EXPERT SYSTEMS ARCHITETURE FOR IMAGE CLASSIFICATION USING MORPHOLOGICAL OPERATORS

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We propose a fuzzy expert system architeture for image classification, whose rules are implemented through translation invariant mathematical morphology operators. The use of the architecture is illustrated by an expert system that classifies an area of the Tapajós National Forest, in Brazil.

1 Introduction

The use of *mathematical morphology* has produced many applications in several areas of image digital processing, particularly in what regards pattern recognition in binary images [13]. Work on the classification of gray level images using mathematical morphology is, still in its early stages, hut has already produced some results [5,6,10].

This paper proposes the use of *fuzzy sets* and translation invariant operators of mathematical morphology to build expert systems for image classification. Using such a methodology, it is possible to create simple and powerful expert systems that leads to satisfactory classifications with only a small number of rules.

Section 2 presents the basic concepts of fuzzy sets theory, mathematical morphology and *expert systems*. Section 3 presents a general expert system architecture for image classification using fuzzy sets theory as underlying knowledge representation model and its implementation using mathematical morphology. Section 4 presents a classifier developed by using this methodology, for an area in the National Forest of Tapajós, in the Brazilian state of Pará. Finally, Section 5 brings the conclusion.

2 Basic Concepts

Three research fields are relevant to understand this work: fuzzy sets theory, expert systems and mathematical morphology.

2.1 Fuzzy Sets Theory

In (classical) set theory, each subset A of an universe X can be expressed by means of a membership function $\mu_A : X \to \{0,1\}$, where, for a given $a \in X$, $\mu_A(a) = 1$ and $\mu_A(a) = 0$ respectively express the presence and absence of a in relation to A. A *fuzzy set* [15] or fuzzy subset is used to model an ill-known quantity. The membership function of a fuzzy set A is a mapping $\mu_A : X \to [0,1]$, where [0,1] can be any bounded scale. We say that a fuzzy set A of X is "precise" when $\exists c^* \in X$ such that $\mu_A(c^*) = 1$ and $\forall c \neq c^*$, $\mu_A(c) = 0$. A fuzzy set A will be said to be "crisp" when $\forall c \in X, \mu_A(c) \in \{0,1\}$.

The intersection and union of two fuzzy sets are performed respectively by t-norm and t-conorm operators, which are commutative, associative and monotonic mappings from $[0,1]$ to $[0,1]$. Moreover, a t-norm $\top$ (respec. t-conorm $\perp$) has 1 (respec. 0) as neutral element.

2.2 Mathematical Morphology

Mathematical morphology studies mappings between complete lattices. Mappings between bounded chains are particular cases. Bounded chains are very important for our study because the elementary operators of mathematical morphology (dilation, erosion, anti-dilation and anti-erosion) can be constructed from elementary operators between bounded chains, the so called ELUT [1].

Definition. Let be K_1 and K_2 be two bounded chains and let Ψ be a mapping from K_1 to K_2. Then:

- Ψ is a *dilation* $\Leftrightarrow$ Ψ is increasing and $\Psi(\min K_1) = \min K_2$.
- Ψ is a *erosion* $\Leftrightarrow$ Ψ is increasing and $\Psi(\max K_1) = \max K_2$.
- Ψ is a *anti-dilation* $\Leftrightarrow$ Ψ is decreasing and $\Psi(\min K_1) = \max K_2$.
- Ψ is a *anti-erosion* $\Leftrightarrow$ Ψ is decreasing and $\Psi(\max K_1) = \min K_2$.

Furthermore, with the elementary operators of mathematical morphology it is possible to construct new operators to solve image processing problems [2].

2.3 Expert Systems

Expert systems [12] use the knowledge of an expert in a given specific domain to answer non-trivial questions about that domain. For example, an expert system for image classification would use knowledge about the characteristics of the classes present in a given region to classify a pixel in an image of that region. This knowledge also includes the "how to do" methods used by the human expert. Usually, the knowledge in an expert system is represented by rules of the form:

$$\text{IF } \langle \textit{condition} \rangle \text{ THEN } \langle \textit{conclusion} \rangle.$$

A simple rule of image processing could then be:

IF the gray level of a pixel is between 0 and 13 in band #4
THEN the class of the pixel is *River*.

Most rule-based expert systems allow for the use of connectives AND or OR in the premise of a rule, and of connective AND in the conclusion.

