Yang et al. [15] proposes an unsupervised variational segmentation approach of color–texture images Comparing to state-of-the-art unsupervised segmentation methods on a substantial of color texture images, their approach achieves a significantly better performance on capture ability of homogeneous region/smooth boundary and accuracy.

Dimitriou et al. [16] present a motion segmentation method attempting to address some of the major issues in the area. Namely, they propose an efficient framework where more complex motion models can be seamlessly integrated both maintaining computational tractability and not penalizing non translational motion. This algorithm uses an approach based on graph theory and resolves occlusion cases in a robust manner. Extensive experiments demonstrate the flexibility and robustness of the method. The segmentation results are competitive compared to the state of the art.

Wang et al. [17] propose a pixel classification based color image segmentation using quaternion exponent moments.Experimental results show that the proposed method has very promising segmentation performance compared with the state-of-the-art segmentation approaches recently proposed in the literature.

Tian et al. [18] proposes a method of image segmentation based on super pixels. The method is applied to achieve the segmentation of synthetic aperture radar (SAR) image. Firstly, the super pixels are extracted based on multi-scale features. Then, the fuzzy c-means (FCM) clustering based on super pixels is implemented, in which the influence of neighboring and similar super pixels is incorporated into FCM and the influential degree is optimized to improve segmentation performance. Experimental results show that the proposed method can achieve an impressive accuracy of SAR segmentation. For application extension, when they extract corresponding feature from several types of specific images, the proposed method is able to achieve better segmentation performance.

1.8 Conclusion

Image segmentation is an important task in computer vision, whose goal is to partition an image into multiple sets, with all the pixels in the single set has the same labels. In this paper, we have briefed various steps that are used in final segmentation of image. In this work, we have considered superpixel based micro segmentation in first step, in which turbo pixels has been developed. Before this wavelets has been applied for getting multi-scale image features. Further fuzzy-c-means clustering has been applied to make super-pixels. In this step, basic FCM has been modified in which a new objective function has been used. The decision making to put turbo-pixels in FCM clusters has been decided by the closeness of GLCM features of turbo-pixels. Here we give an overview of different steps which will be useful for better segmentation at final step. In future work, these techniques will be implemented and amendments will be tried to get better results.

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