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A COMPUTATIONAL INTELLIGENCE APPROACH FOR EARTH RESOURCE SATELLITE IMAGE PROCESSING, CLASSIFICATION AND DECISION-MAKING

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ABSTRACT

An intelligent system for processing images obtained by earth resource satellites is presented in this paper. This hybrid computational intelligent approach merges neural and fuzzy approaches in a neurofuzzy decision system for visual perception and pattern recognition. This intelligent hybrid system for visual-driven decision making employs, first, a neural system for image classification in charge of extracting information through a mapping from visual input to output datum. The resulting classification is, latter, furnished as input data to the fuzzy decision support system for dealing with inherent uncertainty and imprecision present in the available information. Advantages of both techniques are exploited in a complementary manner. This paper aims to demonstrate the technical viability of a computational intelligence model based on a hybrid neuro-fuzzy component when dealing with images from earth resource satellites. Thus, the hybrid system is able to deal with imprecision or noise in the information generated within image processing. The neuro-fuzzy system suggested in this paper attempts to insert new mechanisms in the geographic image processing and treatment in the space sector. Results indicate that the proposed hybrid neural-fuzzy system achieves its goal. Moreover, it put together different perspectives for a common solution characterized by remote sensing, environment engineering and digital image computing that guarantee an efficient response for this area of study.

INTRODUCTION

This paper presents a hybrid computational intelligent system for processing and deciding upon images furnished by satellites. Important for protecting the environment, the proposed system is an alternative to support specialists in the task of image treatment for helping them in dealing with image skillfully and efficiently.

An artificial Neural Network (NN) and fuzzy system based on fuzzy set theory and fuzzy logic (FL) are explored in a complementary manner. The artificial neural classifier supplies information to a fuzzy decision support system to deal with uncertainty and imprecision present in available image information. The neural system for image classification is in charge of extracting information through a mapping from visual input to output datum.

Employing the fuzzy system for making decisions is related to its desirable attribute to cope with imperfect knowledge, i.e., information that are uncertain, imprecise, vague or partially true. Thus, the hybrid system is able to deal with imprecision or noise in the information generated within image processing.

A reason for choosing such a multidisciplinary approach is the opportunity of exploiting the integration of distinct areas. Geographic and cartographic information, only to mention few, put together concepts and perceptions from scientific field, public policies, sociology, anthropology etc.

Such process aims to establish a straight relation between the human vision and the inference ability of specialists. The most studied forms of perception in a machine are vision, hearing and touching [1]. Although, hearing and touching are important – for example, in robotics for voice command and tactile feedback hold – vision that is selected as the main subject for the perception field. Roughly speaking, the image processing consists of identifying the main characteristics of an image as seen by human beings without the concern of what it represents. Elimination of distortions, aberrations, noise filtering, brightness correction, shade, saturation, contrasts adjustment and others are some examples.

The classification process consists of, among many, the extraction of information to recognize patterns and homogeneous objects. This is very useful in several applications. Artificial Neural Networks (NN) is an efficient approach largely applied to pattern recognition and classification [2], [3], [4]. Only to mention few, examples are processes that require extremely precision of image manipulation, target detection of image furnished by satellites, virtual reality systems, extra-perceptive simulations that allow the machine deal with imprecision and vagueness [5], [6], [7], [8], [9], [10].

The main goal in this paper is to demonstrate the technical viability of a computational intelligence approach based on a hybrid neuro-fuzzy component when dealing with images from earth resource satellites.

PROBLEM STATEMENT

Finding out a mechanism for geographic image processing and treatment in the space sector is necessary. This processing system must guarantee mutual low cost and high reliability and quality, in special, when dealing with images from satellites, for example, sized 650 by 839 and 24 bits per pixel. Further, earth resource satellites usually supply more than 200 thousands images and deals with more than 10 thousands types of fauna and flowers.

Consider, for instance, the image depicted in Fig.1 obtained from CBERS 1 satellite. This image represents the northeast *Rio-Grandense* plateau, located at 139 kilometers from *Porto Alegre*, the capital of the *Rio Grande do Sul* state, *Brazil*. This area is inserted in a large part of the National Forest named *São Francisco de Paula* covered predominantly by native species. The National Forest of São Francisco de Paula constitutes a Unit of Conservation (UC) due to its sustainable use.

