Reprinted from

Symposium on

Machine Processing of

Remotely Sensed Data

June 29 - July 1, 1976

The Laboratory for Applications of
Remote Sensing

Purdue University
West Lafayette
Indiana

IEEE Catalog No.
76CH1103-1 MPRSD

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TREE SYSTEM APPROACH FOR LANDSAT DATA INTERPRETATION†

R. Y. Li and K. S. Fu
School of Electrical Engineering
Purdue University
West Lafayette, Indiana 47907

ABSTRACT

This paper describes a tree system approach which interpretates highways and rivers from LANDSAT pictures. The basic definitions of tree grammars and tree automaton and a grammatical inference procedure are first introduced. The interpretation process is conceived as a process of continuous verification of the hypothesized descriptions of objects in the picture. The LANDSAT imagery map of Lafayette, Indiana is used as a training data set and tree grammar is inferred from the interpretation process. The versatility of this set of syntactic rules is tested on a different data set and the initial results are reported.

I. INTRODUCTION

As the ability of satellites to gather data for the purpose of survey and monitoring of earth resources grows, the need to fully automate the recognition process of a large number of pictures obtained by satellite photography is also becoming more evident. In the past, the use of pattern recognition techniques has been very successful in the classification and interpretation of the data taken from agriculture fields, vegetation, water, soil, etc. However, these methods usually employ only spectral and/or temporal properties of the objects and neglect the spatial relationships among classes in the picture. Difficulties could then arise when one is dealing with smaller objects such as bridges, highway, river, etc. because the surrounding environment changes greatly the expected reflectance of those objects due to the resolution size. For instance, the gray level of a segment of the highway is digitized from a combined reflectance of concrete surfaces, grasses, trees, etc. Sometimes it is impossible to distinguish this class from, say, suburban scenes where similar features dominate. In cases like this, one has to extract a certain geometric feature from the data in order to interpret them more accurately. In other words, properties such as shape, size, and texture must be used to delineate one from the other among classes of similar spectral properties.

†This work was supported by the National Science Foundation Grant ENG 74-17586 and the ARPA Contract F30620-75-C-0150.

Often, the spatial relationships such as "surrounded by," "near by," and directional references can also be explored to locate classes of large areas where no definite shapes exist, such as those found in land use classification. For instance, in the study by Todd & Baumgardner[1] on land use classification of the Marion County (Indianapolis), Indiana, an overall accuracy of about 87 percent is reported using only the spectral information. Difficulties were encountered in the spectral separation of grassy (open country, agriculture) area and multi-family (older) housing. One solution to this problem consists of spatially dividing the data into urban and rural land use prior to classification. Over 95 percent accuracy of recognition may be achieved by this manual preprocessing step in their analysis. The use of syntactic methods to describe the spatial relationship has recently been suggested[2]. Brayer and Fu went further by constructing a hierarchical or tree graph model to contain the spatial distributions of all classes in the entire scene[3]. For instance, the earth scene consists of urban and rural area, and the urban area consists of the downtown area surrounded by the inner city area with near-by suburban area and a system of highways. These classes are then classified by utilizing their spatial relationships which are expressed in terms of syntactic rules; namely, those of a web grammar. The study undertaken here is similar to this approach, but a tree system is used as the main tool to interpret LANDSAT data where traditional approaches have not achieved satisfactory results.

II. BASIC DEFINITIONS OF TREE SYSTEM

The use of formal linguistics in describing physical patterns have received increasing attention recently[3]. The string representation has been used very often due to the availability of existing results in formal languages. But it is inadequate and sometimes inconvenient for descriptions of high-dimensional patterns or multiconnected graphs, so there is a need of developing higher dimensional pattern description languages. Recently, Fu and Bhargava have proposed the use of tree grammars for pattern description[5]. Tree grammars are generalizations of string grammars.

A tree grammar becomes a string grammar when the ranks of all variables are one or zero. We shall see that the use of tree grammars is justified because of their ability to describe easily the recursive nature of the physical patterns under consideration. Furthermore, a tree automaton can be easily constructed from a given tree grammar to recognize the trees generated.

