PATTERN CLASSIFICATION USING RELATIVE CONSTRAINTS

Mark J. Carlotto

TASC, 55 Walkers Brook Dr., Reading, MA 01867

ABSTRACT

An approach to pattern classification based on relative constraints in a discrete relaxation framework is described. Classical pattern classification techniques partition feature spaces into disjoint decision regions where thresholds are absolute, i.e., fixed numerical quantities. The approach described here defines pattern classes relative to one another and so results in decision boundaries that depend on the data being classified. Such a formulation leads to a classification scheme based on finding unambiguous labelings (assignments of single classes to objects) using a discrete relaxation labeling algorithm. Classes are defined exclusively in relative terms, using fairly weak constraints. As a result, there are not many locally incompatible hypotheses to eliminate by Waltz filtering. A ranking scheme is developed which orders hypotheses so that unambiguous labelings can be quickly found through depth-first search. When an unambiguous labeling does not exist, classes can be assigned by picking the most compatible hypotheses. Results of work in progress in classifying Landsat multispectral imagery are presented. The ability to recognize basic surface material categories in two scenes using relative descriptions of surface material classes is demonstrated.

1. INTRODUCTION

Classical statistical pattern classification techniques use fixed numerical thresholds (e.g., derived from training data) to classify unknown data. Although such techniques may be optimal when the unknown data are similar to the training data, classification performance may degrade if significant variability is encountered. An alternative is to use heuristic techniques and knowledge that is more general and qualitative in nature, but possibly inconsistent and incomplete. The present work addresses the problem of classifying patterns in domains where there is significant variability in the data. The approach is based on the use of relative constraints to define the classes of interest with respect to one another and discrete relaxation to apply the constraints to the data to be classified. By defining pattern classes relative to each other, the decision boundaries depend on the data being classified and so can adapt to changes in the data. The application currently under investigation is the classification of surface materials in Landsat multispectral imagery.

The organization of the paper is as follows: Section 2 reviews previous work in discrete relaxation labeling and related work in multispectral classification. Section 3 describes a discrete relaxation algorithm for classification that uses relative constraints. Several examples are presented to illustrate its use in Section 4. In Section 5 early results in using the technique to classify surface material categories in two Landsat scenes are presented. Future work is outlined in Section 6.

2. PREVIOUS WORK

Relaxation and constraint labeling techniques can be traced back to early work by Waltz [1]. The problem addressed was that of interpreting line drawings of 3-D objects using knowledge about the compatability of line junctions. Feldman and Yakimovsky [2] developed a semantics-based region analyzer which segmented and labeled images of simple scenes using constraints such as "doors are square", "pictures are hung on walls", etc. Tenenbaum and Barrow [3] developed an interpretation-guided segmentor similar in concept to the one above based on a Waltz's filtering ideas. Rosenfeld, et al [4] formalized the theory of discrete, fuzzy, and probabilistic relaxation methods.

The use of statistical pattern recognition techniques in remote sensing is well known [5]. The problem of how to extend "spectral signatures" derived in one image set to another has received considerable attention. The multiplicative and additive signature correction technique (MASC) developed by Henderson [6] matches clusters in an unknown data set to those in a known one. Related work by Fischler and Elschlager [7] addressed the problem of matching graphical structures using local information. One application was matching

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the feature spaces of two terrain scenes and is similar in some ways to cluster matching.

3. CLASSIFICATION BY DISCRETE RELAXATION LABELING

Let $A = \{a_1, a_2, \ldots, a_N\}$ be the set of objects we wish to classify, $\Omega = \{\omega_1, \omega_2, \ldots, \omega_K\}$ be the set of possible labels or classes for the objects, and $\Phi = \{\phi_1, \phi_2, \ldots, \phi_M\}$ be the set of properties defined over the set of objects. The value of the m^{th} property of the n^{th} object is denoted $a_n(\phi_m)$. Although we do not refer directly to the numerical values of classes, the notation $\omega_k(\phi_m) > \omega_{k'}(\phi_m)$ means that in terms of the m^{th} property, the k^{th} class is strictly greater than the k'^{th} class. The set of hypotheses, $H = A \times \Omega = \{h_{nk}\}$, represents all possible pairings of objects and labels; h_{nk} is the hypothesis that object a_n is a member of class ω_k. $R = \Phi \times \Omega \times \Omega = \{r_{mkk'}\}$ is the set of constraints where $r_{mkk'}$ implies $\omega_k(\phi_m) > \omega_{k'}(\phi_m)$ for $k \neq k'$. Since $r_{mkk'}$ is the same as $\neg r_{mk'k}$, there are at most MK(K-1)/2 unique constraints, some of which are redundant as they may be implied by others, i.e., $r_{mk_1k_2}$ and $r_{mk_2k_3} \rightarrow r_{mk_1k_3}$. If for the m^{th} property, there is no ordering relation between the k^{th} and k'^{th} classes, the corresponding constraint $r_{mkk'}$ is said to be undefined. If the two classes do not in any way depend on one another, all $r_{mkk'}$ for $m = 1,2,\ldots, M$ are undefined.