Units of Conservation aims to make possible the natural resources be shared for (i) scientific

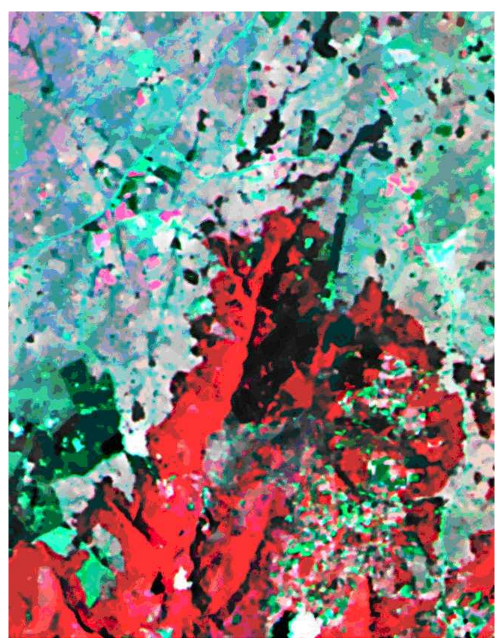


Fig. 1. Geographic image from an earth resource satellite.

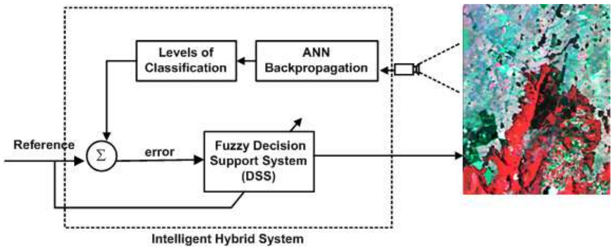


Fig. 2. Image example for evaluation.

studies, (ii) environmental education, (iii) conservation and preservation of natural patrimony, and (iv) forest exploration of products and sub-products, such as wood, seeds of Araucaria and so on [11].

The image employed in this work follows a RGB color system and is sized as previously presented. Through this image it is expected to test and validate the procedure of neuro-fuzzy hybrid system. A detailed description of the image may be obtained in [12].

Exploring new techniques of image treatment by using computational intelligent techniques may be an alternative for satisfying the requirements of this area. The neuro-fuzzy system suggested in this paper attempts to insert new mechanisms for automatic image evaluation and decision making. The work developed is mostly based on a previous approach when applied in automatic focus checking and adjustment in video monitor manufacturing [6].

The schematic diagram that depicts the hybrid system merging NN and FL is shown in Fig.2. A digital camera installed in an artificial satellite captures images from earth. After pre-processing, the images are processed by a NN to identify patterns and to classify them in different levels. Afterward, these results are furnished as input data to the fuzzy decision support system. The fuzzy system is employed to determine the best alternative for decision.

The main focus is, then, to characterize what sort of activity should be carried out in that region due to earth resource image classification. These activities range from exploration of forest products and sub-products to environmental education, preservation and maintenance of the world natural patrimony.

NEURO-FUZZY SYTEM

Neural Classifier System

An artificial neural classifier is applied in order to classify the image into 8 patterns previously defined. The multilayer backpropagation neural net (BKNN) is chosen due to its extensive use in several complex problems. Additionally, it presents a simple gradient descent method to minimize the total square error of the output computed by the net with the advantage of saving computational cost.

The neural network employed during the process of image pattern recognition is of the feedforward architecture while the adjustment of training assignment enforced by the learning rules is the back-propagation algorithm [3], [13]. The advantage of this approach is to process non-linear information characteristics; to perform tasks with parallel behavior; to be tolerant to fault and noise; and to demonstrate abilities of learning and generalizing.

The general architecture of the artificial neural net is shown in Fig. 3. The BKNN is defined with 3 input neurons formed by the RGB colors, 24 neurons in hidden layer and 8 outputs relative to the patterns which include: araucaria; native forest, pinus, shadow, road, clouds, exposed ground and field. The output signal is normalized to -1 and +1 with hyperbolic transfer function once each element of the output represents one class. The number of hidden neurons is heuristically determined.