A regular tree grammar over $<V_T, \gamma>$ is a four-tupled $G_t = (V, \gamma, P, S)$ where $<V, \gamma'>$ is a finite ranked alphabet with $V_T \subseteq V$ and $\gamma'/V_T = \gamma$, $V_N = V - V_T$, the set of non-terminals. P is the production rules of the form $A \rightarrow B$, if there is a production $\phi \xrightarrow{a} \psi$ in P such that ϕ is a subtree of A at a, and B is obtained by replacing the occurance of ϕ at a by ψ. S is a finite subset of T_V, called axioms, where T_V is the set of trees over alphabet V.

The tree language generated by a tree grammar G_t is defined as

$$L(G_t) = \{\alpha \in T_{V_T} \mid \text{there exists } Y \in S \text{ such that } Y \Rightarrow \alpha\}$$

where T_{V_T} is the set of trees containing only terminal symbols.

A tree grammar $G_t = (V, \gamma, P, S)$ is expansive if each production in P is of the form

$$Y_o \rightarrow \begin{array}{c} x \\ \diagup \quad \diagdown \\ Y_1 \ldots\ldots Y_n \end{array}$$

where $Y_o, Y_1, \ldots\ldots Y_n$ are non-terminals, x is a terminal.

We also know that for every regular tree grammar G_t, one can effectively construct a tree automaton M_t such that $T(M_t) = L(G_t)$ where $T(M_t)$ is the set of trees accepted by M_t. We are interested in knowing the relation between tree automata and tree grammars, since the patterns will be described by a tree grammar and a tree automaton can be used to recognize these patterns.

Let $<V_T, \gamma>$ be a ranked alphabet and $V_T = \{x_1, \ldots\ldots x_n\}$. A tree automaton over V_T is a system $M_t = (Q, f_1, \ldots\ldots f_k, F)$ where

1. Q is a finite set of states
2. for each i, $1 \leqslant i \leqslant k$, f_i is a relation for $Q^{\gamma(x_i)} \rightarrow Q$
3. $F \subset Q$ is a set of final states

If each f_i is a function, f_i: $Q^{\gamma(x_i)} \rightarrow Q$, then M_t is determinable. Otherwise, it is non-deterministic.

The response relation p of a tree automaton M_t is defined as follows:

1. If $x \in V_{T_o}$, then $p(x) \rightarrow q$ iff $q \in Q$
2. If $x \in V_{T_n}$, $n > o$, then $p\left(\begin{array}{c} x \\ \diagup \diagdown \\ t_1 \ldots t_n \end{array}\right) \rightarrow q$

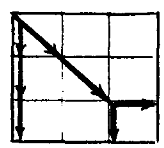
   iff there exists $q_1, \ldots\ldots q_n \in Q$ such that $f_x(q_1, \ldots\ldots q_n) \rightarrow q$ and $p(t_i) \rightarrow q_i$, for $1 \leqslant i \leqslant n$, $t_i \in T_{V_T}$.

The language accepted by M_t is defined as $T(M_t) = \{t \in T_{V_T} \mid \text{there exists } q \in F \text{ such that } p(t) \rightarrow q\}$. M_{t_1} and M_{t_2} are equivalent iff $T(M_{t_1}) = T(M_{t_1})$.

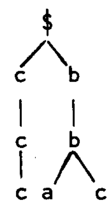
We summarize the construction procedures of tree automaton for a regular tree grammar as follows:

1. To obtain an expansive tree grammar (V', γ, P', S) for the given regular tree grammar (V, γ, P, S) over alphabet V_T.
2. The equivalent nondeterministic tree automaton is $M_t = (V' - V_T, f_1, \ldots\ldots f_n, \{S\})$, where $f_x\ (q_1, \ldots\ldots q_n) = q_o$ if $q_o \rightarrow x\ q_1, \ldots\ldots q_n$ is a rule in P'. If f_i, $1 \leqslant i \leqslant k$, is a function, them M_t is deterministic; otherwise, M_t is non-deterministic.

As an example, if we denote a$\rightarrow$, b$\searrow$, c$\downarrow$, then the following multi-connected graph



can be written in tree form as



Sometimes when the patterns are not quite linear due to noise or distortion, we can apply a transformational grammar to linearize them.

