

ON-BOARD SATELLITE IMAGE COMPRESSION BY OBJECT-FEATURE EXTRACTION

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ABSTRACT:

Recent developments in sensor technology make possible Earth observational remote sensing systems with high spectral resolution and data dimensionality. As a result, the flow of data from satellite-borne sensors to earth-stations is likely to increase to an enormous rate. This paper investigates a new on-board unsupervised feature extraction method that reduces the complexity and costs associated with the analysis of multispectral images and the data transmission, storage, archival and distribution as well. Typically in remote sensing a scene is represented by the pixel-oriented features. It is possible to reduce data redundancy by an unsupervised object-feature extraction process, where the object-features, rather than the pixel-features, are used for multispectral scene representation. The proposed algorithm partitions the observation space into exhaustive set of disjoint objects. Then, pixels belonging to each object are characterized by object 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 a factor of more than 25, and some new features of the scene have been extracted.

1. INTRODUCTION

On-line data redundancy reduction is especially important in data systems involving high resolution remotely sensed image data which require related powerful communication, archiving, distribution and scene analysis. A complex scene is composed of relatively simple objects of different sizes and shapes, each object of which contains only one class of surface cover type. The scene can be described by classifying the objects and recording their relative positions and orientation. Object-based scene representation can be thought of as a combined object detection and feature extraction process. The object extraction is a process of scene segmentation that extracts similar groups of contiguous pixels in a scene as objects according to some numerical measure of similarity. Intuitively, objects have two basic characteristics: they exhibit an internal regularity, and they contrast with their surroundings.

Because of the irregularities due to the noise, the objects do not exhibit these characteristics in an obvious sense. The ambiguity in the object detection process can be reduced if the spatial dependencies, which exist among the adjacent pixels, are intelligently incorporated into the decision making process. The proposed multispectral image compression algorithm is an "on-line pre-processing algorithm that uses unsupervised object-feature extraction" to represent the information in a multispectral image data more efficiently. This algorithm incorporates spectral and contextual information into the object-feature extraction scheme. The algorithm uses local spectral-spatial features to describe the characteristics of objects in the scene. Examples of such features are size, shape, location, and spectral features of the objects. The local spatial features (e.g., size shape, location and orientation of the object in the scene) of the objects are represented by a so-called spatial-feature-map;

the spectral features of an object are represented by a d-dimensional vector. The technique is based on the fundamental assumption that the scene is segmented into objects such that all samples (pixels) from an object are members of the same class; hence, the scene's objects can each be represented by a single suitably chosen feature set. Typically the size and shape of objects in the scene vary randomly, and the sampling rate and therefore the pixel size are fixed, it is reasonable to assume that the sample data (pixels) from a simple object have a common characteristic. A complex scene consists of simple objects; any scene can thus be described by classifying the objects in terms of their features and by recording the relative position and orientation of the objects in the scene.

We introduce the basic components that make up the structures of an analytical model for scene representation in an efficient measure space. This process is carried out through a specific feature extraction method which maps the original data (pixel observation) into an efficient feature space, called the object-feature-space. This method utilizes a new technique based on a so-called unity relation which must exist among the pixels within an object. The unity relation among the pixels of an object is defined with regard to an adjacency relation, spectral features, and spatial features in an object. The technique must detect objects in real-time and represent them by means of an Object-feature. The unity relation, for on-line object-feature extraction, can be realized by the path-hypothesis. The path-hypothesis is based on the fundamental assumption that pixels from an object are sequentially connected to each other by a well-defined relationship in the observation space, where the spatial variation between two consecutive points in the path follows a special rule. By employing the path-hypothesis and using an appropriate metric for similarity measure, the scene can be segmented into objects.