3 An Expert System Architecture for Image Classification

Classifiers assisted by expert systems emerged as an alternative to reduce the computational cost of numerical classifiers. A great advantage of these classifiers is that the decision process can be sufficiently rich but involve only a few pieces of information. Also, knowledge stored as rules is explainable, reusable, and can be treated in a simple way [8]. A disadvantage is that they will not necessarily respond rightly when employed out of the context for which they were designed, contrary to what generally happens with exclusively numerical methods. Some practical implementations of such classifiers can be found in the literature: the ICARE system [4] uses a fuzzy expert system that employs a statistical pre-classifier, maps and old classifications of a region, to classify an image; another classifier [7] combines heuristic and numerical methods to classify ice on the sea using radar images; works derived from the ICARE system [9,14], use neural networks in the pre-classification process. In those systems that use numerical pre-classifiers, the expert system can be regarded as a post-classifier.

In the following subsections, we present a general expert system architecture for image classification that uses fuzzy sets theory as knowledge representation model. Then we present how mathematical morphology operators can be used to implement the rules in this architecture.

3.1 Expert System Architecture

Let us suppose we want to classify the pixels of an image f into m classes. Image f can be defined as a mapping of the rectangle $E \subseteq Z^2$ into a bounded chain K. A binary image f is a mappring from E to $K_1 = \{0,1\}$ and a gray level image f is a mappring from E to $K_2 = \{0,1,...,255\}$. Each ordered pair $\mathbf{p}= (p, f(p))$ is called a pixel, where $p \in E$ represents its position in the image and $f(p)$ is its gray level. Here we sometimes use the term *information surface* to refer to a mappring from E to K; such a mapping may represent an image as well as a fuzzy set membership function.

We propose here an image classifier having a fuzzy rule-based expert system architecture, in which the premises of rules are translated throught the compositions of mathematical morphology operators [11]. The firing of a rule on an image f results in a set of n information surfaces $g_k : E \times K' \to K'$, $k = 1, ..., n$, where $g_k(\mathbf{p})$ corresponds to the degree of compatibility between the pixel at position p with class c_k and K' is a bounded chain. The system is implemented using two levels of abstraction: 1) rules provided by experts are translated into sequences of mathematical morphology operators; and 2) the n information surfaces g_k obtained by the application of these sequences are aggregated to yield the classification for each pixel in image.

The expert system architecture proposed here is able to treat the whole image at the same time. For the sake of simplicity, we will detail the treatment as if the image was composed of a single pixel. Let us suppose that all the rules in the knowledge base only employ the connective AND in the premise (the treatment for connective OR can be found elsewhere[11]):

R_j : IF $attr_1(\mathbf{p}) = A_{1j}$ AND ... AND $attr_{N_j}(\mathbf{p}) = A_{N_j j}$ THEN $class(\mathbf{p}) = B_j$

where A_{ij} and B_j, $i = 1, ..., N_j$, $j = 1, ..., m$ are fuzzy sets, $attr_i(\mathbf{p})$ is an attribute in the premise and $class(\mathbf{p})$ is the attribute in the conclusion.

The universe of discourse of B_j is $C = \{c_1, ..., c_n\}$, the set of possible classes. The universe of discourse of each A_{ij} depends on attribute $attr_i$, and is not necessarily discrete. Given $\mathbf{p}$, its classification is made in three stages:

a) The compatibility of $\mathbf{p}$ in relation to the premise of each rule is verified. This yields a preliminary classification of $\mathbf{p}$ in relation to the class in the conclusion of each rule.

b) The preliminary classifications yielded by the rules are aggregated into an imprecise global classification. Therefore $\mathbf{p}$ can be classified as belonging to more than one class.

c) A precise class is assigned to the pixel, i.e. a decision is reached about the classification of $\mathbf{p}$.

In stage (a), the classification of $\mathbf{p}$ in relation to rule R_j obeys the following scheme:

a.1) The values of attributes $attr_i$ in relation to $\mathbf{p}$ are compared to fuzzy sets A_{ij}. This yields the compatibility degree of $\mathbf{p}$ in relation to each of the premises of a rule R_j and is calculated as

$$h_{ij}(\mathbf{p}) = \mu_{A_{ij}}(attr_i(\mathbf{p})).$$

a.2) The general compatibility degree of $\mathbf{p}$ in relation to rule R_j is then calculated as

$$h_j(\mathbf{p}) = \top(h_{1j}(\mathbf{p}), ..., h_{N_j m}(\mathbf{p})),$$

where $\top$ is a t-norm e. g. operator min.

a.3) The pixel classification is derived (according to rule R_j) by applying an implication function between the general compatibility degree $h_j(\mathbf{p})$ and the rule conclusion, given by B_j. This value is given by fuzzy set $B'_j(\mathbf{p})$ in C:

$$\mu_{B'_j(\mathbf{p})}(c_k) = \triangledown(h_j(\mathbf{p}), \mu_{B_j}(c_k)),\ k = 1, ..., n,$$

where $\triangledown$ is an implication function. Although t-norms are not implication function, they are the usual choice for $\triangledown$. The fuzzy classification of $\mathbf{p}$ in relation to rule R_j is thus represented by $B'_j(\mathbf{p})$.

