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Fuzzy Training Based on Segmentation Using Spatial Region Growing

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Abstract : This study proposes an approach to unsupervisedly estimate the number of classes and the parameters of defining the classes in order to train the classifier. In the proposed method, the image is segmented using a spatial region growing based on hierarchical clustering, and fuzzy training is then employed to find the sample classes that well represent the ground truth. For cluster validation, this approach iteratively estimates the class-parameters in the fuzzy training for the sample classes and continuously computes the log-likelihood ratio of two consecutive class-numbers. The maximum ratio rule is applied to determine the optimal number of classes. The experimental results show that the new scheme proposed in this study could be used to select the regions with different characteristics existed on the scene of observed image as an alternative of field survey that is so expensive.

Key Words : Training Samples, Spatial Region Growing, Fuzzy Classification, Cluster Validation.

1. Introduction

Most of statistical classifiers in image processing require prior knowledge about the contents of the scene, including the number of distinct classes and the statistical properties related to the classes. Since the ground characteristics are often unknown for many practical applications in remote sensing, the classifier usually utilizes training samples to estimate the statistical parameters defining the classes. However, it is extremely difficult to locate adequate training fields for all the ground cover classes and the process of gathering training samples is very expensive. This study proposes an alternative approach for the field survey on the spot studied, in which training samples are unsupervisedly generated from observations. The samples can be applied for the supervised classifier.

The proposed method is in two stages. First, it finds the best partition of the image field using the spatial region growing segmentation (Lee, 2001, 2004), which is a hierarchical clustering operation (Anderberg, 1973) of step-by-step merging of smaller clusters into lager ones with the restriction that pixels in a cluster should be spatially contiguous. The segmentation algorithm is based on the local mutually closest neighbors (MCN) and multi-window operation using a pyramid-like structure to increase computational efficiency. Any two regions, which are adjacent each other in the partition, is supposed to be non-uniform on a given statistical criterion. The resultant partition from the segmentation is

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dependent on the criterion determining the level corresponding to the best partition in the hierarchy of the clustering algorithm. For the adequate criterion, the segmentation procedure then segregates inner regions, which correctly define the classes, from the uncertain regions in the boundaries between different classes. In the second stage, the fuzzy training procedure is employed to gather training samples. The fuzzy method, which conducts iterative identification of expected maximum-likelihood parameters of the class (Liang *et al.*, 1992), is applied for the segmented regions in order to determine the sample classes of ground truth. This scheme iteratively estimates the parameters of the sample classes by decreasing the number of classes assumed for the scene of observed area, and continuously computes the ratio of log-likelihoods of two consecutive class-numbers. The optimal number of classes is determined at the point with the maximum ratio.

The algorithm is evaluated with simulation data and then applied for the Calibrated Airborne Multi-spectral Scanner (CAMS) data acquired from Bolivar Peninsula that is located at the mouth of Galveston Bay in Texas. The CAMS data have approximately 4m spatial resolutions and are comprised of 6 bands recorded by optical sensor and one band of thermal sensor. This paper is organized as follows. Section 2 contains a brief description of the CN-chain spatial clustering for image segmentation. The fuzzy training to gather training samples and determine the class-number classification is presented in Section 3. Experimental results with both simulated data and remotely-sensed data are reported and discussed in Section 4. Finally, conclusions are stated in Section 5.

2. CN-chain Spatial Region Growing

One essential structural characteristic involves hierarchy

· **E-step**-Calculateing Indicator Vectors

$$s_{km}^{(h)} = \frac{w_k^{(h)} f_k(X_m \mid \theta_k^{(h)})}{\sum_k w_k^{(h)} f_k(X_m \mid \theta_k^{(h)})}$$

$$f_k(X_m \mid \theta_k^{(h)}) \propto \left| \Sigma_k^{(h)} \right|^{-\frac{N_m}{2}} \exp\left\{ -\frac{1}{2} \sum_{j \in J_m} (\mathbf{x}_j - \mu_k^{(h)})' \, \Sigma_k^{(h)-1} (\mathbf{x}_j - \mu_k^{(h)}) \right\}$$

Conditional Probabilities of Data Set $\mathbf{X}_m$ belonging to Class k at hth Iteration

$$\sum_k s_{km}^{(h)} = 1$$

· **M-step**-Computing Maximum Likelihood Estimates of $\mathbf{W}$, Θ

$$w_{km}^{(h+1)} = \frac{1}{N} \sum_m N_m s_{km}^{(h)}$$

$$\mu_k^{(h+1)} = \frac{1}{N w_{km}^{(h+1)}} \sum_m s_{km}^{(h)} \sum_{j \in J_M} \mathbf{x}_j$$

$$\Sigma_k^{(h+1)} = \frac{1}{N w_{km}^{(h+1)}} \sum_m s_{km}^{(h)} \sum_{j \in J_M} (\mathbf{x}_j - \mu_k^{(h+1)})' \, (\mathbf{x}_j - \mu_k^{(h+1)})$$

$$N = \sum_m N_m$$

Fig. 1. EM steps to generate Fuzzy Vectors.

