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Image Segmentation with Modified K-Means Clustering Method

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***Abstract:** Image segmentation is used to recognizing some objects or something that is more meaningful and easier to analyze In this paper we are focus on the the K means clustering for segmentation of the image. K-means clustering is the most widely used clustering algorithm to position the radial basis function (RBF) centres. Its simplicity and ability to perform on-line clustering may inspire this choice. However, k-means clustering algorithm can be sensitive to the initial centres and the search for the optimum centre locations may result in poor local minima. Many attempts have been made to minimise these problems In this paper two updating rules were suggested as alternatives or improvements to the standard adaptive k-means clustering algorithm. The updating methods are proposed to give better overall RBF network performance rather than good clustering performance. However, there is a strong correlation between good clustering and the performance of the RBF network. The sensitivity of the RBF network to the centre locations will also be studied.Thus we will test the modified K means different set of images.*

***Key Words:** Image Segmentation, Anisotropic Diffusion ,Smoothing Filters, Contrast Enchancement.*

I. INTRODUCTION

When we look at a scene with our eyes, the visual system in the brain convert a complex scene in an instant, into a simple scene containing a collection of objects. It is actually the process of subdividing an image into basic parts and extracting these parts. With the advancement of technology, computer vision slowly is becoming a big part of our society. It has been used in many applications such as detecting cancer cells from a medical image, roads from a satellite image and many other useful applications. Therefore, in image analysis and pattern recognition Image Segmentation plays a vital role. It plays a critical part of image systems, and it is one of the most difficult tasks in image processing, a s it determines the quality of the final result of analysis.

II. DIFFERENT IMAGE SEGMENTING TECHNIQUES

The most important step in Image Segmentation is to generate a compact description of an Image.

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In order to do that following two approaches could be used a) Contour Segmentation (edge detection and contour tracing), b) Region Segmentation (Grouping of connected pixels in to regions of uniform properties)We propose, in this paper, Region Segmentation Algorithm based on a edge preserving smoothing filter, the symmetric nearest neighbor mean and a fast anisotropic diffusion. The details of of the algorithm are discussed below Segmentation based on edge preserving smoothing filter and anisotropic diffusion

a) Edge Preserving Smoothing Filter

Edge preserving smoothing filters cognominate edge preserving noise-cleaning filters. Systematic Nearest Neighbour (SNN) filters, in many of the correlative studies of edge-preserving noise smoothing techniques, is considered to give the best results in smoothing and preserving edges. Therefore, SNN is most widely used as an Image Improvement Technique. Westman et al has used a SNN filter to preprocess color images before segmenting them. The principle on which the SNN filter works is stated below

The SNN filter makes use of both the Spatial and Gray value information in the neighbourhood of pixel to be processed. In a squre window, half the number of Pixels is selected by choosing one pixel nearestin Gray value to the center pixel from each pair of pixels located symmetrically opposite the center. Only the selected pixels are used to compute a new value for the center pixel.

b) Anisotropic diffusion

In Image processing, anisotropic diffusion is also called Perona–Malik diffusion. It is used to remove the Image Noise without loosing the significant parts of the image content and other details that are important for the Image interpretation. This technique enhance the contrast by using a modified heat diffusion equation.

This technique is a discontinuity-preserving smoothing approach and is closely related to the adaptive smoothing proposed by Chen et al. The principle is that a pixel should become weighted average of its neighbors.

The weight resemble the continuity measures of these pixels. Repetitive Implementaion of anisotropic diffusion is Adaptive smoothing in which the unwanted edges will disappear along with repetition. However, this scheme is considered to be slow, and to avoid this slowness we use Toboggan Contrast enhancement as proposed by Fairfield