The training set of the neural net is composed of 54 control points/class with 40000 epochs

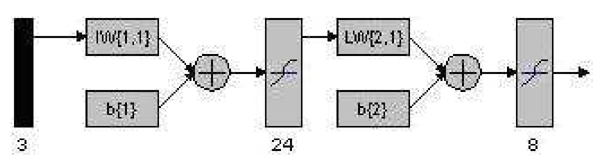


Fig. 3. Image example for evaluation.

and quadratic error chosen to be 0.001. The deviation error in time is shown in Fig. 4. It is possible to observe that throughout the training stage the error decreases and presents some bursts of variation. The great variations exist because some classes are very similar generating perturbations in the net when the input test class and the targets are compared. The next step after training is to validate the neural classifier system. This stage used 108 control points/class different from training set.

After image classification, results are presented in Table 1. Rows are the patterns: Araucaria (A), Native forest (N), Pinus (P), Field (F), exposed Ground (G), Road (R), Clouds (C), and Shadow (S). These results are, then, compared with distinct methods in [12] when using the same image and an integrated neural net based on three systems composed by a multilayer perceptron, a LVQ algorithm and a RBF with a kappa index of 77.2%. A possibilistic-based algorithm achieved a kappa index equal to 84.7% in [8]. The proposed method reached a kappa index of 82.8% showing that the adopted neural net in the qualification and testing data satisfy mostly the expected requirements. Thus, the neural network for classifying regions and classes previously defined presented appropriate consonance and correlation when compared to the original image and previous works.

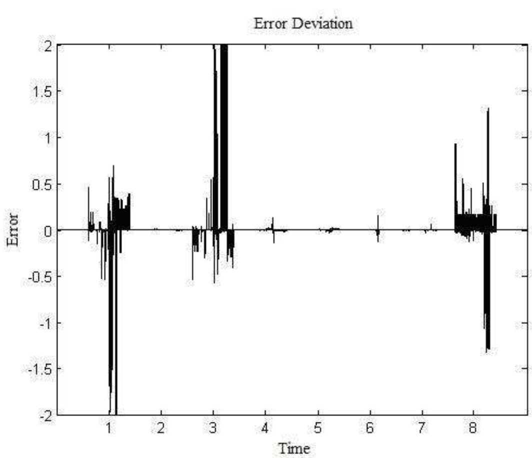


Fig. 4. Deviation of training error of the neural net.

TABLE 1
RESULTING CLASSIFICATION.

	C1	C2	C3	C4	C5	C6	C7	C8
A	74	0	30	0	0	0	0	2
N	0	108	0	0	2	0	1	3
P	19	0	60	0	0	0	0	11
F	0	0	0	104	0	12	3	0
G	0	0	0	4	106	0	0	0
R	0	0	0	0	0	92	6	0
C	0	0	0	0	0	4	98	0
S	15	0	18	0	0	0	0	92

Nevertheless, in visual patterns, for instance, images may suffer influences that introduce imprecision and uncertainty in the final choice. It is well established that geographic data obtained from satellite images carry, not rarely, vague information and uncertainty concerning the region of classification. Technical problems with sensors, clouds or shadows could cause some noise in the final image. Therefore, the NN may fail in discriminating the digitalized images. Thus, during the decision process, it is necessary to consider this uncertainty generated by inadequate training and validation set.

Instead of using a classical BKNN approach in which the output assumes a crisp value the approach used in this paper takes into account these uncertainties as described in [6]. In order to accomplish that, it is assigned a fuzzy set to the output value as shown in Fig.5 .

One of the difficulties to design and to simulate a decision-making system is the high level of abstraction of the neural network and the inherent characteristics of the regions of the image. Observing Table 1 it can be notice a certain difficulty of a decision algorithm to deal with class 1 and 3 because of the similar characteristics of data. For example, it illustrates the imprecise and uncertain information and the importance of such a decision-making system utilize the inherent nonlinear characteristics of fuzzy systems as well as the ability to deal with uncertainty, imprecision, vagueness, and partial true of fuzzy set theory and fuzzy logic.

