SEGMENTATION OF SATELLITE IMAGES BY MODIFIED MOUNTAIN CLUSTERING

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Abstract

Segmentation of satellite images is an important issue in various applications. Though clustering techniques have been in vogue for many years, they have not been too effective because of several problems such as selection of the number of clusters. This proposed work tackles this problem by having a validity measure coupled with the new clustering technique. This method treats each point in the data set, which is the map of all possible color combinations in the given image, as a potential cluster center and estimates its potential with respect to the other data elements. The point with the maximum value of potential is considered to be a cluster center and then its effect is removed from the other points of the data set. This procedure is repeated to determine the different cluster centers. At the same time we compute the compactness and the minimum separation among all the cluster centers, also the validity function as the ratio of these quantities. The validity function can be used in making a choice of the number of clusters. This technique has been compared to the Fuzzy C-means technique and the results have been shown for a sample color image of satellite data.

1. Introduction

Segmentation of satellite images is an important task required in many fields. It is especially of a great significance in the area of Geographical Information Systems (GIS) as this helps in planning the activities in the development of resources, study of changing environment and observing the impact of disasters. The basis of segmentation may be mainly made on the image properties such as color or texture [1] or both. Mostly, color can be used in the segmentation of such images, but textural features may also prove to be useful. The perfect segmentation has eluded the researchers still forcing them to try alternative approaches. However, we will make an attempt to use the color property in this paper. In view of wide acceptability and facility of fuzzy approach, we mainly devote our attention on these approaches for the segmentation of color images [2]. Some of the important contributions are the fuzzy C-means approach [3] and robust clustering [4]. However, we will follow the mountain clustering of Yager and Filev [5] but modify the same for increased efficiency and adaptability to the color imagery in the lines of Azeem et al. [6].

The organization of this paper is as follows: Section 2 presents a brief review of modified mountain clustering technique. Results of application this to color images are given in Section 3. Discussion of the results is relegated to Section 4 followed by conclusions in Section 5.

2. Modified Mountain Clustering

The purpose of clustering is to do natural groupings of large set of data, producing a concise representation of system's behavior. Yager and Filev [5] proposed a, simple and easy to implement, mountain clustering algorithm for estimating the number and location of cluster centers. Their method is a grid based three-step procedure. In the first step the hyperspace is discretized with a certain resolution in each dimension so that grid points are obtained. The second step uses the data set to construct the mountain function around all grid points. The third step generates the cluster centers by an iterative destruction of mountain function. Though this method is simple but the computation grows exponentially with the dimension of hyperspace. In the n dimensional hyperspace with m number of grid lines in each dimension, the number of grid points that must be evaluated is m^n.

We present a modified form of Yager and Filev's method as reported in Azeem et al. [6]. For an image of size $\boldsymbol{r}\times\boldsymbol{c}$ with $\boldsymbol{l}$ color levels, our data set consists of the R, G, B components of each color, and the frequency of occurrence of the intensity. We assume that each data point, which in this case is represented by four dimensions each, has potential to become a cluster center instead of grid points. This modification makes the computation complexity independent of the dimension, because the number of grid points is equal to the number of data points. The second advantage of this modification is that it eliminates the need to specify a grid resolution, in which a compromise between accuracy and computational complexity must be struck. The procedure of the modified method is as follows:

Let us define the jth data in $\mathbf{x}\times y_p$ hyperspace as follows:

$$\mathbf{x}_{jp} \equiv \{\mathbf{x}_j, y_p(j)\} = \{x_1(j), x_2(j), \ldots, x_n(j), y_p(j)\} \qquad \forall\ j = 1, \ldots, M. \quad (1)$$

where, $\mathbf{x}_j = \{x_1(j), x_2(j), \ldots, x_n(j)\}$. Without loss of generality, we normalize each dimension of hyperspace, so that data points are bounded by hypercube. The normalized data point $\overline{\mathbf{x}}_{jp}$ are defined as:

$$\bar{\mathbf{x}}_{jp} \equiv \left\langle \mathbf{x}_{jp} - (\mathbf{x}_{jp})_{\min} \right\rangle \cdot / \left\langle (\mathbf{x}_{jp})_{\max} - (\mathbf{x}_{jp})_{\min} \right\rangle \qquad \forall\ j = 1, \ldots, M. \tag{2}$$