III. INFERENCE OF TREE GRAMMAR

When the physical shape of the class under consideration is completely known and fixed, it is possible to write down the syntactic rules directly to describe its structure. If this is not the case, we have to construct a set of grammatical rules by examining a set of sample patterns known to come from that class in order to describe that particular class. This set of inferred rules should be able to describe and predict other sample patterns which are of the similar nature as the original training samples and presumably in the same class. Bhargava and Fu have suggested an inference procedure for tree grammars[6]. The basic idea consists of the following three steps:

1. Try to discover the syntactic structure of each given tree sample by looking for repetitions and dependent relationships, called repetitive substructures (RSS).

2. Decide what sublanguages make up the language and generate nonterminals for each sublanguage.

3. Combine equivalent nonterminals which have almost the same sublanguages and determine the appropriate relationships among sublanguages. The flow chart implementing the inference procedure is shown in Figure 1.

To start the inference process, we first find the types of terminals or primitives that will fit the subparts of the picture patterns for a given window size. After this initial extraction process, we have to decide the most probable combinations of primitives which occur as neighbors of each other in the set of observed training samples. These combinations are then applied to the training data set to test their recognition effectiveness. When the result appears to be satisfactory after some additions and deletions of the combinations, we can choose this set of patterns to represent the training samples. The appropriate grammar can then be inferred from these samples by following those three basic steps of grammatical inference. This process of learning can be repeated for higher levels if we are dealing with patterns of larger size. To prove the acceptance of the inferred grammar by other non-training sample patterns, a set of test data should be used. The success of this final step should prove that the spatial relationships among data samples of a particular class can be utilized in a broad sense.

IV. EXPERIMENTAL RESULTS

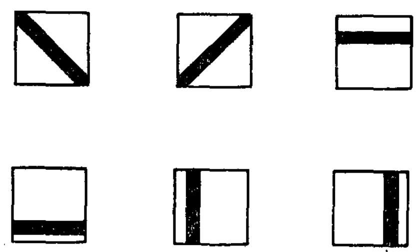
In the actual implementation of the above procedures, we first choose the LANDSAT imagery map of Lafayette, Indiana as the training data set. The original 17 clusters are further combined into seven ground cover types. They are general agriculture area, pasture with wheat dominant, forests, commercial area, residential area, highways and rivers. Among them, rivers and highways could serve as excellent examples for syntactic pattern recognition because of their simple shapes and the relative failures of statistical approaches. Our purpose would be to separate the lake or pond from the river and highway from any spectral similar features. Although we might expect that highways are usually built as a straight connection between two locations, in reality this is not true. The highways are built as straight lines only locally, but not globaly, in order to avoid the fatigue of the drivers. However, highways occasionally curve locally for directional changes when some natural obstacles such as rapid elevations occur. As a result, certain geometric requirements of a highway must be satisfied:

1. The width of a highway has an upperbound.

2. The local curvature of a highway has an upperbound to follow the requirement of maximal speed of automobiles.

The river, on the other hand, has a less rigid upperbound than highway in terms of local curvature. In other words, the river could make a sharper turn. In general, we can expect the river to exhibit the same linear pattern as the highway does. A small creek branching out from a river can be interpreted as the entrance or the exit road from the superhighway. For simplicity, we shall not write separate grammars for rivers and highways in our present study.

The lowest level or the primitives selected for both river and highway are based on a 2 X 2 pixel window of the following patterns:



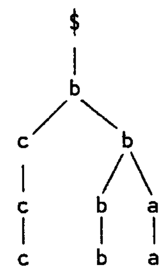
In short, this first-level extraction will eliminate all isolated points. Its main purpose, however, is to generate the terminals for further learning. The next step is to find the most probable combinations of primitives which occur as neighbors of each other in the river and highway data samples. For the sake of convenience, we choose a set of 4-tuple patterns which are more representative of suburban highways than, say, streets in commercial areas or any other features which reflect like a mixture of concrete and grass, like those appearing quite extensively in the new residential area in south Lafayette. Those 4-tuple patterns are shown in Figure 2.

After a series of trials and errors, we deduce a set of 26 combinations which give us a good result in terms of showing the Wabash River and Interstate Highway 65 in the Lafayette area. The ground truth in this case is provided by an infrared photography of the Lafayette area. The pointwise classified data of the Lafayette area is shown in Figure 3. The result from the syntactic method with selected pattern combinations is shown in Figure 4 for both highways and river. Since the 4-tuples can be applied in both directions, we really learn the highway and river structures from the 13 combinations shown in Figure 5.

