ANCILLARY DATA EXTRACTION USING NUMERIC AND SYMBOLIC INFORMATION: A NEURAL NETWORK APPROACH

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Abstract

The problem of extracting information issued from several sources of information turns out to be a very important issue in intelligent systems. This problem is encountered in expert system.
In the field of remote sensing and geograpphic information system, this question is well known. In this paper we propose means of extracting complex geographical information from standard geographical information by neural networks techniques.

I. Introduction

Nowadays most cartographic applications manage with satellite imagery, but almost all of them limit themselves to in-image information (spectral or textural features, multitemporal images...).
Actually when somebody analyzes a satellite image, he takes into account a lot of "a priori", "out-image" knowledge to reach a satisfactory interpretation.
A photointerpreter who wants to produce a vegetation map for example, will manage with three types of information sources.[DESACHY 88]DESACHY89]
First: of course satellite image
second: available cartographic information (topography, soils quality etc...)
third: his knowledge of local vegetation types characteristics.
So it's quite an evidence that one should "add" to image information, the domain expert knowledge "know-how" and the cartographic data in order to "understand" the image.

Our team has already conceived an expert system ICARE (Image CARtography Expert) based on production rules and certainty factors. The aim of the system is to improve usual supervised classification used to produce "maps" from remote sensing imagery. [DESACHY90]
The expert knowledge is stored in a knowledge base as a set of production rules with certainty factors. The fact data base is composed of the image to be interpreted and the associated geographic information system.

II. Mapping expert system description

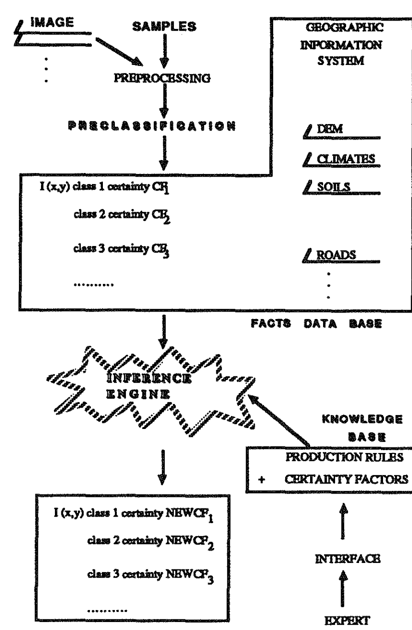

Fig. 1 GENERAL SCHEMA OF THE EXPERT SYSTEM

II.1 Knowledge description

The system is conceived for automatic cartography and the expert's knowledge, we are managing with is related to classification problems, it means that this knowledge concerns the classes we are looking for in the image, and handles information existing or computable in the geographic information system or eventually on the image itself.
Example:
"Pines are principally located on south versants from 800m to 1500m."
- "Principally", is an adverb which shows uncertainty on the knowledge.
- "south versants", concerns the aspect which may be deduced from the digital elevation model.
- "from 800m to 1500m", concerns the digital elevation model directly.
This knowledge unit will be translated in the following production rule in the ICARE system

" IF (class pines) THEN
(elevation from 800m to 1500m)
AND (south versants) ".

To the adverb "principally" corresponds a value of certainty factor of the rule, which estimates the frequency degree of the class pines in the given context (-1 means 0% , 0 means 50%, +1 means 100%)
The expert expresses his knowledge with predefined keywords related to objects that can be extracted from the geographic information system.
-Valley, versant, ridge, plateau, irrigated zone, road, village, clay, rocky ...etc.
Keywords for relation capabilities: Far away, near, around ...etc.
Keywords for uncertainty expressions Always(+1.), often(+0.8),..., seldom(-0.8), never(-1.).

The system manages with simple and complex data. Simple data means that data is extracted easily by image reading (radiometric responses from satellite image), or by performing a simple processing on it (slope and aspect images from the DTM image).
Complex data means that informations are obtained by more difficult processing, which sometimes introduces fuzzy symbolic knowledge.
For example an irrigated zone is an information which needs expert knowledge of what an irrigated zone really is?.

An expert can define such zones, as zones which are always near hydrographic network and frequently less than 300m and often near roads for example.
This knowledge can be represented by a production rule as defined above.

IF(Irrigated zone) Then
(always near hydrographic network) AND
(frequently less than 300m) AND
(often near road).

We propose to resolve this kind of extracting information problems by neural networks techniques, the result is a decision map giving a realisation degree of the corresponding rule for each point.

III. Neural networks for knowledge representation

A rule corresponds to a particular situation and describes the ideal context for realisation of a complex situation with related frequency degrees, and is represented by a neural network.[ZAHZAH92a]

The net's inputs are represented by realization degrees of all possible atomic propositions expressed in the conclusion part of the rule , "near a road", "elevation less than 300m", "near hydrographic network",etc...
These inputs take values in the interval [-1,+1], the value -1 corresponds to the case of false/absent proposition, +1 when it is true/present, and 0 to the case of unknown/no information, these values are modulated by the frequency degrees associated globally to the rule or to each atomic proposition.