After the neural network analysis, its result is furnished as input to a fuzzy system which, in turn, will decide based on a known class previously recognized and a set of rules.

Fuzzy Decision-Making System

Based on the expertise obtained from specialists, this approach addresses to demonstrate the importance of their knowledge and perception in the decision-making model. Such a process attempts to establish a straight relationship between the human vision potential and the inference capacity of a specialist. The decision-making process is the critical part of the system since it requires specialized knowledge for satisfying the multiple requirements.

In order to preserve and explore of natural resources in the region it is worth, as close as possible, emulating a human specialist for decision-making. Mimic this human decision process is carried out by a set of rule-based system given in (1). For input linguistic variable it is defined four membership functions associate to input linguistic terms: Araucaria, Native, Pinus and others (Fig. 6(a)) meanwhile for output linguistic decision variables there are the following linguistic terms: Extract, Preserve, Not-Consider and Evaluate (Fig. 6(b)).

$$
\begin{array}{l}
R_1\text{: If } (x_1 \text{ is Araucaria) then } (y \text{ is Extract)}\\
R_2\text{: If } (x_1 \text{ is Pinus) then } (y \text{ is Extract)}\\
R_3\text{: If } (x_1 \text{ is Native) then } (y \text{ is Preserve)}\\
R_3\text{: If } (x_1 \text{ is Others) then } (y \text{ is Not-Consider)}\\
R_5\text{: If } (x_1 \text{ is Araucaria) and } (x_2 \text{ is Pinus)}\\
\qquad \text{then (y is Extract)}\\
R_6\text{: If } (x_1 \text{ is Araucaria) and } (x_2 \text{ is Native)}\\
\qquad \text{then (y is Evaluate)}\\
R_7\text{: If } (x_1 \text{ is Araucaria) and } (x_2 \text{ is Others)}\\
\qquad \text{then (y is Extract)}\\
R_8\text{: If } (x_1 \text{ is Pinus) and } (x_2 \text{ is Native)}\\
\qquad \text{then (y is Evaluate)}\\
R_9\text{: If } (x_1 \text{ is Pinus) and } (x_2 \text{ is Others)}\\
\qquad \text{then (``y is Extract'')}\\
R_{10}\text{: If } (x_1 \text{ is Native) and } (x_2 \text{ is Others)}\\
\qquad \text{then (y is Preserve)}
\end{array}
\tag{1}
$$

The universes of discourse are subdivided into the interval [-1,3]. The linguistic term labeled Others is intended to encompass the classes like clouds, shadows, road or field, since the purpose of using such an image is preservation or exploration of natural resources. The decision-fuzzy system is modeling using Larsen product for fuzzy relation and the defuzzification method is the Center of Area (COA).

The membership functions are used to deal with the difficulty of exploratory usage of the