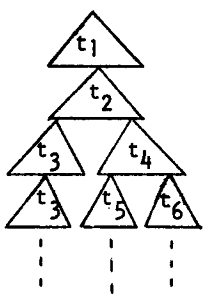
It is possible for us to go one level further but these 13 patterns are probably sufficient for us to infer a tree grammar based on their structural information. Five of them are just straight lines, meaning no directional changes. The other eight have directional changes of no more than 45 degrees. It is true that these patterns only represent a segment of the highway and the river structures but their repetitive natures are certainly valid in the general context. Thus, we have completed the step (1) of the inference procedures.

The next step is to discover what subtrees make up the tree language and generate nonterminals for each subtree. We can divide those 13 patterns into three categories; they are shown as the three rows in Figure 5. If we denote a → (horizontal line segment), b ↘ (diagonal line segment), and c ↓ (vertical line segment), then the tree representation of the following superhighway pattern

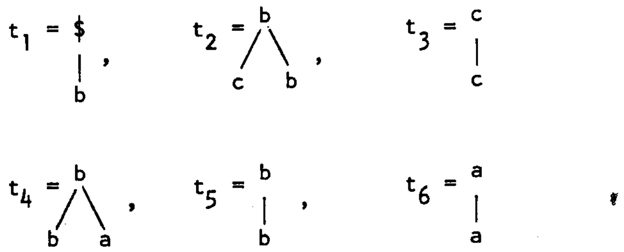
will be



The subtrees of depth one within this tree can be expressed in terms of the following representation



where the repetitive substructures (RSS) for the sublanguage are



Continuing in this fashion and following the flow chart in Figure 1, we obtain the following tree grammar for highway (or river) patterns:

$G_t = (V, \gamma, P, S)$

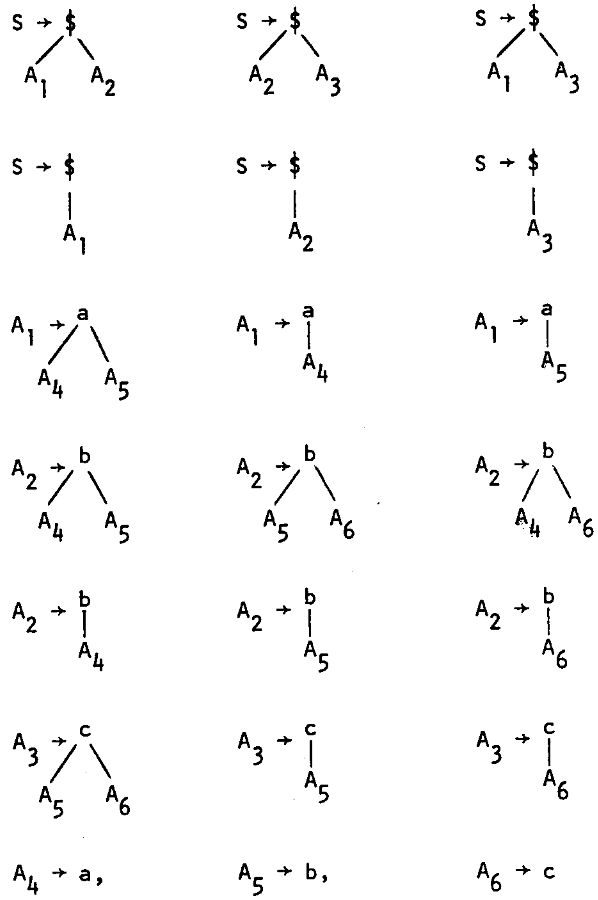
$V = \{s, a, b, c, \$, A_1, A_2, A_3, A_4, A_5, A_6\}$

$V_T = \{a, b, c\}$

$\gamma(a) = \{2, 1, 0\}$, $\gamma(b) = \{2, 1, 0\}$, $\gamma(c) = \{2, 1, 0\}$

$\gamma(\$) = \{2, 1\}$

P:



Corresponding to this tree grammar, we can then construct a tree automaton

$M_t = (Q, f_\$, f_a, f_b, f_c, F)$ over V_T

$Q = \{A_1, A_2, A_3, A_4, A_5, A_6, q_F\}$, $F = \{q_F\}$,

$V_T = \{\$, a, b, c\}$

$f_\$ (A_1, A_2) = q_F$

$f_\$ (A_2, A_3) = q_F$

$f_\$ (A_1, A_3) = q_F$

$f_\$ (A_1) = q_F$

$f_\$ (A_2) = q_F$

$f_\$ (A_3) = q_F$

$f_a (A_4, A_5) = A_1$

$f_a (A_4) = A_1$

$f_a (A_1) = A_1$

$f_b (A_4, A_5) = A_2$

$f_b (A_5, A_6) = A_2$

$f_b (A_4, A_6) = A_2$

$f_b (A_4) = A_2$

$f_b (A_5) = A_2$

$f_b (A_6) = A_2$

$f_c (A_5, A_6) = A_3$

$f_c (A_5) = A_3$

$f_c (A_6) = A_3$

$f_a = A_4$

$f_b = A_5$

$f_c = A_6$

After an input tree extracted from a picture window is applied, if the tree automaton is in q_F then the picture contains a highway (or river) pattern. If the tree automaton reaches any other state we conclude that this particular picture does not have what we are looking for.

The tree automaton is tested on a new data set, that of Grand Rapids, Michigan. The total number of pixels being studied are about 57940, half of them mainly in the suburb, the other half mainly in the inner city. However, due to its poor resolution highway data has to be preprocessed using a local region expansion algorithm. In other words, a proper preprocessing algorithm can connect up those missing points in the data set which are due to inadequate reflections of highway surfaces whose ground covers are only a fraction of the pixel size ($\sim 79 \times 56$ m^2). The method of preprocessing as employed is illustrated in Figure 6. This process essentially has the effect of lengthening and thicking the data samples.

The results on Grand Rapids, Michigan show that with appropriate preprocessing the highways in suburban areas can be detected as a road-like feature. In urban areas, there are too many streets and concrete parking lots confused as highways. On the other hand, the river, which is usually easier to find due to good resolution, is not so obvious in the lower portion of the urban-area data set due to the confusion with the shadow class. However, these rivers have been successively traced out in our syntactic approach. Figures 7, 8, 9, and 10 give the pointwise classification and the syntactic interpretation of highways and rivers respectively in the Grand Rapids area.

V. CONCLUDING REMARKS

There are some observations that we have obtained from these experiments on LANDSAT data:

1. Syntactic approach, and specifically the tree system approach here, can be very useful in picture recognition by analyzing the geometric patterns of the classes under investigation.

2. The spatial patterns of rivers and highways can be described by tree grammars.

3. The analysis of tree languages by tree automata is a simple and efficient procedure compared with other high-dimensional languages.

4. Preprocessing can be very helpful in handling the resolution problem when the continuity of the feature is very important.

More extensive tests on real data are certainly needed to justify the complete effectiveness and efficiency of the proposed tree system approach for LANDSAT data interpretation.

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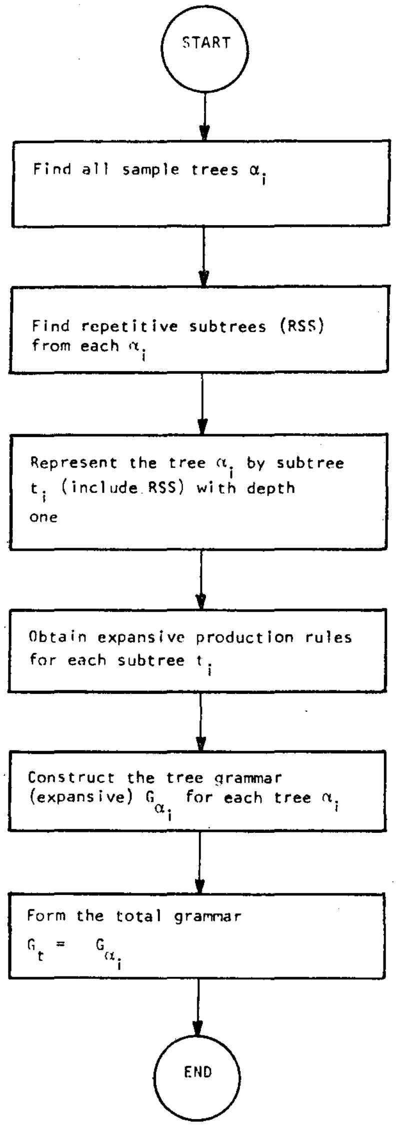