In stage (b), all fuzzy sets $B'_j(\mathbf{p})$ are aggregated into a single fuzzy set B', given by

$$\mu_{B'(\mathbf{p})}(c_k) = \Diamond(\mu_{B'_1(\mathbf{p})}(c_k), ..., \mu_{B'_m(\mathbf{p})}(c_k)),$$

where, the aggregation operator $\Diamond$ is given by a t-conorm, when $\triangledown$ is a t-norm.

Considering now the whole image, n information surfaces $g_k : E \times K' \to K'$ are derived, one for each c_k in C:

$$\begin{aligned} g_k(\mathbf{p}) &= \mu_{B'(\mathbf{p})}(c_k) \\ &= \Diamond_{j=1,m} \mu_{B'_j(\mathbf{p})}(c_k) \\ &= \Diamond_{j=1,m} \triangledown (h_j(\mathbf{p}), \mu_{B_j}(c_k)) \end{aligned}$$

Making $m_{kj} = \mu_{B_j}(c_k)$ and $g_{kj}(\mathbf{p}) = \triangledown(h_j(\mathbf{p}), m_{kj})$, we have $g_k(\mathbf{p}) = \Diamond_{j=1,m} g_{kj}(\mathbf{p})$.

Let us suppose that the conclusion of each rule R_j classifies a pixel to a single class c^*_j, i.e. B_j is a precise fuzzy set. Let us further suppose that $\triangledown$ is a t-norm $\triangledown_\top$. Then, for $c_k = c^*_j$, $m_{kj} = \mu_{B_j(\mathbf{p})}(c^*_j) = 1$ and $g_{kj}(\mathbf{p}) = \triangledown_\top(h_j(\mathbf{p}), m_{kj}) = \triangledown_\top(h_j(\mathbf{p}), 1) = h_j(\mathbf{p})$. For $c_k \neq c^*_j$, we then have $g_{kj}(\mathbf{p}) = \triangledown_\top(h_j(\mathbf{p}), 0) = 0$.

In this case, for $c_k = c^*_j$ in rules which use only connective AND, we get:

$$g_{kj}(\mathbf{p}) = \top_{i=1,N_j}\ \mu_{A_{ij}}(attr_i(\mathbf{p})) \tag{1}$$

$$g_k(\mathbf{p}) = \Diamond_{j=1,m}\ \top_{i=1,N_j}\ \mu_{A_{ij}}(attr_i(\mathbf{p})) \tag{2}$$

In stage (c), a "defuzzification" is performed, i.e. only one class is assigned to each pixel. Here we choose for $\mathbf{p}$ the class for which $\mathbf{p}$ has the greatest membership degree in information surfaces g_k. We could also assign more than one class to each pixel, e.g., a pixel classified by rules as belonging to both c_1 and c_2 classes, could be classified as belonging to the "imprecise" class $c_{\{1,2\}}$, . In this case, one way to obtain the classification would be to apply a pre-fixed threshold l_k to each information surface g_k.

3.2 Implementation Using Mathematical Morphology

Mathematical morphology operators can treat the whole image at once, and can be seen as first order logic functions. In our work, we use these operators mostly to extract image attributes for the expert system and to implement fuzzy characteristics such as "near", "very near", "distant", "very distant", etc. For simplicity, the operator mainly used in the applications developed so far has been the threshold operator of mathematical morphology, which transforms a gray level image into a binary one. The use of such operator induces a loss of information, which can be partially solved by a reconstruction operator. In the cases for which the threshold operator gives reasonable results but with some spurious points, the sup-generating operator can be used to eliminate these points.

In what follows, we use three examples of rule implementations to illustrate the use of morphological operators. The result of the application of the rules on a given image depends on the choice of the implication function, the t-norms and the t-conorms. In the remaining of this text, we shall deal with crisp fuzzy sets, mapping from a given domain to codomain $\{0, 255\}$. We will use the following conventions to specify the domain of a membership function: g_A denotes a mapping with domain E; $\widetilde{A}$ denotes a mapping with domain $\{0, ..., 255\}$; $\widetilde{b_A}$ denotes a mapping with domain $\{y, n\}$; and $\widetilde{c_A}$ denotes a mapping with domain C, where C is the set of classes in a given application.