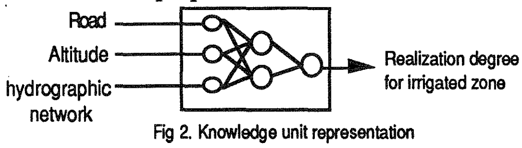

Fig 2. Knowledge unit representation

A knowledge unit R is considered as a combination of disjunctive and conjunctive propositions as one knows how to map a complex rule into a simple expression with no redundancy propositions [ZAHZAH92b]

$$R=\bigcup_{i=1}^{n} P_i \qquad Pi=\bigcap_{j=1}^{m} p_{i,j}$$

$$p_{i,j} = <cf_r>_{p_{i,j}} \quad <cf>_{p_{i,j}}$$

pi,j is an atomic premise, and is expressed by a frequency degree given to the premise itself(cfr), followed by a realization degree of the premise(cf). The knowledge unit R is realized, if at least one of its disjunctive proposition Pi is realized. For the learning stage, the net learns how each disjunctive proposition and its negation are realized .

Learning R consists in the following process : when inputs are in the context of R, the output is set to the maximum value of realization of the rule, when inputs are in a wrong context of R, the output is set to the minimum value of realization of the rule , and intermediate values are output for intermediate situations.[ZAHZAH92a][ZAHZAH92b]
example:

R → "IF "favourable context" THEN
(often A AND always B) OR (seldom C AND never D)"

This rule is defined by four atomic propositions (A, B, C, D), the adverbs "often" and "always " tell us about the frequency to bein the context of A (resp B), "often" means that about 80% of favourable contexts in the context of the premise A, "always" means that 100% of them are in the context of the premise B. The same reasoning is done with (seldom C and never D)

III.1 The learning step

The input values of the net, for the learning stage are examples in the outstanding cases, where each premise may be totally realized or not. The net produces its inner representation and hence, generalizes and resolves the intermediate situations. At this level the adverbs are totally ignored.

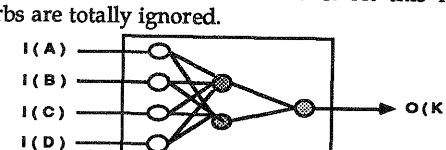

Fig 3. A neural network for representation of ((often A and always B) or (seldom C and never D))

I(A)	I(B)	O(K)
1	1	1
1	0	a
1	- 1	b
0	0	0
0	1	a
0	- 1	c
- 1	1	b
- 1	0	c
- 1	- 1	- 1

Fig. 4 input/output for learning the rule if "favourable context" then (A and B)
$O(k)= f(I(A), I(B)), -1<c<=0<b<a<1$

The nets are hierarchical networks of nodes, that contain processing units which perform a memoryless nonlinear transformation on the weighted sum of their inputs. A node produces a continuous-valued output between -1.0 and 1.0. Weights are positive or negative real values during training. The output O(k) gives the realization degree of the rule belonging to the interval [+1 -1], +1 corresponds to the maximum value of the realization of the rule, -1 to the minimum value, and the value 0 corresponds to the case of total uncertainty. The net uses the backpropagation learning algorithm [RUMELHART,1986].

For instance , we learn the net that, when all the premises of a given rule are realized (all the correspondant inputs are set to 1), then the output is set to 1 (maximun degree of realization of the concerned rule), when all the premises are impossible (all the correspondant inputs are set to -1) the output is set to -1 (minimum degree of realization of the corresponding rule), and when half of the rule's premises are realized and the rest are not, or no premise at all is realized, then the net learns that the situation is more favourable for the first case than in the second one, and must output values which are relatively great and little for the two respective cases

Geometrically, the system simulates the behavior of the function of Fig5. For a multidimensional system, the net resolves the system :

$[-1\ +1]^n$ --o--> [-1 +1] , O(k) = f(I(P1),I(P2),...,I(Pn))

where Pi are premises, I(Pi) are certainty factors and O(k) is the realisation degree of the context defined by the knowledge unit. When learning

"if favourable context then (A and B)",

the inputs for the premises C and D are desactivated, and when learning

"if favourable context then (C and D) "

the inputs for A and B are disactivated.

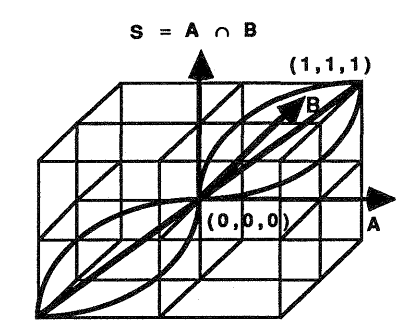

Fig. 5 The system's behavior for the recognition of a rule S=A ∩ B (A and B are any given proposition).