of scene information. Under the constraint of the hierarchical structure, it is then possible to determine natural image segments by combining hierarchical clustering with spatial region growing. Hierarchical clustering (Anderberg, 1973) is an approach for step-by-step merging of small clusters into larger ones. Clustering algorithm utilize a similarity/dissimilarity measure that is computed between all pairs of candidates being considered for merging, a rule for selecting the pairs to be merged, and a rule for "cutting" the hierarchical tree. The computational efficiency of hierarchical clustering segmentation is mainly dependent on how to find the best pair to be merged. The closest neighbor of region j is defined as

$$\mathrm{CN}(j) = \arg\min_{k \in \mathbf{R}_j} d(j, k)$$

where $d(j, k)$ is the dissimilarity measure between regions j and k, and $\mathbf{R}_j$ is the index set of regions considered to be merged with region j. The pair of regions is then defined as MCN iff $k = \mathrm{CN}(j)$ and $j = \mathrm{CN}(k)$. It is easily shown that the best pair is one of the MCN's. Thus, the search is limited in the set of MCN's in the hierarchical clustering procedure.

For the region growing segmentation, the clustering procedure successively merges a pair among them of two regions which neighbor in image space, that is, $\mathbf{R}_j$ is the collection of the regions which are spatially adjacent with region. If all the pixels in the sample image are initially considered to be individual clusters, the algorithm requires exorbitant memory for the values associated with the merging process for large multi-channel imagery. According to the merger, the neighbor configuration and the set of MCN's must be updated, and the computational time for the update of the configurations and the search of the best pairs exponentially increases as the number of clusters in the initial state increases. To alleviate the memory problem and improve the computational performance of the algorithm, a multi-window strategy of boundary blocking operation can be used by constructing a pyramid-like hierarchy system (Lee, 1990).

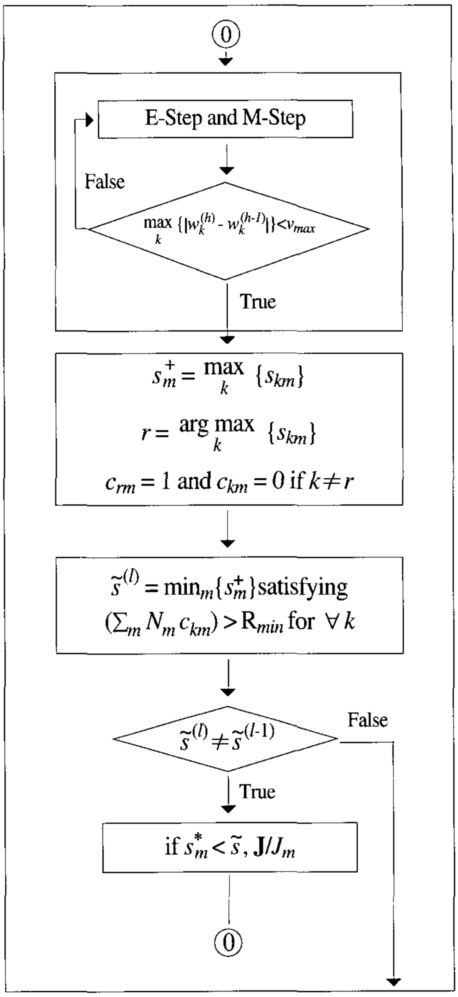

Fig. 2. Fuzzy Training.

3. Fuzzy Training

Consider a problem classifying M regions in K classes. The data set of region m, $\mathbf{X}_m = \{\mathbf{x}_j, j \in \mathrm{J}_m\}$, where J_m is the index set of pixels in region m and $\mathbf{x}_j$ is the data vector of pixel j, is associated with an unobserved image class k, which is to be estimated. This association between $\mathbf{X}_m$ and class k can be specified completely with an unobserved indicator vectors, $\mathbf{s}_m =$

$\{s_{km}, k=1, \cdots, K\}$. In ideal situation, the kth element of $\mathbf{s}_m$ has unit value and all the other elements are zero if region m belongs to class k. The mixture probability distribution of the complete data set $\mathbf{Z} = \{\mathbf{X}_m, \mathbf{s}_m\}$ is then expressed as

$$F(\mathbf{Z} \mid \mathbf{W}, \Theta) = \prod_m \prod_k w_k^{s_{km}} f_k^{s_{km}} (\mathbf{X}_m \mid \Theta_k)$$

where $\mathbf{W} = \{w_k\}$ represents the weights of the components $\{f_k\}$ in the mixture distribution, $\Sigma_k w_k = 1$, and $\Theta = \{\theta_k\}$ is the set of parameters that define the classes. The fuzzy procedure calculates the indicator variables $\{s_{km}\}$ as fuzzy vectors in the E-step, and the likelihood of $\mathbf{W}$ and Θ is maximized in the M-step using $\{s_{km}\}$ estimated in the E-step (Ling *et al.*, 1992). For the assumption of additive Gaussian image model, EM iterative approach to compute the fuzzy vector is summarized in Fig. 1.