Let $\mu_{\widetilde{dark}}$, $\mu_{\widetilde{very\_dark}}$ and $\mu_{\widetilde{b_{river}}}$ be defined respectively as

$$\mu_{\widetilde{dark}}(s) = \begin{cases} 255, & \text{if } s \leq 13 \\ 0, & \text{otherwise} \end{cases}; \qquad \mu_{\widetilde{very\_dark}}(s) = \begin{cases} 255, & \text{if } s \leq 10 \\ 0, & \text{otherwise} \end{cases};$$

$$\mu_{\widetilde{b_{river}}}(y) = \begin{cases} 255, & \text{if } y = yes \\ 0, & \text{if } y = no \end{cases}$$

A rule in the system could then be:

R_1 : *IF radiometry of band #4=* $\widetilde{dark}$
AND radiometry of band #5= $\widetilde{very\_dark}$ *THEN position* $\in$ $\widetilde{b_{river}}$.

Membership functions $\mu_{\widetilde{dark}}$ and $\mu_{\widetilde{very\_dark}}$ are LUTs of threshold operators that applied to a gray level image (in this case, at bands #4 and #5) yield binary images as result. These functions are dilations and erosions, in conformity to the definitions in Section 2.3. All membership functions appearing in R_1 are crisp, but any membership function could be equally used. Let us suppose we have $\triangledown = \top = \min$ and $\Diamond = \max$. Considering that the conclusion of R_1 represents a precise fuzzy set, using equations (1) and (2) we obtain the information surface $g_{b_{river}}(\mathbf{p})$ from R_1:

$$g_{b_{river}}(\mathbf{p}) = \min\{\mu_{\widetilde{dark}}(f_4(p)), \mu_{\widetilde{very\_dark}}(f_5(p))\}$$

Expression $\mu_{\widetilde{dark}}\ (f_4(p))$ is by definition of the composition $\mu_{\widetilde{dark}} \circ f_4(p)$ and expression $\mu_{\widetilde{very\_dark}}(f5(p))$ is by definition $\mu_{\widetilde{very\_dark}} \circ f_5(p)$, where f_4 and f_5 denote bands #4 and #5, respectively. Then:

$$g_{b_{river}}(\mathbf{p}) = \min\{\mu_{\widetilde{dark}} \circ f_4(p), \mu_{\widetilde{very\_dark}} \circ f_5(p)\}$$

The compositions used in $g_{b_{river}}$ are threshold operators of mathematical morphology [1]. Therefore $g_{b_{river}}$ can be rewritten as

$$g_{b_{river}}(\mathbf{p}) = \min\{\text{threshold}_{[0,13]}(f_4)(p), \text{threshold}_{[0,10]}(f_5)(p)\}.$$

Another example of rule is R_2:

$R_2:$ *IF position* $\in \widetilde{near\_a\_river}$ *AND position* $\in \neg\widetilde{b_{river}}$
THEN position $\in \widetilde{b_{margin}}$.

where $\widetilde{near\_a\_river}$ is a fuzzy set defined in terms of the distance function $\Psi_d(f)$ [11]

$$\mu_{\widetilde{near\_a\_river}} = \text{threshold}_{[0,10]}\ \Psi_d(g_{b_{river}}),$$

$\neg\widetilde{b_{river}}$ is the complement of fuzzy set $\widetilde{b_{river}}$, calculated as $\mu_{\neg\widetilde{b_{river}}}(p) = 255 - \mu_{\widetilde{b_{river}}}(p)$, and $\widetilde{b_{margin}}$ is defined by

$$\mu_{\widetilde{b_{margin}}}(y) = \begin{cases} 255, & \text{if } y = \text{yes} \\ 0, & \text{if } y = \text{no} \end{cases}$$

With the same specifications used above for $g_{b_{river}}$, we obtain for $g_{b_{margin}}$:

$$g_{margin}(\mathbf{p}) = \min\{\mu_{\widetilde{near\_a\_river}}(p), f_{255}(p) - g_{b_{river}}(\mathbf{p})\}$$

where f_{255} is a white image, i.e. $\forall p \in E, f_{255}(p) = 255$.