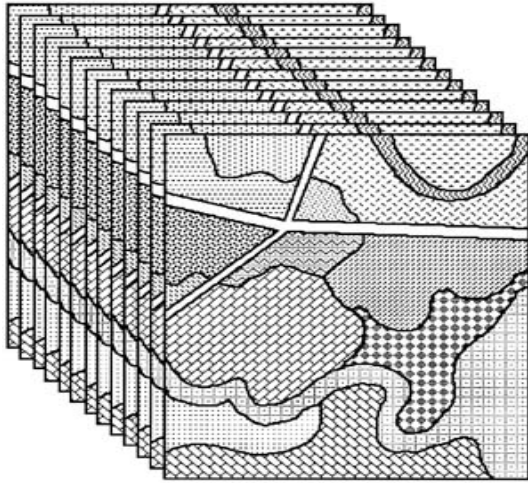


Figure 1. MSS image Object-Based scene representation

2. MODELLING AND DEFINITIONS

The scene (in this work this is assumed to be part of the Earth's surface) is the target of the remote sensing system, which is under investigation and the interest is to extract information about the scene's structure and content (Tso and Mather, 2001). The desired information is assumed to be contained in the spectral, spatial, and temporal variation of electromagnetic energy coming from the scene which is gathered by the sensors (Hapke, 1993). Typically a complex scene is composed of relatively simple objects of different sizes and shapes, each object of which contains only one class of surface cover type. The scene is often described by classifying the objects and recording their relative positions and orientation in the scene in terms of tabulated results and/or a thematic-map.

In a remote sensing system, primary features of a scene are formed by multispectral observations, which are accomplished by spatially and spectrally sampling the scene. A multispectral sensor samples several spectral dimensions and one spatial dimension from the scene at a given instant of time. The second spatial dimension can be provided by the motion of the platform which carries the scanner over the region of interest, generating a raster scan; alternately, the raster can be provided by area array detector. Thus, through the data acquisition system, the scene may view in an image from taken at each of a number of electromagnetic wavelengths. This image can be thought of as a multi-layer matrix whose elements are called pixels (Tso and Mather, 2001). 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 neighbours. 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 of the distinctive characteristics of the spatial dependence in multispectral data is that the spectral separation between two adjacent pixels is less than two non-adjacent pixels, because the sampling interval tend to be generally smaller than the size of an object; i.e., two pixels in spatial proximity to one another are unconditionally correlated with the degree of correlation decreasing as the distance between them increases. The results of study on measurement of different order statistical spatial dependency in image data, specially the measurement of first, second and third order amplitude statistics along an image scan line show considerable correlation between adjacent pixels.

Seyler concluded, from the measurement of the distribution of the difference between adjacent pixels, that the probability that two adjacent pixels have the same grey level is about 10 times the probability that they differ by the maximum possible amplitude difference. Kettig (Kettig and Landgrebe, 2001) by measuring the spatial correlation of multispectral data showed that the correlation between adjacent pixels is much less when conditional upon being with an object, as compared to unconditional correlation. High correlation among adjacent pixels in the observation space represents redundancy in scene data. When such redundancy occurs, reducing the size of the observation space should be possible without loss of information.

As previously stated the scene is assumed to consist of relatively simple objects of different sizes and shapes (see Figure 1). The resolution of the spatial representation depends on both pixel size and the interval between samples, which are usually equal. By under-sampling information is lost; however, over-sampling will cause increased redundancy. Typically the size and shape of objects in the scene vary randomly, Figure 1, and the sampling rate, and therefore the pixel size, is fixed; it is inherent in image data that data-dimensionality (the number of spatial-spectral observation for scene representation) increases faster than its intrinsic-dimensionality (the size of the smallest set which can represent the same scene, numerically, with no loss of information). Because the spatial sampling interval is usually comparable to the object size, it follows that each object is represented by an array of similar pixels. Therefore, scene segmentation into pixels is not an efficient approach for scene representation; however, a scene can be segmented into objects, and since the shape and size of objects match the scene variation, scene representation by simple-objects is more efficient.

Object detection refers to finding the natural groups among the contiguous pixels. In other words, the data is sorted into objects such that the "Unity Relation" holds among members of the same object and not between members of different adjacent objects. Object extraction and clustering are similar in the sense that they both are methods of grouping data; however, spatial considerations make clustering and object extraction different. Because an object can be textured, the pixels within an object might not form a compact cluster in the measurement (observation) space. Also, because there can be several instances of a particular class of entities in a single image, nonadjacent objects might be nearly identical in observation space. Another difference is that in object extraction, the existence of a partition that completely separates objects is guaranteed. However, in clustering, if we allow underlying classes with overlapping density functions, the classes can never be completely separated in the observation space. Object extraction can be thought of as transforming the original image, which is a pixel-description of a scene into an arrangement of object-description.