where,

$$(\mathbf{x}_{jp})_{\min} = \left\{ \min_{j=1}^{M} x_1,\ \min_{j=1}^{M} x_2,\ \ldots,\ \min_{j=1}^{M} x_n,\ \min_{j=1}^{M} y_p \right\} \tag{3}$$

and

$$(\mathbf{x}_{jp})_{\max} = \left\{ \max_{j=1}^{M} x_1,\ \max_{j=1}^{M} x_2,\ \ldots,\ \max_{j=1}^{M} x_n,\ \max_{j=1}^{M} y_p \right\} \tag{4}$$

Treating each data point as a cluster center, we define a measure of potential, which is a mountain function, of data point $\bar{\mathbf{x}}_{rp}$ as a function of distance $d^2(\bar{\mathbf{x}}_{rp}, \bar{\mathbf{x}}_{jp}) = (\bar{\mathbf{x}}_{rp} - \bar{\mathbf{x}}_{jp})\mathbf{Q}(\bar{\mathbf{x}}_{rp} - \bar{\mathbf{x}}_{jp})'$ between $\bar{\mathbf{x}}_{rp}$ and all other data points given as

$$P_{r,1} = \sum_{j=1}^{M} \exp\left[-\left(\frac{d^2(\bar{\mathbf{x}}_{rp}, \bar{\mathbf{x}}_{jp})}{d_1^2} \right) \right] \qquad \forall r = 1, 2, \ldots, M \tag{5}$$

Where, $\boldsymbol{Q}$ is a (n+1)×(n+1) positive definite matrix and d_1 is the positive constant defining the neighborhood of data point. Data points outside radial distance d_1 have a little influence on the potential. It is evident from the mountain function that potential value of datum is an approximation of the density of data point (cardinality) in the vicinity of datum. The higher the potential value of each of the data points in hypercube, the higher the chance of being a cluster center. The first cluster center is selected with the highest value of $P_{r,1}$ as follows:

$$\bar{\mathbf{c}}_{1p} = \bar{\mathbf{x}}_{1p}^{*} \Leftarrow\ P_1^{*} = \max_{r=1}^{M}(P_{r,1}) \tag{6}$$

For the selection of second cluster center, the potential value of each data point is revised in order to deduce the effect of mountain function around the first cluster center as follows:

$$P_{r,2} = P_{r,1} - P_1^{*} \,\mathbf{exp}\left[-\left(\frac{d^2(\bar{\mathbf{x}}_{rp}, \bar{\mathbf{c}}_{1p})}{d_2^2} \right) \right] \qquad \forall r = 1, 2, \ldots, M \tag{7}$$

where, d_2 is the positive constant defining the neighborhood of cluster center. It is evident from Eqn. (5) that the data points near the first cluster center have greatly reduced potential value and are unlikely to be selected as the next cluster center. After revision of potential value of each data point, second cluster center is selected with the highest value of $P_{r,2}$ as under:

$$\bar{\mathbf{c}}_{2p} = \bar{\mathbf{x}}_{2p}^{*} \Leftarrow\ P_2^{*} = \max_{r=1}^{M}(P_{r,2}) \tag{8}$$

Similarly, for the selection of k^{th} cluster center, revision of potential value for each data point is done as:

$$P_{r,k} = P_{r,k-1} - P_{k-1}^{*} \,\mathbf{exp}\left[-\left(\frac{d^2(\bar{\mathbf{x}}_{rp}, \bar{\mathbf{c}}_{(k-1)p})}{d_2^2} \right) \right] \qquad \forall r = 1, 2, \ldots, M. \tag{9}$$

and k^{th} cluster center is selected with the highest value of $P_{r,k}$ as under

$$\bar{\mathbf{c}}_{kp} = \bar{\mathbf{x}}_{kp}^{*} \Leftarrow\ P_k^{*} = \max_{r=1}^{M}(P_{r,k}) \tag{10}$$