Figure 1. Flow Chart for Tree Grammar Inference

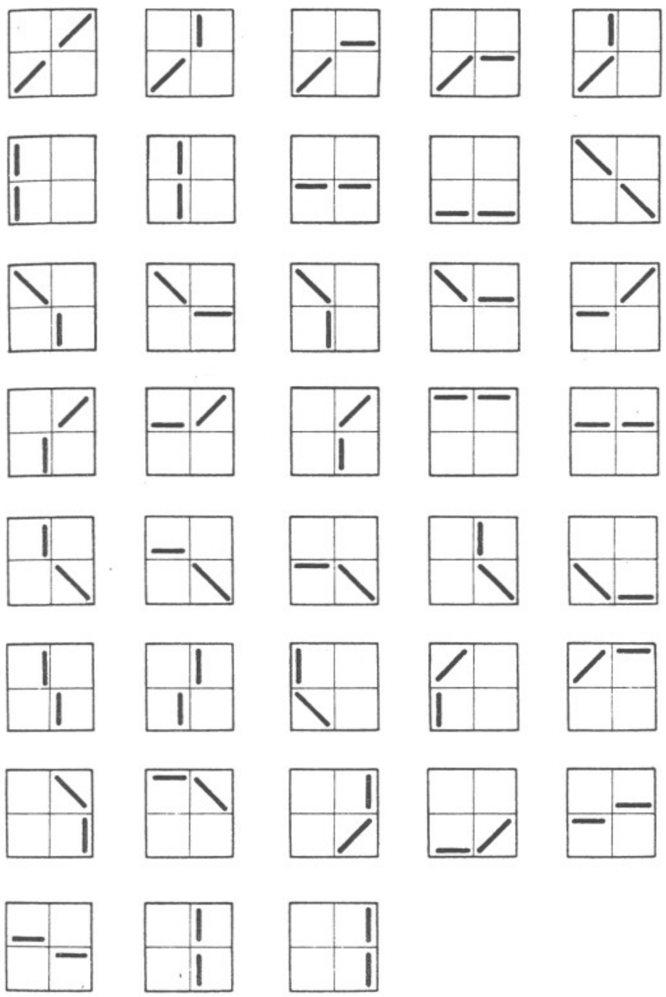


Figure 2 4-Tuple Patterns

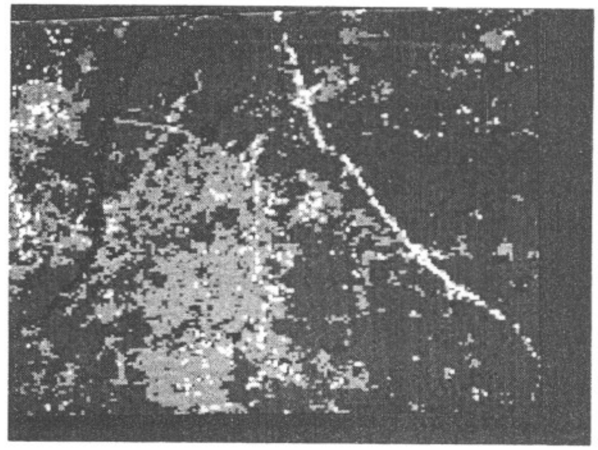


Figure 3 Pointwise Classification of LANDSAT Data of the Lafayette Area

Figure 4 Syntactic Interpretation of Highway and River Patterns in the Lafayette Area

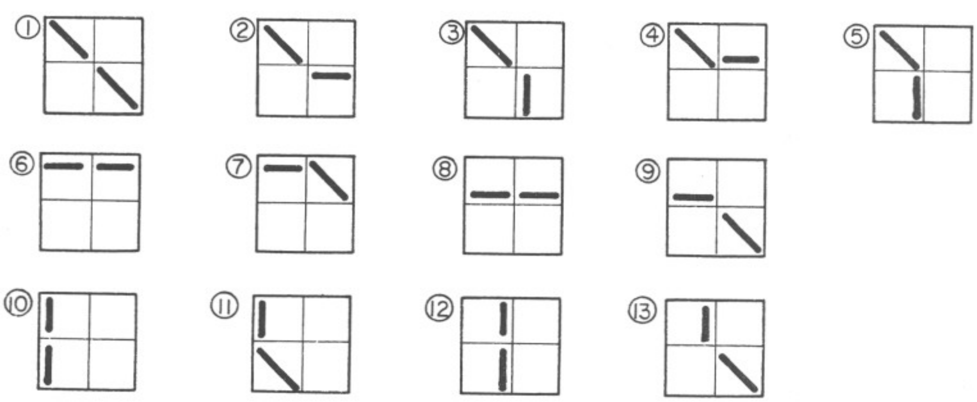
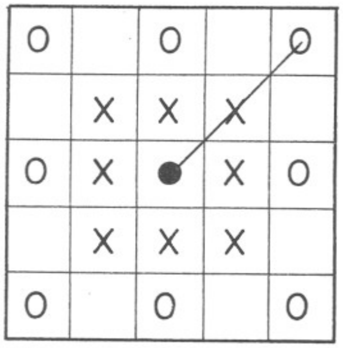