An object-description is often better than a pixel-description, for two basic reasons:

- 1- More information about the scene entity is available from a collection of pixels associated with the object than from an individual pixel associated with the scene. This fact has been exploited by "object" classification algorithms that make a classification decision for each group of image points, for example by sequential classification (Tso and Mather, 2001). The potential advantages of object classification are especially great when class probability

densities differ in shape but exhibit a high degree of overlap. Classifying objects instead of pixels also allows the measurement and use of spatial characteristics such as size, shape and texture, which have been found to be useful in classification.

- 2- An object representation is often more compact than a pixel description. This savings in storage space or transmission speed occurs if objects contain enough points so that specifying the locations and essential properties of the objects takes fewer bits than specifying the collection of individual pixel properties.

In the analysis and processing of multispectral images one encounters a large amount of data. To enable efficient processing of this data, it would be preferable to have an underlying model that explains the dominant characteristics of the given image data. Subsequent processing of the images can be efficiently accomplished by using the models fitted to the data. With the above scheme, a scene is segmented into spatially disjoint objects (Ghassemian & Landgrebe, 1987).

Objects in imaged scenes are describable by sets of relevant attributes or features (Ghassemian & Landgrebe, 1988). These features represent distinct measurements or observable properties. The object's initial measurements, which are encoded as pixel-features, are subsequently subjected to an object-feature transformation. Each of the objects contains a union of similar pixels, and the union of the simple objects represents the whole scene. All pixels of an object, whose pixels satisfy the unity relation, can be represented by an object-feature set (Ghassemian, 1990).

The accuracy of this system (the information content in the object-feature-set) is dependent on the parametric primitives who are used in object- feature construction; however, this accuracy has an upper bound which is controlled by the level of noise which exists in the acquired data. In the analysis of a set of data points in multidimensional space, the need to choose the most relevant features frequently arises. Feature selection techniques are used to find properties of objects in the scene which can serve as the strongest clues to their identification.

One way to characterize this dependency, among the neighbouring pixels, is to represent it by a unity relation. The unity relation among the pixels of an object means that an object consists of contiguous pixels from a common class where their features are statistically similar. The keys to the unity relation among the pixels of an object 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 (Ghassemian & Landgrebe, 2001):

- 1- 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. The subset of L (spatial-feature) whom their corresponding pixels having an adjacency relation with the pixel X_k is represented by the set A_k , called neighbourhood set.
- 2- 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. This means that the distance between these attributes, in an appropriate metric-space, is less than unit, $d_s(X_r, X_k) < 1$.

Let $R(.)$ be a relation on pixel-feature-set P. When the relation exists it is represented by $R(.)=1$, otherwise by $R(.)=0$. Then

$R(.)$ is a unity relation provided that it satisfies the following properties for all X_r, X_k, X_m belonging to pixel-feature-set P:

I- Similarity and Adjacency Properties:

$$R(X_r, X_k)=1 \text{ if and only if } d_s(X_r, X_k) < 1 \text{ and } r \in A_k$$

II- Reflexive Property:

$$R(X_k, X_k) = 1$$

III- Symmetric Property:

$$R(X_r, X_k) = R(X_k, X_r)$$

IV- Transitive Property:

$$X_r, X_k) = 1 \text{ and } R(X_r, X_m) = 1 \implies R(X_m, X_k) = 1$$

The unity relation is defined by a property between two individual pixels in an object, can be extended to the property between a pixel and an object. We had pointed out that, the unity relation in the observation space is defined by an adjacency relationship together with a similarity criterion among the pixels' attributes. 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 objects, is a consequence of the dissimilarity of features from neighbouring pixels where two adjacent objects 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. The path of sequential association, which pixels follow in the spectral space, from a continually evolving hypothesis regarding the object definition. Elements in this path are determined on a spectral basis relative to the current status of all other adjacent objects 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 object in spatial space, thus incorporating both spectral and spatial information in that association of pixels with objects.

It should be realized that the path-object P_i is defined in the spectral space and it is different from a spatial path in the scene. A path-object P_i is represented by its spectral- feature S_i , spectral variation regularity V_i , and the path end point X_{ki+1} . The path hypothesis thus determines a possible sequence of points in the observation space for each object, which implies that each object forms a well-defined sequence in observation space, called the path-object. The succession of consecutive observations describes a particular trajectory in the observation space. Any change in the behaviour of two consecutive points (the end point of the path-object X_{ki+1} and the current pixel X_i) in this trajectory can define a start point of a new object.