To stop this procedure, Yager and Filev [5] have used the criterion $P_k^{*}/P_1^{*} < \delta$ (δ is a small fraction). The choice of δ affects the results. Small value of δ results in large number of cluster centers and large value of δ results in less number of cluster centers. It is difficult to establish a single value for δ that works well for all data. To overcome this difficulty a gray region of δ value bounded by two limits δ_u and δ_l is used. The upper limit δ_u is the threshold for absolute acceptance of cluster center and the lower limit δ_l is the threshold for complete rejection and the end of clustering process. In the gray region, a good trade-off between reasonable potential value and sufficient distance from the existing cluster center is used to accept a data point as a cluster center:

$$\frac{P_k^{*}}{P_1^{*}} + \frac{d_{\min}}{d_1} \geq 1 \tag{11}$$

where, $d_{\min}$ = minimum distance between $\bar{\mathbf{c}}_{kp}$ and previously selected all cluster centers.

The optimum number of clusters for the data set $\boldsymbol{D}_M = \{\boldsymbol{x}_t, y_p(t)\}_{t=1}^{M}$ is decided by the validity function S which is the ratio of compactness and separation [7] :

$$S = \frac{\sum_{k=1}^{m} \sum_{r=1}^{M} \mu_{r,k}^2 \left\| \bar{\mathbf{x}}_{rp} - \bar{\mathbf{c}}_{kp} \right\|^2}{M \min_{i \neq j} \left\| \bar{\mathbf{c}}_{ip} - \bar{\mathbf{c}}_{jp} \right\|^2} \ ; \tag{12}$$

where, the membership function $\mu_{r,k}$ represents the degree of association of r^{th} data to the k^{th} cluster center and is defined as:

$$\mu_{r,k} = \exp\left[-\left(\frac{d^2(\bar{\mathbf{x}}_{rp} - \bar{\mathbf{c}}_{kp})}{d_2^2} \right) \right] \tag{13}$$

Let Ω_c denote the optimal candidate at any value of c; then the solution of

$$\min_{c_{\min} \leq c \leq c_{\max}} \left(\min_{\Omega_c} S \right) \tag{14}$$

is assumed to yield the most valid fuzzy clustering of the data set. S has a tendency to decrease eventually when the number of cluster centers is very large. So, the value of S is meaningless when the number of cluster centers gets close to M. Since in practice the feasible number of clusters is much smaller than the number of data points M there is a reason to select $d_{1,\min} = 0.2 d_{1,\max}$

3. Results and Discussion

The algorithm described above has been applied to the 340×320-pixel pseudo colored satellite image of a glacier with 256 color levels shown in Fig.1. During the application, matrix $\boldsymbol{Q}$ in Eqn. (5) has been considered to be an identity matrix, making the distance $d^2(\bar{\mathbf{x}}_{rp}, \bar{\mathbf{x}}_{jp})$ Euclidean in nature. The value of d_1 was taken as 0.15 and d_2 as 0.23. Though the effect of d_1 is on mountain function makes the two potential values closer or farther numerically. The effect of d_2 is noticed in terms of number of significant clusters. A large d_2 makes membership larger hence more pixels are grouped in to one cluster. Eventually, the number of cluster decreases with increase in d_2.

While grouping the color levels into various clusters, we consider only a quarter of the cluster centers initially calculated based on their corresponding potential values considered along with the user defined validity criteria. By this, the number of clusters is found to be 11, which are sufficient for the reconstruction of the original image, almost entirely. These are shown as clusters 1-11. It is observed that when the modified mountain clustering technique is applied on test images, we obtain the most acceptable results for images in which colors are visibly more distinct. The results of modified mountain clustering have been compared with those fuzzy C-means clustering. Identical results are also obtained with fuzzy C-means clustering when number of required clusters is taken to be 11. The validity mesures for the clusters are given in Table 1 and Table 2. Also, the normalized cluster centers are listed in the tables. It is observed that in modified mountain clustering, clusters are identified one after another. Some of the segments in modified mountain clustering are more prominent in color. In fuzzy C-means clustering, we too have similar clusters but they are dim. This is because replicas of the same clusters with less intensity also occur. This fact can be used to assert that with the modified mountain clustering, we can choose the distinct numbers of clusters. If we want to have more number of clusters, then inclusion of one or more new cluster does not pose any problem in the proposed approach, whereas in fuzzy C-means clustering, the clustering has to be done all over again. For small images, the fuzzy C-means is better but clustering of large image size, the modified mountain clustering is a better option.