III.2 System operation

At this level the adverbs preceding the premises in the rule are integrated in the following manner: effective inputs for the net will be the products of certainty factors of the premises, with their corresponding frequency degrees (0.8 for "often, +1.0 for always etc..). At the learning stage, the rule is learned with frequency degrees equal to 1, as if the rule is all defined by "always", and at the operating stage, these frequency concepts are introduced in order to represent the knowledge as it has been expressed by the expert.

The desactivation of an input is performed by assigning a zero value to cfr. After the presentation of the pixel's context to the net , the system produces it's realization degrees of the rule.

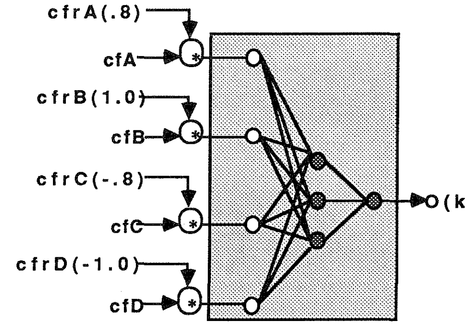

Fig6. net representation of knowledge: (often A and always B) or (seldom C and never D)

IV Application

We applied this method to extract complex information described by fuzzy symbolic knowledge unit from DTM, derived information (hydrographic network map)[ZEHANA92] and roads map. We tested our method with several definitions of irrigated zones, by changing adverbs.

image1 corresponds to the DTM image, it is represented in four elevation levels, white regions are the highest zones, and dark regions are the lowest zones.
image2 represents the rods map
image3 represents the hydrographic network

Image4 represents the result by applying the first definition of "irrigated zone " to the method:
IF(Irrigated zone) Then
(always near hydrographic network) AND
(frequently less than 300m) AND
(often near road).

Actually, the resulting image is a set of points in the interval of [-1,+1], image4 , image5, image6 are representations by classes. White regions are the most favourable zones to the corresponding definition, gray regions are less favourable, and so on.

Image 5 represents the second definition given by the following rule:
IF(Irrigated zone) Then
(often near hydrographic network) AND
(often less than 300m) AND
(often near road).

Image 6 is the result by using the third definition
IF(Irrigated zone) Then
(always near hydrographic network) AND
(frequently less than 300m) AND
(never near road).

We can see from the resulting images, the changes of the patterns with modification of definitions. favourable zones increase when adverbs are less restrictive , and decrease when adverbs are more restrictive.

Conclusion

We have applied this neural net technique to represent expert knowledge for complex premises computation in the frame of ICARE expert system. This technique can be used to produce decision map for any given realistic problem , as
"Where rice can be cultivated?"
"What are the exposed regions to fire ?" or
" What are the exposed regions to erosion ?"
It may also be introduced in the frame of geographical information systems in order to produce priority maps for problem solving.

