IMAGE SEGMENTATION METHODS

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1. Introduction

Images are considered as one of the most important medium of conveying information.Understanding images and extracting information from them so that the informationcan be used for other tasks is an important aspect of many industrial applications. Image segmentation refers to the process of partitioning a digital image into meaningful segments.A great variety of segmentation methods has been proposed in the past decades. The choice of a segmentation technique over another is made by type of an image and characteristics of the problem. In this paper we present the state of the art segmentation techniques, which are k-means and mean shift algorithm.

2. K-means algorithm

K-means algorithm is an unsupervised clustering algorithm that classifies the inputset of data into multiple clusters based on their distance from each other, where the distance isgiven by pixels' intensity, color, texture or combination of these. [7]In the k-means algorithm each cluster is represented by its centroid (mean). Minimum distance between an evaluated point and a centroid is used as a criterion for assignment of a pointto the related cluster.[7] The points are clustered around centroidsμ_i, $i = 1, \ldots, k$ which are obtained by minimizing the objective

$$J = \sum_{i=1}^{k} \sum_{x_j \in S_i} (x_j - \mu_i)^2 \tag{1}$$

where there are k clusters $S_i, i = 1, \ldots, k$;μ_i is the geometric centroid and x_j is the *n-th*data point in S_i. The task of k-means is to find the minimum of$J$function hence its objective is to minimize the average square Eucklidean distance of data points from their cluster where the cluster center is defined as the mean of data points in a cluster.

In k-means algorithm initial clusters are created by choosing *k* random values from set of data points. These random values represent initial centroids of clusters.Such an initialization of a cluster is known as seeding stage. In the next stage, which is known as labeling,is every point x_i assigned to a cluster C_j with criterion of minimal Euclidian distance satisfied.Following the assignment of every point to the nearest cluster, centroids are recalculated in update stage. Each centroid C_j is recalculated as a mean of all assigned points$x_i \in C_j$.

Both labeling and update stage are repeated until all points are firmly assigned to a cluster and clusters centroid positions are no longer being changed. However, final result is influenced by initial position of centroids. [7]

3. Mean shift segmentation

Mean shift is an unsupervised clustering segmentation method,where the number of data clustersis unknowna priori. It is a generally effective segmentation technique and has become widely-used in the vision community. [3]

Mean shift defines a window around every data point and computes mean of all data points within this window. Then it shifts the center of the window to this calculated mean and repeats this algorithm till it converges.The way mean shift algorithm computes a mean within a window comes fromthe idea that all the data points in an*n*-dimensional featurespace are considered as an empirical probability density function where dense regions in the featurespace correspond to the local maxima (also called modes) of the underlying distribution.[4] For each data point mean shift calculates a gradient of density of points in its close surroundings and moves mean position in this gradient's direction as long as the local maxima (mode) is found. In terms of segmentation, it is intuitive that the data points close to these modes should be clustered together. [3] In order to find modes of probability density function the kernel density estimation function is used. Common formula for probability density function for a point in *n*-dimensional space is

$$f(x) = \frac{1}{N}\sum_{i=1}^{N} K(x_i - x) \tag{2}$$

where*x* andx_i are points in *n*-dimensional space, *N* is number of points in surroundings of *x* and *K(x)* is a radial symmetric function called kernel. Mostly used kernels are Epanechnikov, Gaussian and uniform kernel. Epanechnikov kernel is combination of speed and accuracy of uniform and Gaussian kernel. Epanechnikov kernel is given

$$K_e(x) = \begin{cases} c_k(1 - \|x\|^2) \; for \; \|x\| \leq 1 \\ 0 \qquad otherwise \end{cases} \tag{3}$$

From the equation above we can see that kernel profile is defined just on interval $\langle 0,1 \rangle$. For this reason each point is normalized by kernels width *h* which defines size of point's surroundings. After derivation andsubstitution of *h* and kernel formula into equation (2) we get

$$\nabla f(x) = \frac{2c_k}{N.h^2}\sum_{i=1}^{N} g\left(\left\|\frac{x - x_i}{h}\right\|^2\right)\left[\frac{\sum_{i=1}^{N} g\left(\left\|\frac{x-x_i}{h}\right\|^2\right).x_i}{\sum_{i=1}^{N} g\left(\left\|\frac{x-x_i}{h}\right\|^2\right)} - x\right] \tag{4}$$

which is a common formula for density gradient computation. A combined kernel is very often utilized in image analysis.Forsuch a kernel two widths *h* are defined. The first oneh_s is called spatial width which determines size of a window. The second oneh_r is called range width and determines the maximum distance between *x* and x_i in *n*-dimensional color space. Combined kernel is then defined as product of two standalone kernel functions and is given by equation

$$K_e(x) = c_k.k_s\left(\left\|\frac{x^{(s)} - x_i^{(s)}}{h_s}\right\|^2\right).k_r\left(\left\|\frac{x^{(r)} - x_i^{(r)}}{h_r}\right\|^2\right) \tag{5}$$

In segmentation process we need to calculate equation (5) for each data point. In computation we utilize its surroundingspoints position as well as their color values. This process iterates until the size of this vector is smaller than some a priori defined valueε. When this condition is met we save point's position into which the algorithm converged and repeat whole computation for next point. Image areas with similar properties are marked with a number which denotes that points from this area belong to the same cluster.