4. Conclusions

This paper presents a new clustering approach called modified mountain clustering for the segmentation of images. The main concept is that we define a mountain function at each element of the data set, i.e., a set of all possible colors in the given image, which forms a potential cluster, and calculate the strength of this function as a function of distance of neighboring elements. On the basis of the strength it is declared as a cluster and the effect of this is removed on all other data elements. Next, another element is chosen as next potential cluster center. This procedure is repeated until a validity criterion comprising a ratio of compactness of the clusters to the separation among the clusters is violated. The results are comparable to the results of fuzzy C-means technique but computationally much more efficient.

References

[1] R. C. Dubes and A. K. Jain. “Validity studies clustering methodologies”, *Pattern Recognition*, 11:235-254, 1976.

[2] A. Moghaddamzadeh and N. Bourbakis, “A Fuzzy Technique for Image Segmentation of Color Images.” *Proc. of the Third IEEE Conf. On Fuzzy Systems, IEEE world congress on Computational Intelligence*, Vol. 1, pp. 83-88, June 26-29, 1994.

[3] J. C. Bezdek. “Cluster Validity with Fuzzy Sets.” *Journal of Cybernetics*, 3:58-73, 1974.

[4] J.M. Jolian, P. Meer, and S. Bataouche, “Robust clustering with application to Computer Vision”, *IEEE Trans. Pattern Analysis & Machine Intell.*, Vol. 13, pp. 791-802, 1991.

[5] Ronald R. Yager and Dimitar P. Filev, *Essentials of Fuzzy Modeling and Control*, John Wiley & Sons, pp. 246-261, 1994.

[6] M. F. Azeem, M. Hanmandlu, N. Ahmad, “Modified Mountain Clustering in Dynamic Fuzzy Modeling”, *Proc. 2rd Intl. Conf. on Infor. Tech.*,Bhubaneswar, India, Dec. 20-23, pp. 61-65, 1999.

[7] Xuanli Lisa Xie and Gerardo Beni, “A Validity Measure for Fuzzy Clustering”, *IEEE Trans. on Pattern Anal. Machine Intell.*, Vol. 13, No. 8, pp. 841-847, Aug. 1987.

Table 1 : Normalized Cluster Centre and Validity with modified mountain clustering

Segment No.	R	G	B	Freq of Intensity	Validity x 10^{-5}
1	0.7031	0.2891	0.1250	0.0010	0.49
2	0.8672	0.5781	0.2891	0.0008	0.53
3	0.5781	0.4141	0.2891	0.0017	1.83
4	0.8672	0.4141	0.1250	0.0015	1.97
5	0.4141	0.1250	0.0004	0.0025	1.51
6	0.2891	0.1250	0.1250	0.0025	2.10
7	0.7031	0.5781	0.2891	0.0002	2.06
8	0.7031	0.1250	0.0006	0.0005	2.03
9	0.4141	0.2891	0.2891	0.0002	2.43
10	0.8672	0.7031	0.4141	0.0003	2.55
11	0.5781	0.2891	0.1250	0.0017	2.81

Table 2 : Normalized Cluster Centre and Validity with fuzzy C-means clustering

Segment No.	R	G	B	Freq of Intensity	Validity x 10^{-5}
1	0.9710	0.9300	0.8495	0.0006	0.10
2	0.1226	0.0473	0.0487	0.0045	0.43
3	0.3621	0.1104	0.0549	0.0021	2.61
4	0.6770	0.1093	0.0380	0.0006	4.27
5	0.6999	0.4025	0.2722	0.0007	4.51
6	0.4150	0.3326	0.3088	0.0003	3.21
7	0.9259	0.5535	0.0958	0.0007	3.64
8	0.6688	0.5811	0.4230	0.0006	2.23
9	0.9221	0.5907	0.3519	0.0005	2.38
10	0.6974	0.3231	0.0963	0.0012	5.75
11	0.8836	0.7365	0.6225	0.0008	3.47