Let $\lambda[h_{nk}, h_{n'k'}]$ denote the compatability of hypotheses h_{nk} and $h_{n'k'}$. Two hypotheses are compatible

(i) if all $\{r_{mkk'}\}$ are undefined, or

(ii) if $n \neq n'$ and $k = k'$, since two objects may belong to the same class, or

(iii) if $n = n'$ and $k \neq k$, since an object may belong to more than one class, or

(iv) if $n = n'$ and $k = k'$, since a hypothesis is compatible with itself, or

(v) if for each constraint in $\{r_{mkk'}\}$ that is defined, $a_n(\phi_m) > a_{n'}(\phi_m)$ since a_n is associated with ω_k, $a_{n'}$ is associated with $\omega_{k'}$ and $r_{mkk'}$ requires that $\omega_k(\phi_m) > \omega_{k'}(\phi_m)$.

(i) is the case where there are no contraints between the classes; (ii) is possible in situations where the number of objects is greater than the number of classes; (iii) is possible during the initial phases of the labeling process (i.e., during Waltz filtering); (iv) is the trivial case; in (v), if any constraint from the set $\{r_{mkk'}\}$ is violated, then h_{nk} and $h_{n'k'}$ are not compatible.

A labeling is an assignment of classes to objects. A consistent labeling consists of all hypotheses h_{nk} that are compatible with at least one $h_{n'k'}$, $n \neq n'$ and $k \neq k'$. The process of finding consistent labelings, termed Waltz filtering, involves repeatedly applying constraints to hypotheses, eliminating hypotheses which are not compatible with at least one other hypothesis, until the process converges. Rosenfeld, et al [4] proved that this process always converges. An unambiguous labeling assigns only one class or label per object. Ultimately, we are interested in finding unambiguous labelings. Exhaustive search for unambiguous labelings, e.g., via the tree search procedure developed by Waltz, can require the examination of up to K^N labelings. In some domains, unary constraints (e.g., "doors are square") are available and can, in conjunction with Waltz filtering, be used to significantly prune the search tree by eliminating many incompatable hypotheses at the outset. In other domains where classes are only weakly constrained relative to one another, there are few locally incompatible hypotheses and so Waltz filtering is not effective in itself in reducing search.

4. CLASSIFICATION USING RELATIVE CONSTRAINTS

Fig. 1 shows a distribution of clusters (a_1 through a_5) in a two-dimensional feature space. The clusters represent a possible segmentation of an image and are defined by two properties: ϕ_1, brightness (br) and ϕ_2, greenness (gr).

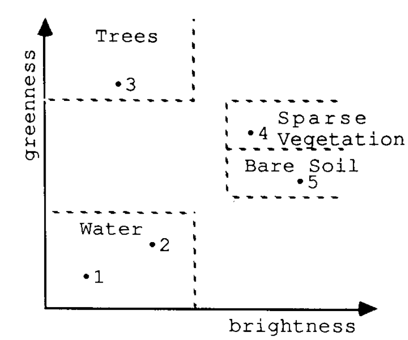

Fig. 1 Distribution of clusters in brightness-greeness feature space

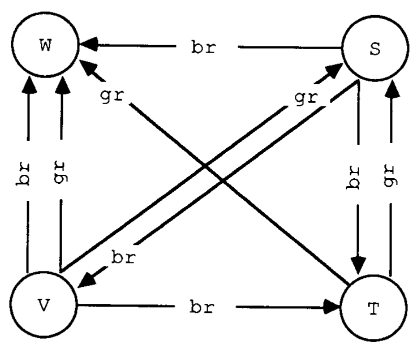

Fig. 2 Directed graph representation of constraints for water (W), trees (T), sparse vegetation (V), and bare soil (S).

(The use of brightness and greenness features are discussed in Section 5.) Initially, we assume that four classes $\{\omega_1, \omega_2, \omega_3, \omega_4\}$ are present in the image: water, bare soil, sparse vegetation, and trees.

