On-Board Satellite MSS Image Compression

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Abstract: In this work a new method for on-line scene segmentation is developed. In remote sensing a scene is represented by the pixel-oriented features. It is possible to reduce data redundancy by an unsupervised segment-feature extraction process, where the segment-features, rather than the pixel-features, are used for multispectral scene representation. The algorithm partitions the observation space into exhaustive set of disjoint segments. Then, pixels belonging to each segment are characterized by segment features. Illustrative examples are presented, and the performance of features is investigated. Results show an average compression more than 25, the classification performance is improved for all classes, and the CPU time required for classification is reduced by the same factor.
Keywords: On-Board, Image Compression, Satellite.

1. Background

On-line data redundancy reduction is important in data systems involving high resolution hyperspectral images which require related powerful communication, archiving, distribution and data analysis subsystems. AMICA (Automatic Multispectral Image Compression Algorithm) is an “on-line preprocessing algorithm that uses unsupervised segment-feature extraction” to represent the information in the multispectral image more efficiently, and to achieve data redundancy reduction. AMICA incorporates spectral and contextual information into the segment-feature extraction scheme.

The algorithm uses spectral-spatial features to describe the characteristics of segments in the scene. A scene consists of the union of segments, such that all pixels from a segment are members of the same class; hence, the scene’s segments can each be represented by a single suitably chosen feature set. Typically the size and shape of segments in the scene vary randomly and mach the scene variation; however, the pixel size is fixed, it is reasonable to assume that scene representation by segments is more efficient. A complex scene consists of simple segments; any scene can thus be described by classifying the segments in terms of their features and by recording the relative position and orientation of the segments in the scene.

The proposed scene representation can be thought of as a combined scene segmentation and feature extraction process, which extracts similar groups of contiguous pixels in the scene as simple segments according to some numerical measure of similarity. Intuitively, simple segments have two basic characteristics; they exhibit an internal regularity, and they contrast with their surroundings. Because of the irregularities due to the noise, the segments do not exhibit these characteristics in an obvious sense. The ambiguity in the segmentation process can be reduced if the spatial dependencies, which exist among the adjacent pixels, are intelligently incorporated into the decision making process.

2. Model and Definitions

The on line object detection, can be thought of as a combined scene segmentation and feature extraction process. It extracts similar contiguous pixels in the scene, as a segment, according to some numerical measure of similarity. A segment consists of union of pixels which have a unity relation with each other. Intuitively, a segment has two basic characteristics; it exhibites an internal regularity, and it contrastes with its surrounding.

Because of the irregularities due to the noise, the segments do not exhibit these characteristics in an obvious sense. The ambiguity in the segmentation process can be reduced if the spatial dependencies, which exist among the adjacent pixels, are intelligently incorporated into the decision making process. The unity relation among the pixels of a segment is constructed with regard to the adjacency relation, the spectral- features and the spatial-feature characteristics in a segment which can be extended to more constraints. Image data is represented by a two-dimensional rectangular array of pixels.

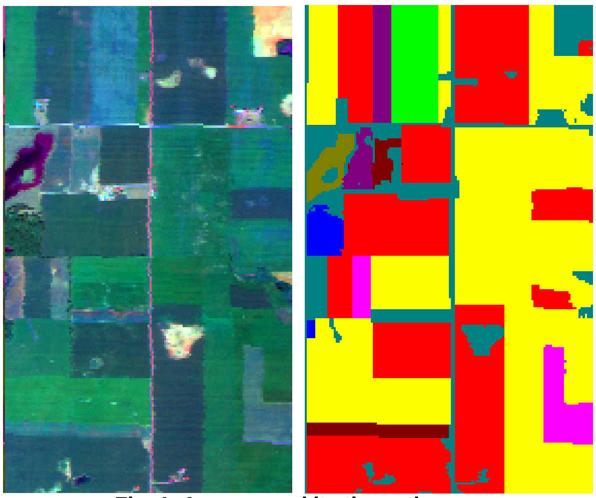

Fig. 1. A scene and its thematic-map

One of the important characteristics of such data is the special nature of the dependence of the feature at a lattice point to that of its neighbors. The unconditional correlation between two pixels in spatial proximity to one another is often high, and such correlation usually decreases as the distance between pixels increases. One way to characterize this dependency, among the neighboring pixels, is to represent it by a unity relation. The unity relation among the pixels of a segment, meanes that a segment consists of contiguous pixels from a common class where their features are statistically similar. The keys to the unity relation among the pixels of a segment are the adjacency relation and the similarity criterion.