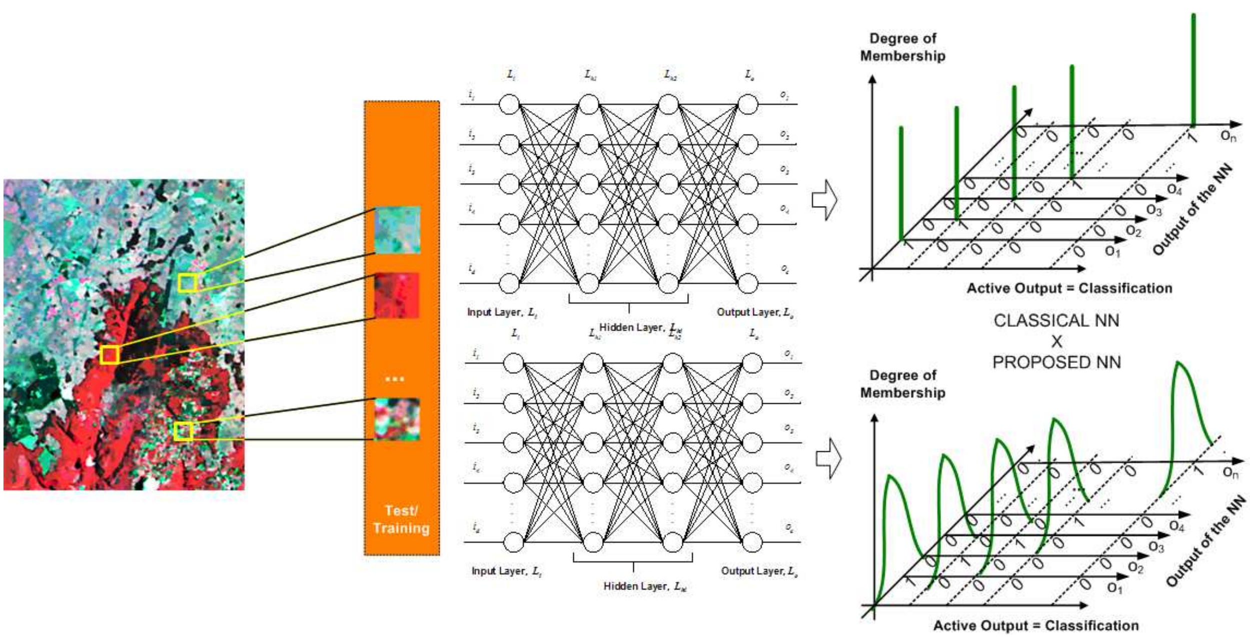
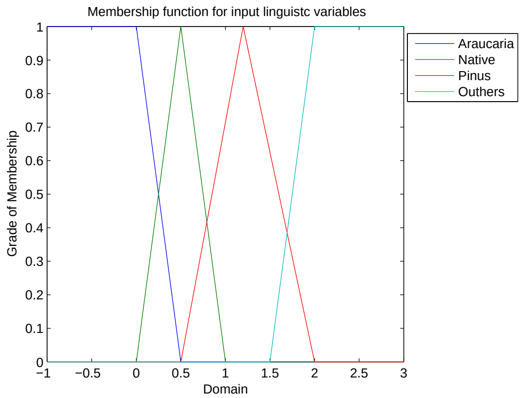
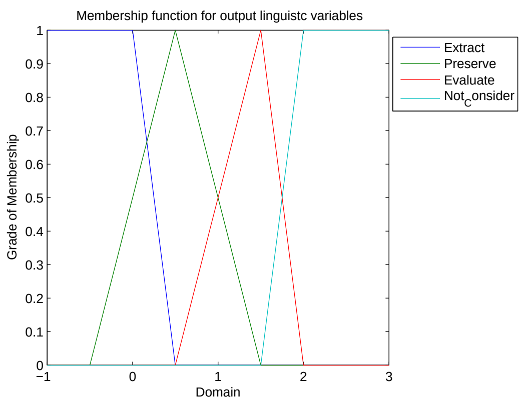


Fig. 5. Overview of the classical and proposed BKNN.



(a) Input linguistic terms.



(b) Output linguistic terms.

Fig. 6. Linguistic terms for the rule-base system.

resources and the possibility to implement public policies to the local population.

The knowledge base compounding the rules is shown in Fig. 7(a), the uncertain measure that is classified by the neural net is presented in Fig. 7(b), the cylindrical extension for input data applied in knowledge base is depicted in Fig. 7(c). The extension principle above the rule-based system is represented in Fig. 7(d). After defuzzification, the final decision supplied by the system is presented in Fig. 7(e) with a value of -0.35 in green and related to the resulting membership function associated mainly to the linguistic term “extract”. In this case, in particular, it is possible to notice a very small area concerning other membership functions. However, since the center of area is employed for finding out the final decision and most of the area is in the extract fuzzy set, then the final result is related to mentioned linguistic term.