Fig. 2 is a directed graph representation of these four classes in terms of only relative constraints. For example, the top arc represents the constraint r_{121}, "bare soil is brighter than water". Fig. 1 also shows a labeling that satisfies all the constraints in Fig. 2. Since it assigns one class per cluster, it is an unambiguous labeling. Qualitatively, unambiguous labelings will be found only if the "structure" of the feature space matches the structure implied by the constraints. The dotted lines in Fig. 1 are the decision boundaries (parallelpipeds in higher dimensional spaces) induced by the constraints in Fig. 2. Their relationships to one another are defined by the constraints, although their numerical values depend on the data being classified (as can be readily verfied by distorting the coordinate axes).

Fig. 3a is a search tree for the above example and contains 4^5 = 1024 paths, each of which corresponds to a labeling. The dotted lines in the figure correspond to the labelings that are eliminated by Waltz filtering. For this example, Waltz filtering eliminates 2 out of 20 possible hypotheses, which given the ordering of the hypotheses, reduces the number of candidate labelings by 50%.

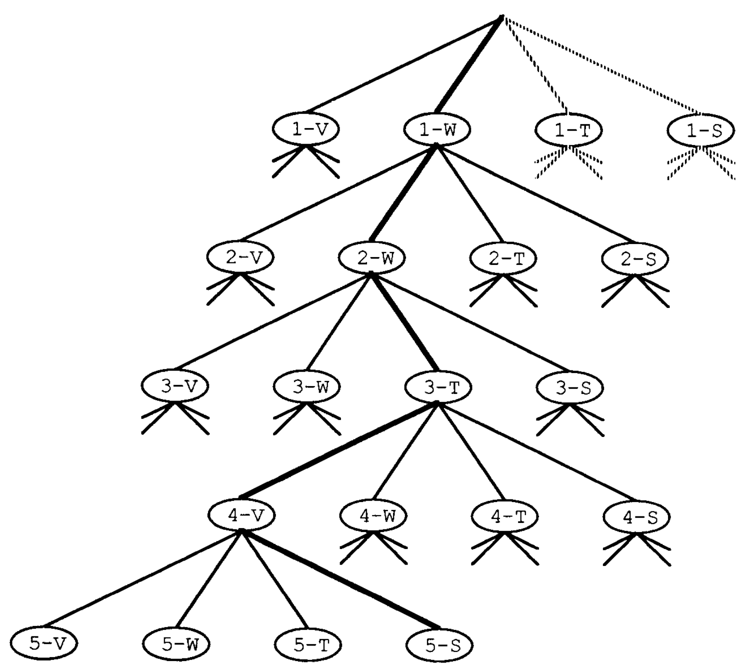

Fig. 3a Hypothesis tree for depth first search for unambiguous labelings for clusters in Fig. 1 and constraints in Fig. 2.

An even more effective way to reduce search is to order hypotheses by their compatibility and to visit those hypotheses first. Table 1 lists, for each of the 18 hypotheses h_{nk} which survived Waltz fltering, a score which equals the number of other hypotheses $h_{n'k'}$ that were incompatible. If a hypothesis is compatible with every other hypothesis in H, its score is zero. In each row the most compatible hypothesis (lowest score) is shown in bold face.The heuristic is that unambiguous labelings will contain hypotheses with high compatibilities (low scores), and conversely, labelings consisting of hypotheses with low scores are likely to be unambiguous ones. The hypotheses which belong to the unambiguous labeling in Fig. 1 are marked with asterisks in Table 1. In this particular example, if the tree is built such that the most compatible hypotheses are examined first (Fig. 3b), the correct labeling is found immediately.

Consider now a second example. Fig. 4 shows the five clusters from the previous example plus a sixth. If we try to label all six clusters in Fig. 4 using the constraints in Fig. 2, no unambiguous labeling exists (Table 2). If a fifth class, clouds, and four additional constraints relating clouds to the other classes are added (namely, clouds are brighter than water, trees, sparse vegetation, and bare soil), the correct unambiguous labeling is obtained (Table 3). It is worth noting however that in this example, the hypotheses which belong to the unambiguous labeling are not always the ones with the lowest scores. Thus, although searching through the most compatible hypotheses provides a good starting point, some backtracking may be needed.

	Classes			
Clusters	W	T	V	S
1	**0***	8		
2	**3***	7	8	7
3	7	**0***	6	10
4	8	5	**5***	6
5	8	8	5	**3***

Table 1 - Hypothesis table for clusters in Fig. 1 and constraints in Fig. 2. Most compatable assignment in bold face; * denotes unambiguous labeling.