Mathematically it can then be said that the unity relation exists between two pixels if they satisfy two criteria simultaneously:

They have an adjacency relation with each other, in the sense that they are spatially contiguous or their spatial distance is filled by a sequence of contiguous pixels from the same class.

They have the same attributes, or they carry equivalent useful information about the scene, in the sense that their features are similar to each other.

The similarity between the pixels' attributes is of basic importance in attempting to test the existence of the unity relation. This is evident since the existence of two adjacent segments, is a consequence of the dissimilarity of features from neighboring pixels where two adjacent segments differ in at least one of the spectral or contextual features. The accuracy of the similarity measure is dependent on the selected metric space used for functional construction and has an upper bound which is controlled by the amount of noise in the system.

The uncertainty in the similarity measure is significantly reduced using the within object regularities. This property is used in the path-hypothesis for unity relation construction. Elements in this path are determined on a spectral basis relative to the current status of all other adjacent segments by the spectral variation between two consecutive points in the path, using a specific metric to be defined presently. Elements in the path are also determined based upon the spectral separation between the current and the most recently preceding pixel of that segment in spatial space, thus incorporating both spectral and spatial information in that association of pixels with segments.

3. Experimental Results

The reliability and quality of features, are measured in terms of; overall misplacement error in the class-map, feature classification performance, and the subjective appearance. The same training samples and decision rule are used in the comparison. The subjective appearance is an appropriate criterion when the ground-truth-map is not accurate enough to be used by other feature evaluators, or when some objects in the scene are more important than the others regardless of the size of the objects. This criterion is used to evaluate the spatial quality of the spatial-feature map (Fig.3). By incorporating the object appearance in the spatial-feature-map into the feature selection strategy, more complex objects in the scene can be detected.

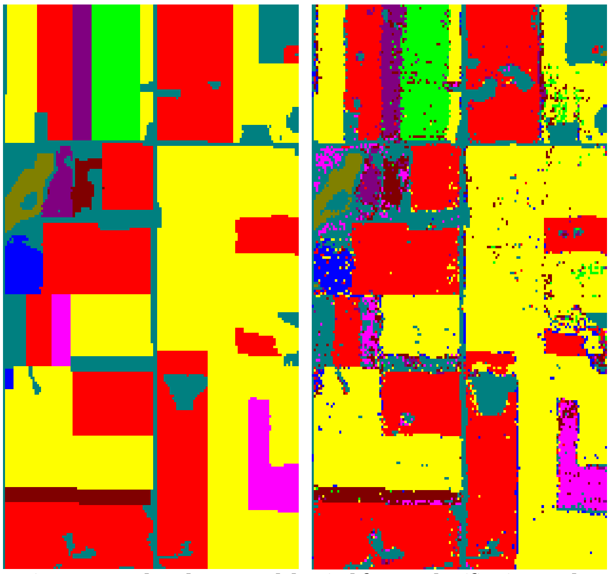

Fig. 2. Ground truth map, and the pixel-feature classification results

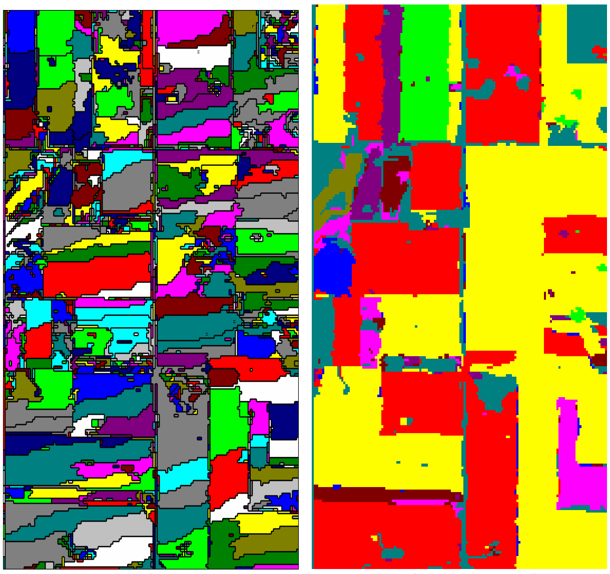

Fig. 3. Spatial-feature map, and the Object-feature classification results

For example some significant within-class variation shows that more information about the complex objects (perhaps soil type covered by vegetation) in the scene might be extracted by using even more complex features. The proposed feature extraction technique is applied to several set of multispectral data. As previously stated, the objective of this experiment is to demonstrate the validity of the unity relationship and the path-hypothesis, and to show that the performance of segment-feature is better than the performance of pixel-feature regardless of the choice of classification decision rule and the training set.