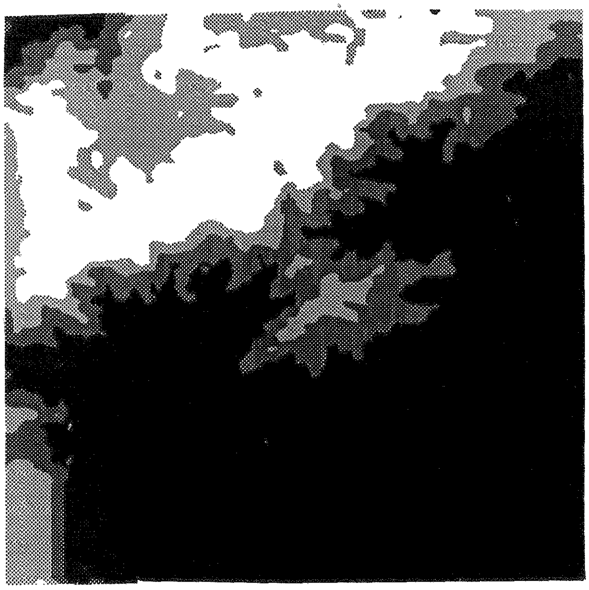

Image 1: DTM

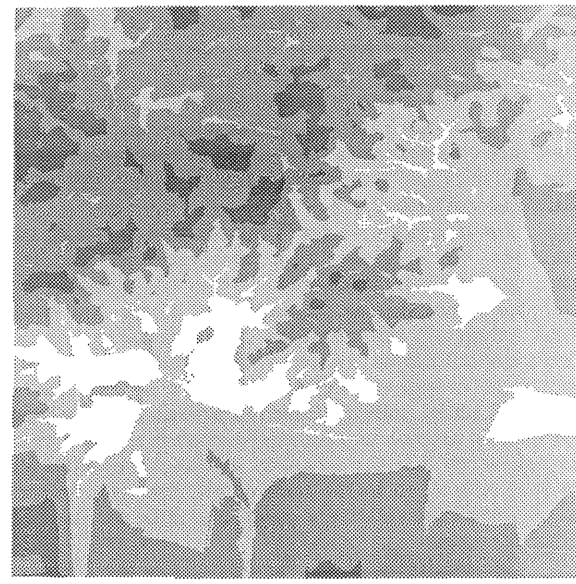

Image4

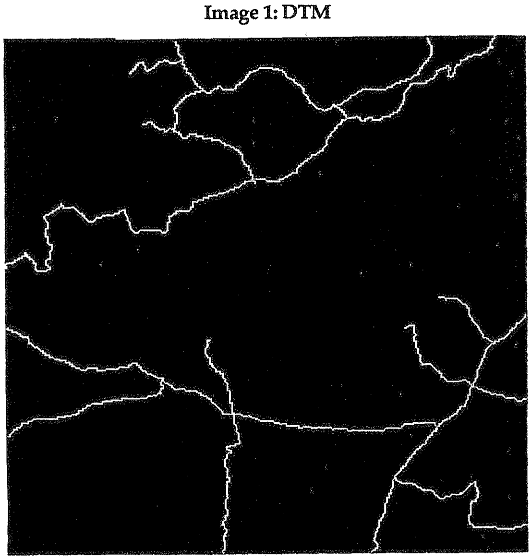

Image2: Roads map

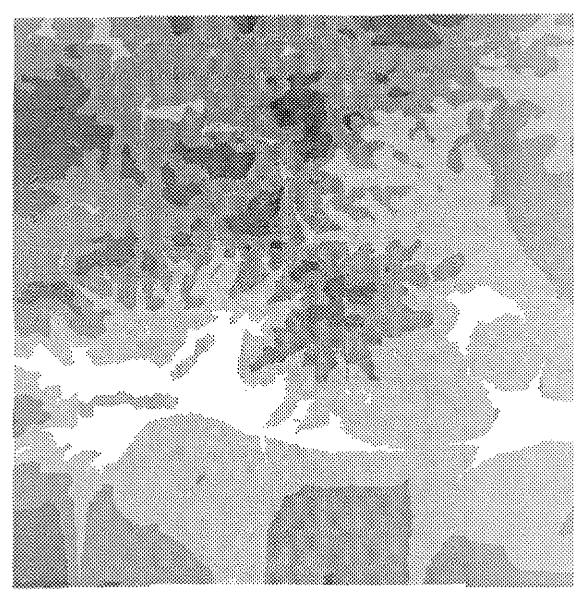

Image5

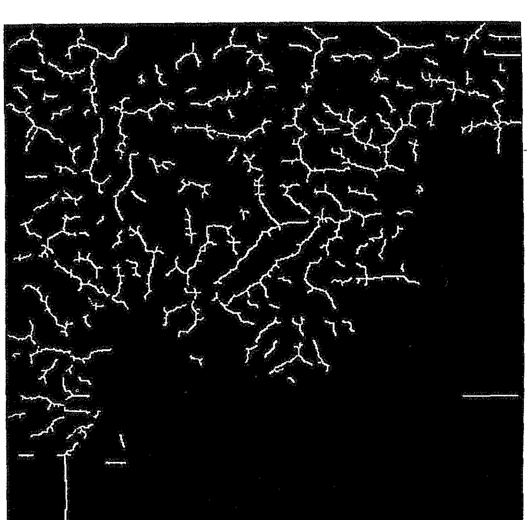

Image3: hydrographic network

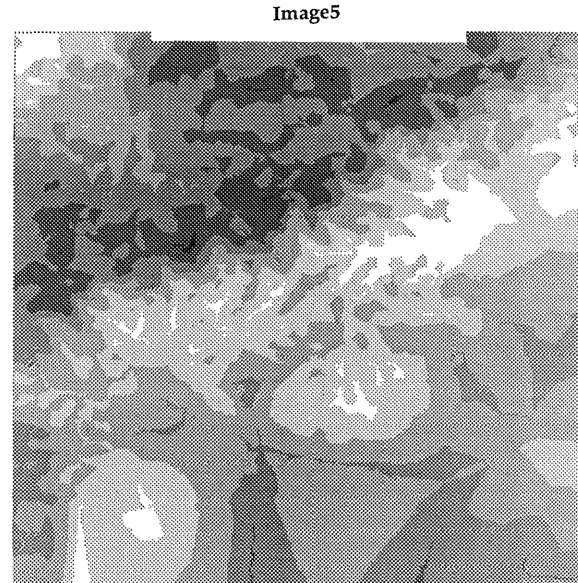

Image6

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