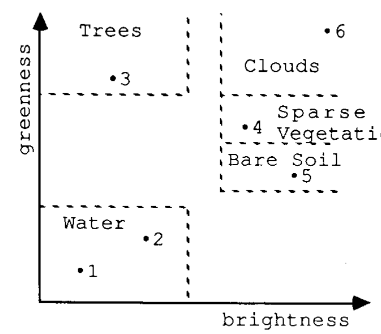

Fig. 4 Distribution of clusters in brightness-greeness feature space

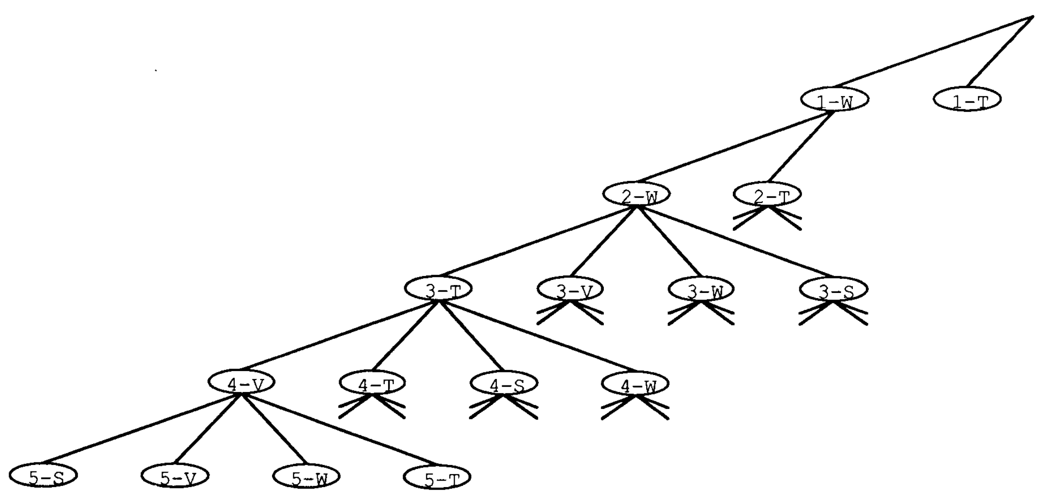

Fig. 3b Search tree ordered so that most compatible hypotheses are considered first.

	Classes			
Clusters	W	T	V	S
1	**0**	9		
2	**3**	8	10	9
3	7	**1**	8	12
4	8	**6**	7	8
5	8	9	7	**5**
6		8	**4**	9

Table 2 - Hypothesis table for clusters in Fig. 4 and constraints in Fig. 2. No unambiguous labeling exists.

	Classes				
Clusters	W	T	V	S	C
1	**0***	9	14	14	
2	**6***	11	12	11	11
3	9	**3***	9	26	15
4	12	10	10*	11	**7**
5	13	14	11	9*	**3**
6		14	9	14	**0***

Table 3 - Hypothesis table for clusters in Fig. 4 and constraints in Fig. 2 plus ones for clouds (C). Note that the hypotheses in the unambiguous labeling are not always the most compatable.

5. MULTISPECTRAL IMAGE CLASSIFICATION EXAMPLE

The primary motivation for the present work is multispectral classification, specifically, the classification of surface materials by their spectral signature alone. The classical approach described by Swain [5] assumes that the surface material classes (SMCs) of interest are represented by multi-variate normal distributions, and involves computing the class conditional statistics from a training data set and using the empirically derived class-conditional models to classify an unknown data set. Here, we segment the imagery into clusters that are assumed to be multi-variate normal but apply only relative knowledge to classify the clusters. Segmentation is accomplished via unsupervised clustering which tends to "over-segment" the data. Clusters are represented by their brightness and greenness values derived using the TM tasseled cap transform [8]. Tasselled cap and similar physically-based transformations provide scene independent measurements of significant physical properties such as soil brightness, greenness (related to the amount of biomass present), and wetness (relative moisture content). The availability of such measures allows us to represent SMCs in relative

Initial experiments in classifying Landsat Thematic Mapper (TM) imagery have been performed. In one, two scenes, about 512x512 pixels in size and acquired in the same pass of the Landsat satellite were processed. Fig. 5a shows the 8 clusters extracted from the first image and hand labeled which we use as "ground truth". The second scene was then classified using a set of constraints derived from this first scene by the precedure described below. Five unambiguous labelings were found and were very similar to one another, e.g., clusters labeled trees in one were labeled brush in another. The labeling with the lowest net score (highest compability) is shown in Fig. 5b. If we use this labeling as the ground truth for the second scene, and derive a set of constraints for classifying the first scene, an identical set of constraints is derived. Applying these constraints to the first scene produces six unambiguous labelings. Interestingly enough, the one in Fig. 5a is the one with the lowest net score. Thus, even though the two feature spaces in Fig. 5 are different, a single set of relative constraints can be used to classify them.