3. FEATURE EXTRACTION

In theory, decision about class membership for a noisy object should be based upon as many observations of the object as possible and preliminary decisions concerning subsets of object-features can provide less than maximally reliability recognition. Thus theoretically, the most reliable decision should be based upon all the pixels in the object. Also in theory, every result achievable with d variables can also be achieved

with $d+1$ variable, but the converse is not true. Thus one might expect that by increasing the number of features the object recognition error rate should decrease or at least stay the same, but in practice quite often the performance of the features will improve up to a point, then begin to deteriorate as further attributes are added. This is referred to as the Hughes' phenomenon (Hughes, 1968). The existence of an optimal set of features is indicated for the representation of the objects, relative to feature selection and feature reliability problem. An object can be described by a set of parametric primitives. Such primitives may be based on observation as well as knowledge about the object. Typically in remote sensing the important primitives, for recognition of an object, are spectral feature and / or contextual features. But since it is usually presumed that the shape and the size of natural objects in a scene (ground cover types) are random and unrelated to the ground cover classes, these features are often ignored in feature extraction and pattern recognition of the ground cover types. However in this work, the objects' geographical features are preserved in the spatial-feature-map \mathbf{L} , and can be used by an appropriate pattern recognition system, if it be necessary. It is assumed that two adjacent objects differ in a measurable way relative to the spectral or contextual features. In this system, a set of points representing similar patterns are represented with the same features. Thus the attributes of \mathbf{P} can be refined by observation which is given by a set of three parametric primitives:

$$Y_i = (S_i, V_i, L_i) \quad (1)$$

Where \mathbf{S} is estimated within-object spectral feature representation, \mathbf{V} is the estimated contextual feature, and \mathbf{L} is the spatial-feature-map or the object geographical shape and location in the scene. Let n be the number of pixels in the object \mathbf{P} , and \mathbf{L} be the corresponding spatial-feature-map, then the object spectral feature \mathbf{S} is estimated by averaging the spectral response of pixels within the object \mathbf{P} . Then the contextual feature, \mathbf{V} , is estimated by averaging the spectral variation of pixels within the object \mathbf{P} .

$$S_i = \frac{1}{n} \sum_{k \in L_i} X_k \quad (2)$$

Notice that the spatial variation can be horizontal, vertical, diagonal, and any other possible spatial direction. The objects with small area, whose number of pixels within the object is not sufficient for contextual feature estimation, will be represented only by the spectral feature. This is done by adjusting the degree of uncertainty in the feature extraction process: the uncertainty about the feature is inversely dependent on the number of pixels that are contained within the object \mathbf{P} .

Although the contextual feature is dependent on the sensor resolution as well as the sensor altitude from the scene, the intra-object spatial variation between adjacent pixels can be a significant factor for on-line object extraction. A metric for testing the unity relationship between the pixel-feature \mathbf{X}_r and object-feature \mathbf{Y}_i is introduced. This metric normalizes the spectral distance by their spectral gradient vector:

$$d_s(X_r, Y_i) = (|S_i - X_r|)^T (\alpha V_i + \beta V_n)^{-1} \quad (3)$$

where $\alpha = (w\mathbf{n}_i/\mathbf{n}_i + w)$ and $\beta = (w^2/\mathbf{n}_i + w)$, \mathbf{n}_i is the number of pixels in the current object, w is the size of observation window, and S_i , V_i , \mathbf{X} and \mathbf{Y} are the same vectors as defined before.

4. FEATURE EVALUATION

The performance of a feature extraction process is measured in terms of the information-bearing quality of the features versus the size of the data set. Classification accuracy is an important quantitative measure of feature quality in applications where the data is automatically interpreted. The comparative performance results for the various feature configurations between the original pixel-features \mathbf{X} and compacted object-features \mathbf{Y} . The features' reliability and quality are measured in terms of overall misplacement error in the scene (OME), feature classification performance (FCP), and subjects' appearance (SOA).