From the resultant partition of the segmentation, the fuzzy tringing procedure can segregate inner regions, which correctly define the classes. The first step of the training is to find the inner regions by applying the EM procedure to all the segmented regions for the number of classes, which is given as the maximum number of classes possibly existed in the image. It is supposed that the fuzzy vector associated with the inner region and its class have unit value. The training samples are then gathered by excluding the regions that have significant indicator variables related to more than one class. Fig. 2 shows a flow chart of Fuzzy Training.

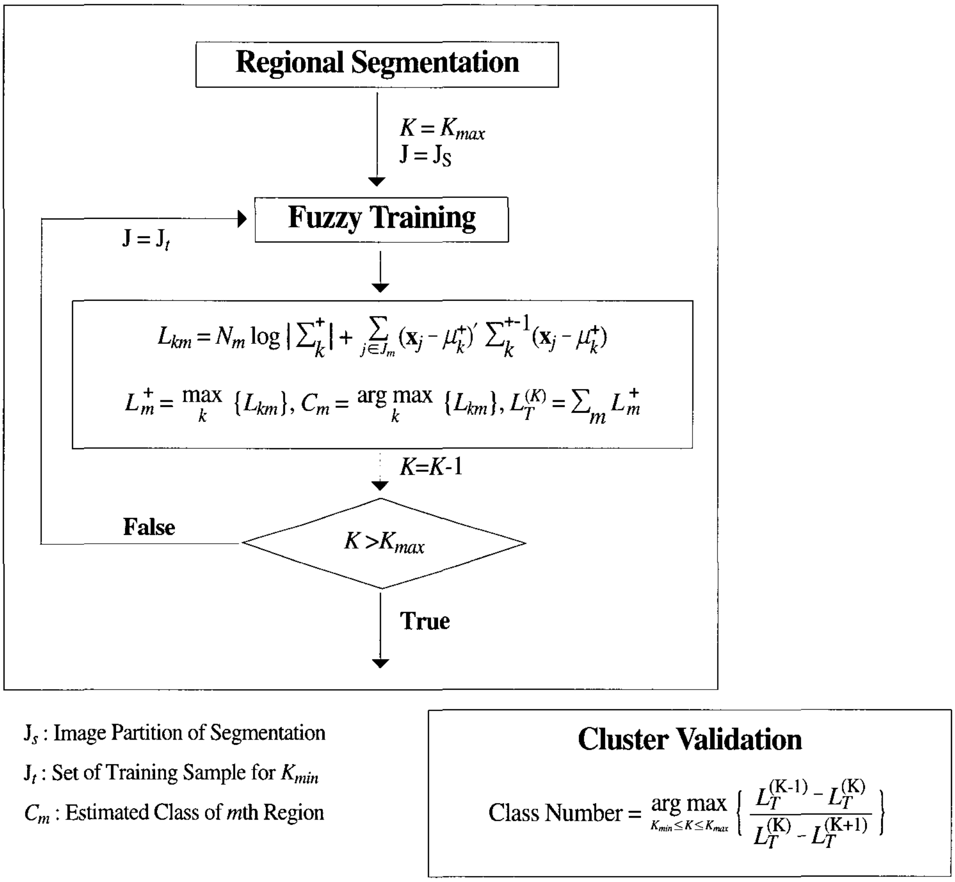

Fig. 3. Algorithm of cluster validation via Fuzzy Training.

Image Pattern

Simulated Noisy Image (Sub-Image)

Fig. 4. Simulation imagery with 5 classes for evaluation of algorithm.

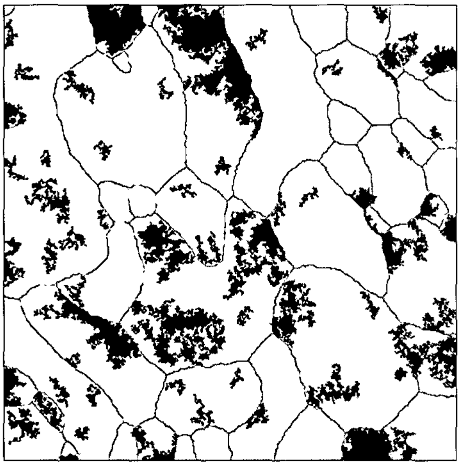

Fig.5. Training areas (92267 pixels with black) selected in fuzzy training and regional class boundaries for simulation imagery of Fig. 4.