In terms of morphological operators, membership function $\mu_{\widetilde{near\_a\_river}}$ is a threshold operator on the distance function. We then have

$$g_{margin}(\mathbf{p}) = \min\{\text{threshold}_{[0,10]}\ (\Psi_d(g_{b_{river}}))(p), f_{255}(p) - g_{b_{river}}(\mathbf{p})\}$$

Let c_{river} be a class in a given application. Rule R_3 relates fuzzy set $\widetilde{c_{river}}$ with fuzzy set $\widetilde{b_{river}}$:

$$R_3 : \textit{IF position} \in \widetilde{b_{river}} \textit{ THEN class} = \widetilde{c_{river}}$$

where $\widetilde{c_{river}}$ is given by: $\mu_{\widetilde{c_{river}}}(c) = \begin{cases} 255, \text{ if } c = c_{river} \\ 0, \quad \text{otherwise.} \end{cases}$

The implementation of rule R_3 by equations (1) and (2), yields image $g_{c_{river}}$ as result, where $g_{c_{river}}(\mathbf{p}) = \mu_{\widetilde{c_{river}(x)}}(c_{river})$.

4 Application

An expert system constructed with the architecture proposed here has been used for the classification of an area of the Tapajós National Forest, in the north of Brazil. The application was developed using bands #3, #4, #5 and #7 from Landsat TM images obtained in August 7th, 1995.

An already existing visual classification with eight classes for the area was used as reference map to allow a comparison with the results obtained by the system [11]. Eight classes were found in the visual classification (see figure 1-Left). Figure 1-Right brings the image classified by the expert system. For a better comparison, the colors are the same in both classifications.

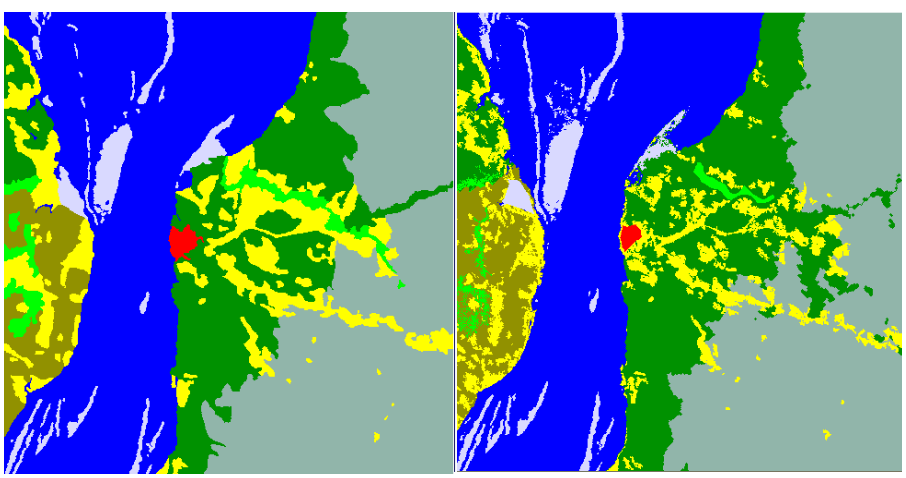

Figure 1: Left - Visual classification results; Right - Classification by the expert system.

According to the visual examination by an expert, the classification results obtained by the system can be considered as quite satisfactory. A numerical comparison between the two classifications has also been performed using the Tau coefficient, considered to be the best coefficient to compare two classification images[3]. The Tau results were 84,11% with variance 7,86 $\times 10^{-7}$, and thus the classification can be considered satisfactory also in statistical terms. It is important to notice that the expert system classification was made using only the expert knowledge modeled by the rules and the original image, without any pre-classification.

5 Conclusion

We have presented a general expert system architecture for image classification that uses fuzzy sets theory as knowledge representation model. The rules are implemented using mathematical morphology operators.

The main contribution of this paper is the homogeneous application of mathematical morphology and fuzzy sets theory for image classification. An application was built with quite satisfactory results, using only the original image and expert knowledge. The translation invariant property of the morphological operators make it easy to extract the attributes from the image, either by characteristics related to shape (mainly in binary images) or by radiometry, independently of their localization in the image. This important characteristic of translation invariant operators allows for the application of the same sequence of operators, with small adjustments, to another image in the same area.

As with any knowledge based system, this approach has the disadvantage of requiring an expert to furnish the rules, in this case, someone with a good knowledge about the region to be classified. Also, a minimum knowledge about mathematical morphology operators is necessary to the application builder. Although the results obtained so far are satisfactory in visual and statistical terms, one can expect better results if the system is used with external data (e.g. maps) or with a numerical pre-classification.

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