The first evaluation is a simple quantitative criterion which has a conventional mathematical form to measure the number of pixels assigned to an incorrect neighbouring object based on the object classification, relative to the total number of pixels in the scene (overall misplacement error). Let GTM represent the ground-truth-map of original data, and let CPM represents the classification-pixel-map result of feature classification. Then the overall misplacement error can be computed by comparison of the CMP and the GTM. The feature classification performance (FCP) measures the number of pixels classified into the correct class relative to the total number of pixels in that particular class. This criterion is used to evaluate the object-feature performance when the effects of classifier decision rule and training samples on the class feature performance should be considered. Good ground truth information is a very important parameter in feature evaluation to minimize the unrelated error in the feature extraction. However, obtaining a valid ground-truth-map (GTM) and registering the multispectral image data with this map is often costly and very time consuming. Thus among the available real data those subsets which have a relatively reliable ground-truth-map should be selected and used for the OME and FCP feature evaluations.

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. In such cases it is often too difficult to define a mathematical expression for a feature quality adequate for quantitative evaluation. In this case visual assessment will be used for this kind of qualification. This criterion is used to evaluate the spatial quality of the spatial-feature-map, for prediction of more information about the scene, by using more complex features, which should be extracted from the training samples. In other words, by incorporating the object appearance in the spatial-feature-map into the feature selection strategy, more complex objects in the scene can be detected. 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 image 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 *object-feature* is better than the performance of *pixel-feature* regardless of the choice of classification decision rule and the training set. To establish the unity relation, the system learns about the functional coefficients simultaneously with the data acquisition process by measuring the object spectral gradient which, is then, normalized within a window.

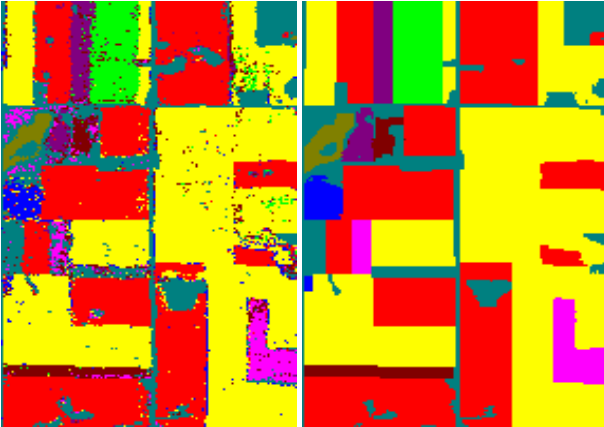


Figure 2. Pixel-Feature Performance and the class map (right)