Figure 5 Basic (First Level) Highway Patterns



● point of reference pixel with sample a

O point at one pixel distance away with sample a

X points patched up by adding sample a to this pixel point if 0 and •'s relationship is established.

Figure 6 Preprocessing

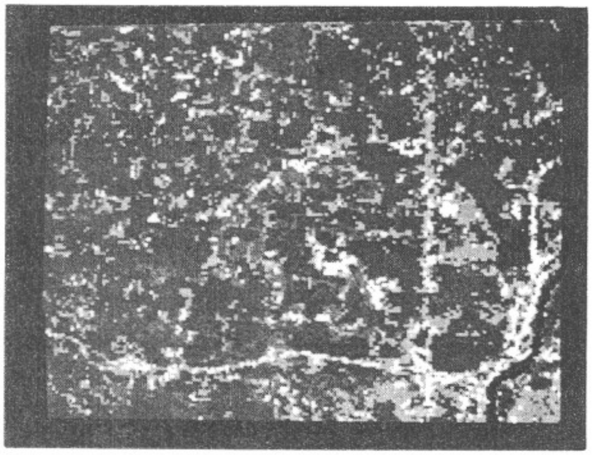


Figure 7 Pointwise Classification of LANDSAT Data of a Suburban Area in Grand Rapids

Figure 9 Syntactic Interpretation of River and Highway Patterns in the Suburban Area of Grand Rapids

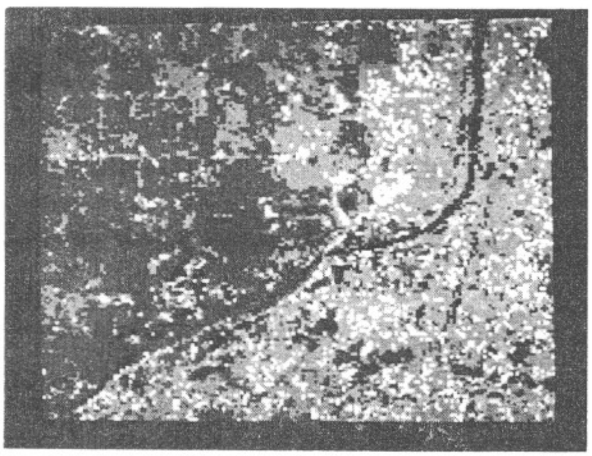


Figure 8 Pointwise Classification of LANDSAT Data of an Urban Area in Grand Rapids

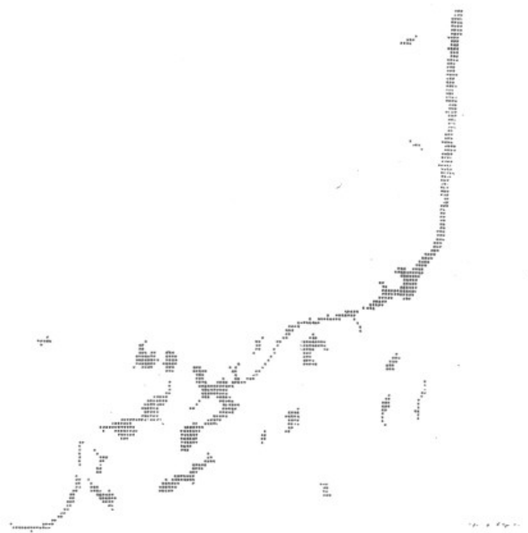


Figure 10 Syntactic Interpretation of River Patterns in the Urban Area of Grand Rapids