4. Experiment

To verify performance of k-means and mean shift algorithm we segmented images obtained from Berkley image dataset. Images segmented by k-means algorithm were partitioned into two, three and four clusters. Mean shift segmentation was conducted with three different values of spatial and color width. After segmentation we did morphological operations on images to get contours of segmented objects and compared these contours with base ground segmentation from Berkley image dataset.

5. Results

In figures (1) and (2) are images segmented by k-means and mean shift algorithm respectively. In figure(1.a) and (2.a) are original images. In figures(1.b), (1.c) and (1.d) is the original image segmented into 2, 3 and 4 clusters respectively. In figures (2.b), (2.c) and (2.d) is the original image segmented with parameters $h_s = h_r = 5$, $h_s = h_r = 15$, $h_s = h_r = 20$ respectively. In figures (5.a), (5.b), (6.a) and (6.b) are contours of images segmented by k-means and mean shift algorithm. In figures (5.c), (5.d), (6.c) and (6.d) are the same images segmented by two different people.

a) b) c) d)

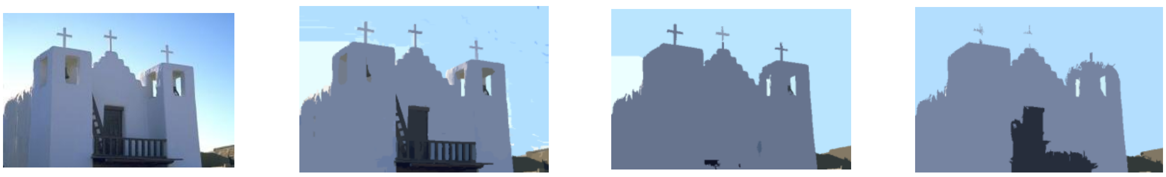
Fig.1: An image segmented by k-means algorithm. Figure a) original image, b), c) and d) original image segmented into 2, 3 and 4 clusters respectively.

a) b) c) d)

Fig.2:An image segmented by k-means algorithm. Figure a) original image, b), c) and d) original image segmented into 2, 3 and 4 clusters respectively.

a) b) c) d)

Fig.3: An image segmented by mean shift algorithm. Figure a) original image, b), c) and d) original image segmented into 2, 3 and 4 clusters respectively.

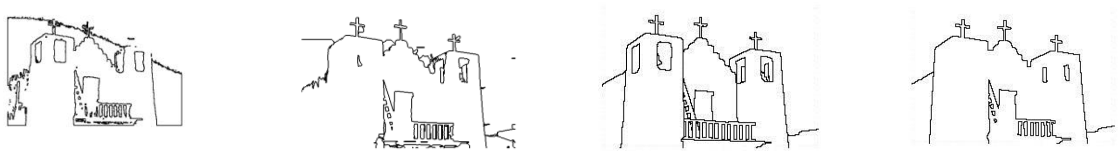


a) b) c) d)

Fig.4: An image segmented by mean shift algorithm. Figure a) original image, b), c) and d) original image segmented into 2, 3 and 4 clusters respectively.

a) b) c) d)

Fig.5: Contours of segmented object. Result of segmentation by a) k-means, b) mean shift, c) person 1 d) person 2



a) b) c) d)

Fig.6: Contours of segmented object. Result of segmentation by a) k-means, b) mean shift, c) person 1 d) person 2

6. Conclusion

As we can see from results above k-means and mean shift algorithms are very powerful state of the art segmentation methods. With right parameters we get segmentation results very similar to human segmentation as we can see from figures (5) and (6). The choice of right parameters depends on complexity of a scene as we can see in figure (1) where the choice of four clusters results in oversegmentation. Also the size of spatial and range width in mean shift algorithm plays significant role in pixel clustering as we can see in figure (3.c) and (3.d) that some plane pixels were assigned to wrong cluster.

Although k-means algorithm is powerful and widely used it has drawbacks. The number of clusters for segmentation needs to be estimated and defined by the user at the initial stage of the segmentation process. An incorrect choice of the number of clusters will invalidate the whole process. The other drawback is that centroids are chosen randomly so k-means gives different results every time. Mean shift is a stable algorithm in terms of achieving the same results but is slower and needs more computation power.

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References

[1] R. Gonzalez, R. Woods: "Digital Image Processing" 2nd edition, Tom Robbins, Upper Saddle River, New Jersey (2007).

[2] R. Dass, S. Devi: "Image Segmentation Techniques", IJECT, Vol. 3, 66 (2012).

[3] C. Pantofaru, M. Hebert: "A Comparison of Image Segmentation Algorithms", Carnegie Mellon University, Pittsburgh, Pennsylvania (2005).

[4] R. Szeliski: "Computer Vision Algorithms", Springer, Redmond, Washington(2010).

[5] S. Tatiraju. A. Mehta: "Image Segmentation using k-means clustering, EM and Normalized cuts", University of California, Irvine, California (2006).

[6] N. Verma, A. Roy, S. Vasikarla: "Medical Image Segmentation Using Improved Mountain Clustering Technique Version-2", In: 7th International conference on information Technology: new generations (ITNG), p. 1556 (2010).

[7] Comaniciu, D., Meer, P., Mean Shift: A Robust Approach Toward Feature Space Analysis, IEEE Transactions on Pattern Analysis and Machine intelligence, vol. 24, no. 5, May 2002