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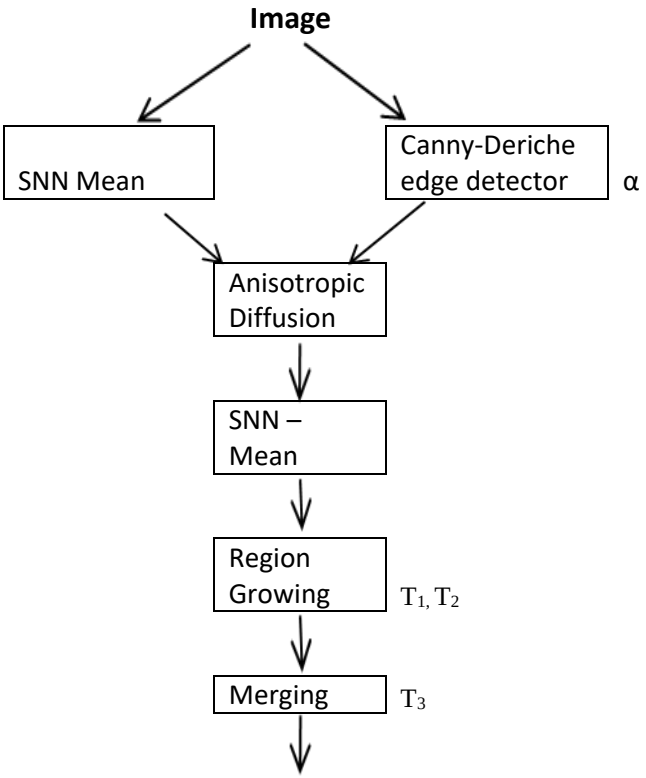
Applying Edge-preserving smoothing and Anisotropic diffusion to the segmentation of images

SNN filters are considered good for Clearing the noises and preserving the edge, but they cannot make potential regions Uniform. Whereas, anisotropic diffusion can make potential regions uniform but it is impressionable to noises. So, we propose to make a collective use of both the techniques to enhance an image before segmenting it. To make Fairfield's diffusion algorithm less impressionable to noises, Canny-Deriche detector can be used by us. The following figure demonstrates our algorithm



Figure

III. K-MEANS CLUSTERING PROBLEMS

The algorithm on which K-Means clustering works is that the initial centers are provided. From these initial centers, the search for Final clusters or centers starts. If the proper Initialization is not done the algorithm may provide a set of poor final centers and this may become serious if we are using the online K-Means clustering algorithm.

Dead centers, local minima and centre redundancy are the three basic problems which we come across during clustering. The centers in which there are no associated data or members is called a Dead Centers. Dead Centers are normally situated outside the data range or between two active centers. This problem may arise mainly due to the fact that the centers have been initialized far from the data. The best possible approach is to select the initial centers randomly from the training data or to pick some random value in between the data range. However, this is a possibility that all the centers are not equally active. Some have too many members which make the center to update frequently and some may not have members so they are hardly updated. The selection criteria should be such that the total distance between the data and the centers could be minimized, so that the data could be properly represented. To measure the distance we can use square error cost function which is very simple and is broadly used, which is illustrated as:

$$E = \sum_{j=1}^{n_c} \sum_{i=1}^{N} \left\| v_i - c_j \right\|^2 \quad (1)$$

where N are the number of data,nc are the number of centers, and vi is the data sample belonging to centre cj. Here, $\|\bullet\|$ is taken to be an Euclidean norm although other distance measures can also be used. In order to minimize the total distance in equation (1), the centers are adjusted according to a certain set of rules during the clustering process. However, in the process of searching for the global minima the centers frequently become trapped at local minima. Poor local minima may be avoided by using algorithms such as simulated annealing, stochastic gradient descent, genetic algorithms, etc. However, these techniques are not considered suitable for online-clustering due to the fact that these involve Heavy Computations. In the present study, the improvements are made based on the adaptive k-means clustering, which do not require heavy computation. The RBF network should have sufficient centers to represent the identified data in order to give a good modeling performance. However, the increase in number of center also increase the tendency for the centers to be located very close to each other or at the same position. In k-means clustering and the unconstrained steepest descent algorithm, , this is the normal phenomenon, as the number of centres becomes sufficiently large.

IV. K-MEANS CLUSTERING ALGORITHM

The two basic versions of K-means clustering are non-adaptive version which was introduced by Lloyd and an adaptive version which was introduced by MacQueen .