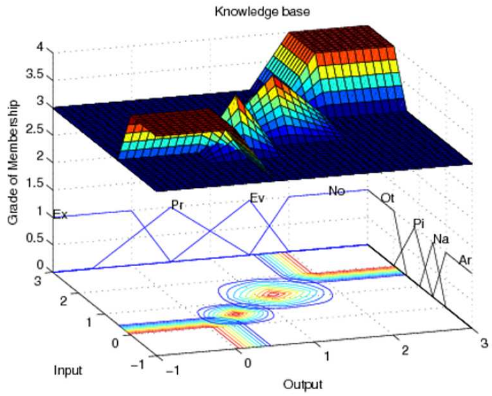
The example carried out here shows the great possibility and major purpose of such a system since it is may be adapted to diverse areas of knowledge. In this case the goal is to verify that an area of an image, like that one presented in Fig. 1 could be previously known just in the moment that it is received by the satellite. Another advantage of this approach is the decision be absolutely technical and not carrying any primacy related to personal or political interests.

CONCLUDING REMARKS

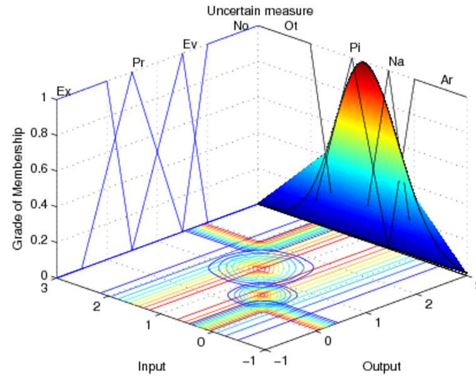
This work presented a neuro-fuzzy system to classify and decide upon satellite images in order to improve the technical methodology and the use of geographical information. The main focus is to characterize what sort of activity should be carried out in a region due to earth resource image classification.

Different of other approaches, the purpose of this paper was to explore a new computational intelligent technique. The neural system, in charge of classifying the image, revealed in conformity with two previous works and a specialist classification. The decision-making system, that is a critical part of the work, since the modeling requires previous knowledge about the problem and the method, brought up also a satisfactory result.

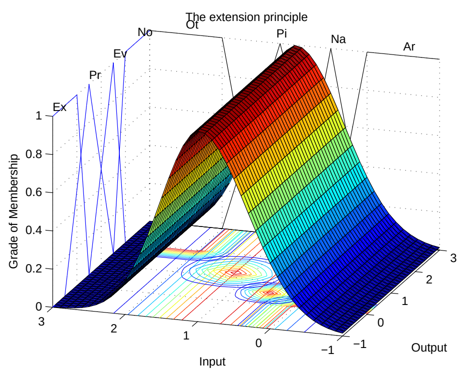
The main goal of demonstrating the technical viability of a computational intelligence approach based on a hybrid neuro-fuzzy component when dealing with images from earth resource satellites is achieved. It is worth mentioning that the hybrid system seems promising and future works could be done to improve the technique. Among many, it could be improved by subdividing the image into regions of interest (ROI) and verify each of them independently. Verify the influence of different fuzzy relations, operator or defuzzification method in the decision-making system is also an alternative for improving the whole system.



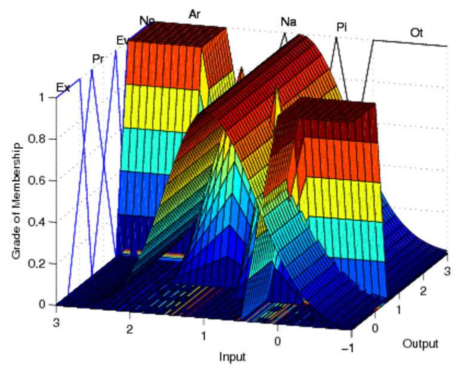
(a) Knowledge Base.



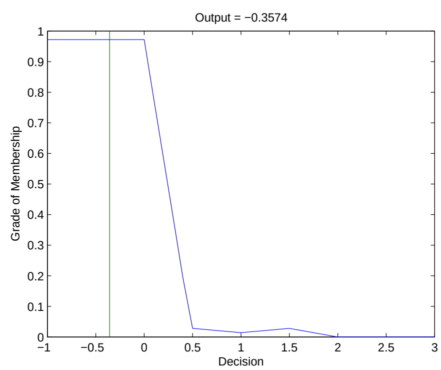
(b) Uncertain measure.



(c) The cylindrical extension.



(d) Extension principle upon rule-based.



(e) Decision-making for output value.

Fig. 7. Example of geographical input data presented to a fuzzy decision-making process.

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