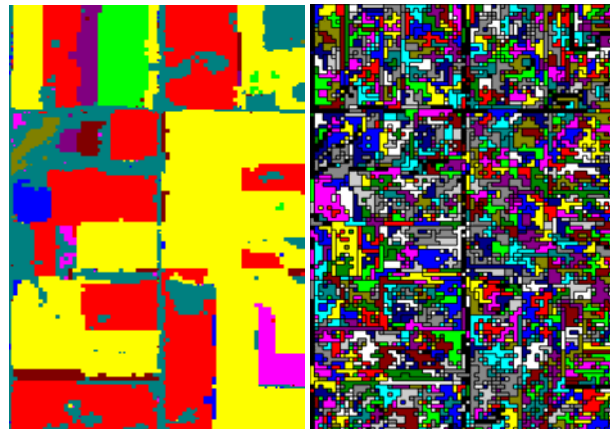


Figure 3. UnsupervisedECHO performance and its feature map

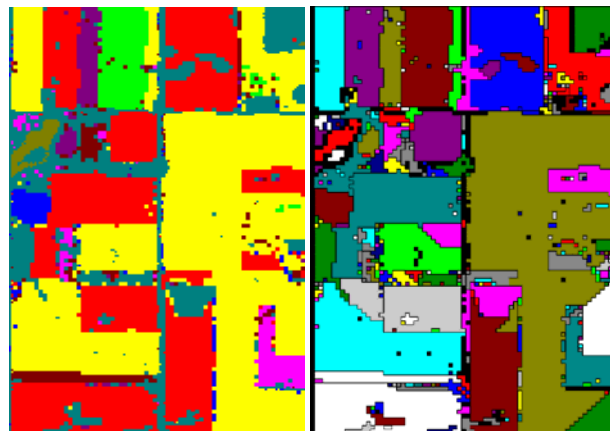


Figure 4. Ssupervised-ECHO performance and the feature-map

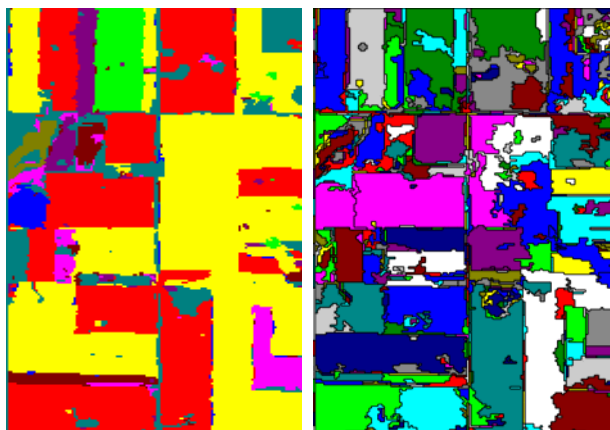


Figure 5. AMICA2 performance and the feature-map (right)

Classification accuracy is dependent on both the classification algorithm and the training sample set, furthermore, it is slightly dependent on the window size. The performance of the object-feature is compared with the performance of the original pixel-features from the same scene, when the M.L. Bayes Gaussian decision rule is selected.

Spectral information of surrounding pixels is correlated with the centred pixel under consideration. In object detection the spectral features of adjacent pixels are considered using neighbouring information; thus the object-feature which we represent them in this experiment only by $(S < L)$ built upon both spectral and contextual information. Therefore, it is expected that the classification accuracy to be higher by using object-feature rather than the individual pixel-feature (notice that we did not consider effect of V in the classification of object-feature using M.L. decision rule). Tables 1 and 2 show, by using the object-feature, for example, the wheat field classified better than when the pixel-features are used for its classification. A test for robustness of the path hypothesis and accuracy of the unity relation shows that the functional based on path-hypothesis, 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, see Figure 5.

5. SUMMARY AND CONCLUSION

In order to reduce data redundancy in multispectral imagery we have proposed a model, based on a scene object-description, for multispectral image representation. We have developed an on-line unsupervised object-feature extraction algorithm (called AMICA) which detects the objects by using the unity relation based on the path-hypothesis. The unity relation among the pixels of an object can be defined with regard to the: adjacency relation, spectral-feature and spatial-feature characteristics in an object. Based on the path-hypothesis the data read sequentially into the system. The unity relation between a current pixel and the path-segments (objects in the observation space) are examined, the current pixel may be merged into an appropriate object or it will initiate a new object. An object is represented by a relevant object-feature set. AMICA is implemented to real multispectral image data. The performance of the object-features is compared with the performance of the original pixel-feature. Three different evaluation strategies (overall misplacement error, feature classification performance and subjective object appearance) are selected for comparative feature evaluation using the pixel-features and the object-features. The experimental results indicate that data volume is reduced by a significant amount (the size of the feature-space for scene representation is reduced by a factor more than 25 which is data dependent). In addition, the accuracy of information extracted from the object-features (as measured by classification accuracy) is greater than obtained when using the original pixel-features.

The correlation among the adjacent pixels in the image data appears in the form of redundancy in the spectral-spatial features. Spectral information of surrounding pixels is correlated with the centred pixel under consideration. In object detection the spectral features of adjacent pixels are considered using neighbouring information. Therefore, it is expected that the classification accuracy to be higher by using object-feature rather than the individual pixel-feature. The improvement of the classification performance is consequence of incorporation of the spatial information in the object-feature extraction decision

rule; however, in addition to that, it could be also a consequence of complexity reduction by data compaction (Hughes, 1968).

Since the classification process is performed in the feature-space (rather than in the observation-space) the algorithm is much faster than conventional ones. The object appearance in the feature-map can be incorporated (by visual assessment) into the feature selection strategy for extraction of more complex objects in the scene. In summary, it appears that the proposed object-feature extraction process has several advantages over most of the conventional techniques.

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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 1. Pixel-Feature performance using Bayes MLC

Number of Features=13,692 Bytes. Compression 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					

Table 2. Object-Feature performance using Bayes MLC