Adaptive k-means clustering is the most frequently used k-means clustering which was based on Eucledian distance. Adaptive k-means clustering can be considered as a special case of the gradient descent algorithm where only the winning clustcer is adjusted at each learning step.

We concentrates only on adaptive k-means clustering as the algorithm can be used for on-line training of RBF network. Adaptive k-means clustering tries to minimise the cost function in equation (1) by searching for the centre cj on-line as the data are presented. As the data sample is presented, the Euclidean distances between the data sample and all the centres are calculated and the nearest centre is updated according to:

$$\Delta c_z(t) = \eta(t)\left[v(t) - c_z(t-1)\right] \quad (2)$$

where z indicates the nearest centre to the data v(t). Notice that, the centres and the data are written in terms of time t where cz(t-1) represents the centre location at the previous clustering step. The adaptation rate, $\eta(t)$, can be selected in a number of ways. MacQueen set $\eta(t) = 1/n_z(t)$, where nz(t) is the number of data samples that have been assigned to the centre up to the time t.

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Darken and Moody [5] used a constant adaptation rate and a square root method $\left(\eta(t) = 1/\sqrt{n_z(t)}\right)$. Another method called search-then-converge has been introduced by Darken and Moody . According to this method $\eta(t)$ is updated using:

$$\eta(t) = \eta(0)\frac{1+\frac{\alpha}{\eta(0)}\frac{t}{\tau}}{1+\frac{\alpha}{\eta(0)}\frac{t}{\tau}+\tau\frac{t^2}{\tau^2}} \quad (3)$$

The basic idea is to keep $\eta(t)$ approximately constant at times small compared to τ and decrease $\eta(t)$ at the rate of α/t as time t becomes large compared to τ. This method yields optimally fast asymptotic convergence if $\alpha > 1/2\beta$, where β is the smallest eigenvalue of the Hessian matrix of the cost function defined in equation (1). Chen et al used an adaptation rate that is updated at each step according to:

$$\eta(t) = \eta(t-1)/\sqrt{1+int(t/n_c)} \quad (4)$$

where int(.) denotes the integer part of the argument and nc is the number of centres.

There is very much same problem of assigning the adaptation rate to adaptive k-means clustering and assigning the learning rate to the back propagation algorithm . These both are based on the gradient descent method except that in back propagation all the parameters are updated at the same time. Therefore, all the methods that are used to choose the learning rate for the back propagation algorithm may also be applied for the adaptation rate in k-means clustering. The usual approach is to update $\eta(t)$ according to the variation of the cost function during the clustering process, such as

$$\Delta\eta(t) = \begin{cases} +a & \text{if } \Delta E < 0 \text{ consistently} \\ -b\eta(t-1) & \text{if } \Delta E > 0 \\ 0 & \text{otherwise} \end{cases} \quad (5)$$

where ΔE is the change in the cost function and, a and b are parameter constants. The term consistently in equation (5) means a constantly decrease of E for the last few clustering steps. Cater [2] suggested that this kind of adaptive scheme can be made more effective if each parameter (the centre in this case) has a different adaptation rate. Another method to improve the back propagation algorithm that may be adapted to k-means clustering is the method of momentum that has been introduced by Plaut et al [8]. For k-means clustering, a momentum term can be included as follows:

$$\Delta c_k(t) = \eta(t)\left[v(t) - c_k(t-1)\right] + \alpha\Delta c_k(t-1) \quad (6)$$

The momentum constant α is between 0 and 1, and is often chosen to be close to 1. In this case, $\eta(t)$ can be a constant or adaptive. Other updating methods such as Newton method, stochastic method and conjugate gradient method may also be adapted to improve the k-means clustering algorithm at the expense of computational time.

In the current study, two updating methods are proposed as alternatives to update $\eta(t)$. The first method update $\eta(t)$ according to:

$$\eta(t) = \eta(t-1)/e^{(1/r)} \quad (7)$$

where $r = n_c + t$ for off-line clustering and $r = \sqrt{n_c + t}$ for on-line clustering. The updating method uses different r for on-line and off-line clustering because in on-line clustering problems, $\eta(t)$ should be decreased rapidly so that the weights of the network can converge properly. This will not be a problem with the off-line clustering since the weights are estimated after the centres are located.