Next, using the training samples and reducing one by one the number of classes, the fuzzy training is successively performed for cluster validation, that is, to determine the best number of classes. In this study, the best number of classes, K^* is selected at the level with the maximum ratio of log-likelihood differences in successive steps, that is,

$$K^* = \underset{K_{\min} \leq K \leq K_{\max}}{\arg\max} \left\{ \frac{LL(\text{K-1}) - LL(k)}{LL(\text{K}) - LL(\text{K+1})} \right\}$$

where $LL(\text{K})$ is the log-likelihood of K classes. Fig. 3 outlines the system to gather training samples from observations including Fuzzy Training and cluster validation.

Finally, the unlabelled regions are assigned into one of the K^* classes by MLC using the class parameters estimated in the fuzzy training.

4. Experiments

Fig 4 displays the simulation data to evaluate the proposed algorithm. This study used a blurring image model to generate simulated observation images, which have class boundary areas with mixed classes. Fig. 5 shows the results of the Fuzzy Training. The training produced good samples to well represent the classes existed in the image as shown in Fig. 5.

Next, the experiment was performed with the airborne CAMS data of 7 bands. The aircraft was flown to produce pixels of approximately 4 m spatial resolution. The 2 km $\times$ 2 km study area, located in southern Bolivar Peninsula near Galveston Bay, Texas, U.S.A., has five general land-cover types, low marsh, high marsh and spoil/barren flats, as well as water and trees. The proposed algorithm was applied to a 500 $\times$ 500 subset of the 7-band CAMS data. The gray-scaled image of the CAMS 3-band (Green, Red, NIR) data is

Table 1. Ratios of log-likelihood differences in sSuccessive Steps for cluster validation.

Number of Classes / Likelihood	9	8	7	6	*5	4	3	2
-2 × Log-likelihood	623793	624755	625175	625531	626192	640228	665488	700478
Difference	770	962	420	356	661	14036	25260	34990
Ratio	5.95	1.25	0.44	0.85	1.86	* 21.21	1.8	1.39

Fig. 6. Gray scale images(left) of CAMS 3-band data (Gree, Red, NIR)over Bolivar Peninsula, Texas.

displayed in Fig. 6. To assess the training results, the ground truth points of 13,192 pixels for all the typical types were sampled from the study area.

The ratios between the log-likelihoods obtained for the consecutive values of 8 iterations of Fuzzy Training are shown in Table 1. As shown in the table, the ratio rapidly increased at the level corresponding to 5 classes, the true number of ground cover types. The CAMS data were also classified with 5 classes by the maximum likelihood classification (MLC) using the ground truth points as training samples. Table 2 contains the distribution of the ground truth points of the land-cover types and the misclassification errors for each class respectively.

5. CONCLUSIONS

This study proposes an approach to generate a sample from observation for training the supervised classifier. It

Table 2. Misclassification errors of ground truth points when using Fuzzy Training samples.

Class / Type	1	2	3	4	5	Total	Error(%)
Water	3881	79				3960	2.0
Low Marsh	183	3336	5	21	1	3546	5.9
High Marsh		8	3219	32		3259	1.2
Trees		2	15	430		447	3.8
Barren Flats	8	7	6	10	1949	1980	1.6
Total						13192	2.9

is important for the practice of remote sensing, in which the ground characteristics are often unknown for many applications. It is difficult to find adequate training fields for all the ground cover classes, and some area is not possible to be accessed because of geographical or political reasons. The field survey is also expensive to gather training samples.

In most of remote sensing applications, there exists geophysical connectedness in the observed scene, the proposed method is based on the segmentation using a spatial region-growing clustering which is advantageous relative to the pixel-by-pixel one for the analysis of the patterns with spatial contiguity.

Under the assumption the inner area of regions are more uniform, the samples for training are selected using a fuzzy vector. The fuzzy vector is supposed to have unit value for the class that the sample belongs to and zero for the otherts. Using EM estimation, the proposed fuzzy training selects out the samples with very close unit values for one class, whose elements have homogenous physical properties,

This study also proposes an approach to select an optimal number of classes existed in the analyzed scene.

For the samples generated from the Fuzzy Training, it successively computes the log-likelihood ratio of two consecutive class-numbers and chooses the number with maximum ratio. It is quite effective to find an appropriate class-number for the scene whose cover types is not complicate.

The experimental results show that the proposed scheme can be used as an approach to train the supervised classifier when the number of classes and the parameters associated with the classes are not unavailable or as an economic alternative for the process of gathering training samples.

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