In the above example, constraints were derived from the hand labeled clusters using a simple deductive procedure. Initially, assume that all $r_{mkk'}$ are true which implies $\omega_k(\phi_m) > \omega_{k'}(\phi_m)$ for all k, k', and m. Next, for all pairs of clusters, a_n and $a_{n'}$ that belong to classes ω_k and $\omega_{k'}$ respectively, if any $a_n(\phi_m) \le a_{n'}(\phi_m)$ then the corresponding $r_{mkk'}$ is false. This is done for all pairs of classes and for all properties. Finally, if $r_{mkk'}$ and $r_{mk'k}$ are either both true or both false, they are not defined, otherwise the one that is true is retained. Fig. 6 depicts the constraints derived by this method for the above example as a directed graph.

Another experiment performed on two sets of imagery acquired by different sensors (Landsat TM and an aircraft TM) over different areas at different times has demonstrated the ability to identify selected surface materials common to both scenes. These results will be presented in a future paper. The results obtained to date suggest that because relative constraints are weak they are more "extendable" but may require supervision to guide their use in unknown situations.

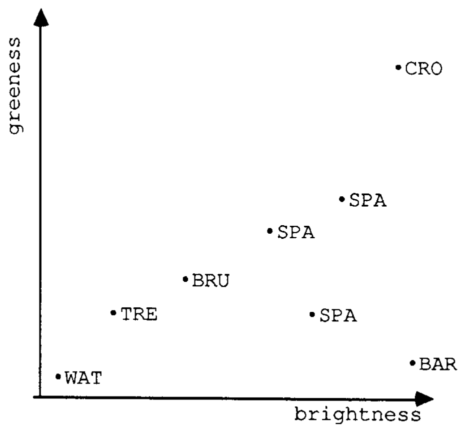

Fig. 5a Labeled clusters in first European scene.

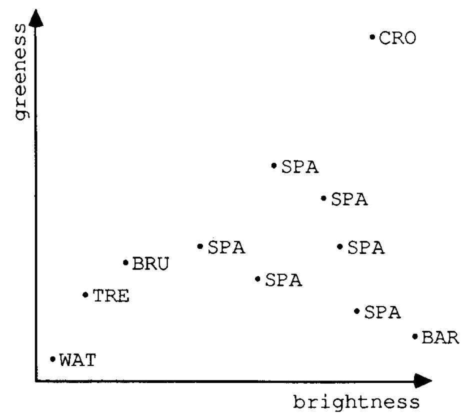

Fig. 5b Labeled clusters in second European scene.

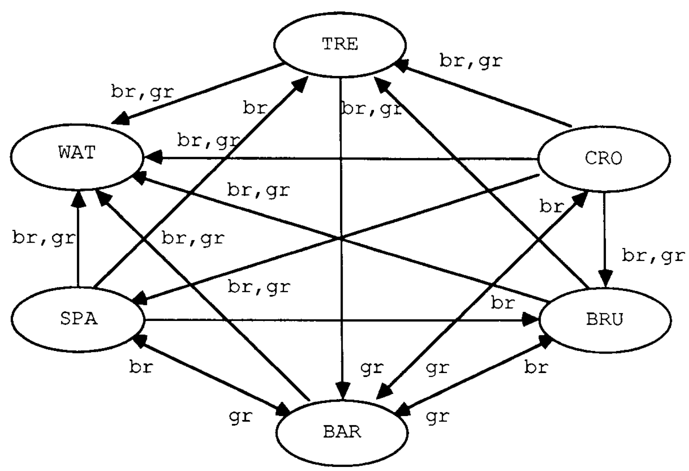

Fig. 6 Directed graph representation of constraints for two European scenes. Classes are WATer, SPArse vegetation, BARe soil, BRUsh, CROps, and TREes.

6. SUMMARY

Additional multispectral data sets are being processed to assess the usefulness of the technique. The goals are to determine the extent to which relative spectral information (class to class) can be used for surface material classification and to determine the tradeoffs between specificity and extendibility. Earlier work addressed the use of relative spectral information (band to band) [9]. Future work may combine the two techniques. The limited resolution of Landsat TM and the lack of structure in such imagery limits the use of geometrical and spatial knowledge present in systems developed by Nagao and Matsuyama [10] and Hanson and Riseman [11] although there use is under consideration. Previous work [2,3] has already demonstrated the use of geometrical and spatial information for scene interpretation. The work reported herein is potentially applicable to autonomous land and remotely piloted vehicles that use color or multispectral imaging sensors.

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