The second proposed updating method updates $\eta(t)$ according to:

$$\eta(t) = \eta(0)\left[e^{-p(t^2/n_c^3)} + be^{-(n_c\eta(t-1))}\right] \quad (8)$$

where p is a constant, 0 < p £ 1 and $b = 1/\left(n_c + n_z(t)\right)$. nc and nz(t) are the number of centres and the number of data assigned to centre cz up to time t respectively. This method involves two terms in the bracket on the right hand side. At the beginning, $\eta(t)$ will be dominated by the first term but as time t becomes large, $\eta(t)$ will converge to the value of b in the second term. The constant term p will determine how long $\eta(t)$ will be dominated by the first term.

In the present study, methods of updating $\eta(t)$ are selected such that the computational time will be minimised, which is beneficial for on-line clustering problems. For this reason the two proposed updating methods (described by equations (7) and (8) together with the three methods that have been used by Chen et al and Darken and Moody are studied:

$\eta(t) = 1/n_z(t)$, the MacQueen method.

$\eta(t) = 1/\sqrt{n_z(t)}$, the square root method

$\eta(t) = a/\sqrt{1+int(t/n_c)}$,

Chen's method, where $a = \eta(0)$ for off-line clustering and $a = \eta(t-1)$ for on-line clustering.

$\eta(t) = \eta(t-1)/e^{(1/r)}$, where r = nc + t for off-line clustering and $r = \sqrt{n_c + t}$ for on-line clustering, the first proposed method.

$\eta(t) = \eta(0)\left[e^{-p(t^2/n_c^3)} + be^{-(n_c\eta(t-1))}\right]$, p is a constant, 0 < p £ 1 and $b = 1/\left(n_c + n_z(t)\right)$

, the second proposed method.

where nc, nz(t) are the number of centres and the number of data assigned to centre cz up to time t respectively. Notice that all these updating methods update the centres based on equation (2).

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V. CONCLUSION

The two techniques of Image Segmentation i.e edge-preserving smoothing filter and anisotropic diffusion which are fast and simple techniques for image segmentation algorithm. In fact, Canny-Deriche edge detector inherently combine the contours segmentation approach with region one. The performance of k-means clustering algorithms using the proposed updating methods in previous section were tested using simulated and real data sets. System S1 was a simulated system defined by the following difference equation:

$$y(t) = 0.3\, y(t-1) + 0.6\, y(t-2) + u^3(t-1)$$

$$+ 0.3u^2(t-1) - 0.4\, u(t-1) + e(t) \quad (9)$$

where $e(t)$ was a Gaussian white noise sequence with zero mean and variance 0.05 and the input, *u(t)* was a uniformly random sequence [-1,+1]. System S1 was used to generate 1000 pairs of data input and output. The second data set, S2 was taken from a heat exchanger system and consists of 1000 samples. A detailed description of the process can be found in Billings and Fadhil. The third data set was taken from system S3 that is a tension leg platform and also consist of 1000 input-output data samples.

Clustering performance was judged based on mean square distance (MSD) defined as:

$$E_{MSD} = \frac{1}{N}\sum_{j=1}^{n_c}\sum_{i=1}^{N}\left(\left\|v_i - c_j\right\|\right)^2 \quad (10)$$

The overall network performance was measured using mean squared error (MSE). The adaptive k-means clustering with updating methods are implemented and tested as part of the RBF network. The weights of the RBF network are updated using Given Least Squares algorithm as in reference [3]. During the testing, the same structures were assigned to all of the RBF networks. In this way, the performance of the clustering algorithm is measured under the same conditions for each updating method.

The data for systems S1, S2, and S3 are divided into two sets, training and testing data sets. For S1 and S3, the first 600 data are used to train the network and the other 400 data are used for testing. For S2, the first 500 data are used for training and the other 500 data for testing.

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