Fig.1 : Results Using Modified Mountain Clustering

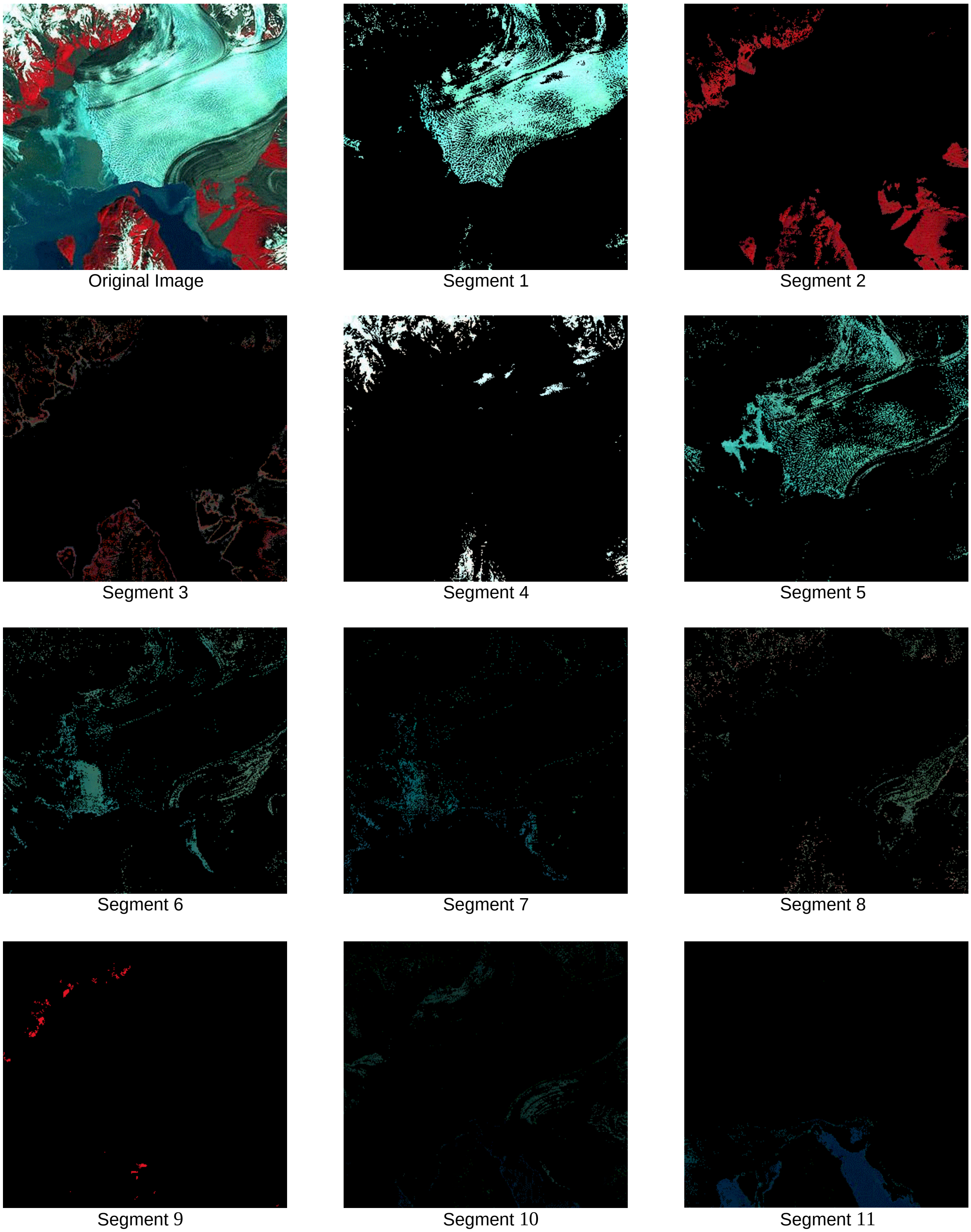

Fig. 2 : Results Using Fuuzzy C-Means Clustering