Figure 3 shows segment-feature classification performance. For example, the wheat field, which is circled, classified better than when the pixel-features are used in Figure 2. It, can detect a single randomly selected pixel in a relatively large soybean field which is replaced by a pixel from some other ground cover types; this pixel is shown in a triangle in Fig. 2 and Fig. 3. As it pointed out, since the classification performance is dependent on the training samples and the ground-truth-map, the spatial-feature-map appearance is a valuable criterion for feature evaluation.

In the spatial-feature-map there is a significant within-class information which can be used for even ground-truth-map evaluation. The appearance of an object in the spatial-feature-map can be intelligently incorporated into the feature selection strategy for extraction of more complex classes in the scene. Fig. 3 shows that there is significant within-class variation, and thus more information about the scene (e.g., soil type and vegetation condition) might be extracted than will be attempted here, perhaps by using even more complex features. Tabels 1 and 2 are exampeles of feature evaluation, using MLC Bayes Gausian decision rule.

4. Conclusions

In this work a new method for on-line scene segmentation is developed. This method utilizes a new technique based on **unity relation,** which must exist among the pixels within a segment. This unity relation among the pixels of a segment is defined with regard to an adjacency relation, spectral features, and spatial features in a segment. The technique must detect segment in real-time and represent them by means of a feature set. The unity relation, for on-line feature extraction, can be realized by the path-hypothesis. The path-hypothesis is based on the fundamental assumption that pixels from a simple segment are sequentially connected to each other by a well-defined relationship in the observation space, where the spectral variation between two consecutive points in the path follows the texture rule (similarity measure).

The performance of feature extraction process is measured in terms of information-bearing quality of the features versus the data set size. The average compression coefficient is more than 25/1. The classification performance is improved slightly for all ground cover classes. The CPU time required for classification is reduced by a factor of more than 25 as well. The feature extraction process may be implemented in real time, thus the feature extraction CPU time is negligible.

References

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Table 1. Pixel_Feature performance using Bayes MLC

Number of Features=369600 Bytes											
True Class	**Classifier results**										
	Corn	Soybeans	Woods	Wheat	Sudex	Oats	Pasture	Hay	Nonfarm	Totals	%Corrct
Corn	8942	102	145	149	1	22	0	22	721	10104	88.5%
Soybeans	6	11717	482	108	8	87	0	14	488	12910	90.8%
Woods	4	10	328	3	0	1	2	0	41	389	84.3%
Wheat	0	8	8	732	0	24	0	9	163	944	77.5%
Sudex	0	17	0	0	1175	21	0	2	4	1219	96.4%
Oats	1	12	0	8	3	508	0	28	43	603	84.2%
Pasture	0	0	0	0	0	0	307	0	32	339	90.6%
Hay	22	1	?1	21	3	52	0	592	54	746	79.4%
Nonfarm	17	69	14	68	1	111	9	81	3176	3546	89.6%
Totals	8992	11936	978	1089	1191	826	318	748	4722	30800	89.2%
Overall Performance = 89.2%						**CPU Time = 51.52 Seconds**					

Table 2. Segment_Feature performance using Bayes MLC

Number of Features=13,692 Bytes. Compresstion Coefficient = 27											
True Class	**Classifier results**										
	Corn	Soybeans	Woods	Wheat	Sudex	Oats	Pasture	Hay	Nonfarm	Totals	%Corrct
Corn	9592	123	17	67	0	6	0	66	233	10104	94.9%
Soybeans	24	12409	209	74	1	27	0	11	155	12910	96.1%
Woods	0	4	385	0	0	0	0	0	0	389	99.0%
Wheat	6	11	12	824	0	11	0	0	80	944	87.3%
Sudex	0	9	0	0	1193	13	0	3	1	1219	97.9%
Oats	4	1	0	2	0	588	0	0	8	603	97.5%
Pasture	0	0	0	0	0	0	339	0	0	339	100.0%
Hay	45	0	0	0	9	1	0	691	0	746	92.6%
Nonfarm	69	136	12	94	8	244	0	118	2865	3546	80.8%
Totals	9740	12693	635	1061	1202	890	339	889	3342	30800	93.8%
Overall Performance = 93.8%						**CPU Time = 1.88 Seconds**					