A Rule Based Fuzzy Approach to the Classification of Man Made Objects in Satellite Image Data

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Abstract: The architecture and implementation of a rule-based fuzzy approach to the detection and classification of man made objects in satellite image data are presented. In a first processing step fuzzy clustering is used to obtain an initial coarse presegmentation of the data. Subsequently, a rule-based fuzzy system performs the classification. Its rules are generated both manually (based on common-sense or higher level expert knowledge) and automatically by a neural network evaluating image features which are difficult to extract or to evaluate directly. Some experimental results, a discussion of the potential of the approach and directions of possible future research conclude the paper.

Keywords: classification of satellite images, rule-based fuzzy systems, neural networks

1 Introduction

In recent years, knowledge-based systems for classification have become more and more popular in the field of remote sensing. They are capable of fusing image data with very different characteristics and numerical as well as non-numerical prior knowledge. An overview of some work is given in [1].

Because of the relatively low resolution of satellite images with respect to the size of the objects to be classified, pixels often do not belong to only one class: A pixel may belong to a part of a house as well as to the neighbouring street. The classification task is further complicated by the fact that expert knowledge commonly contains vagueness and ambiguities. A typical classification rule could be:

“*If an approximately rectangular object is near a street*
then the object could be a house.”

Consequently, the inherent fuzziness led to the introduction of different fuzzy techniques into the process of classification for remotely sensed data [2, 3].

The rules of the fuzzy system may be generated manually or automatically [4]. The former approach requires that experts be capable of formulating their knowledge in the form of rules. The latter, however, often restricts the type and quality of the generated rules. The system presented in this paper combines both methods to overcome the individual limitations.

2 Structure of the Classification System

2.1 The Rule-based Fuzzy System

The core of the classification system proposed in this paper is a rule-based fuzzy system consisting of three different fuzzy rule bases (see Fig. 1).

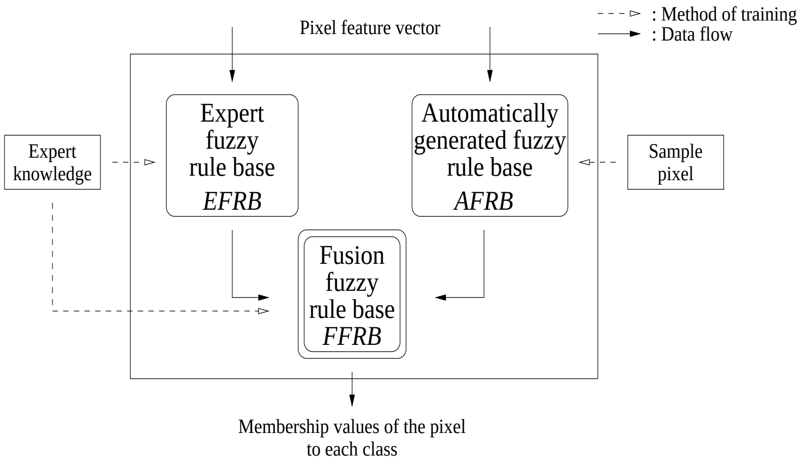


Figure 1: The rule-based fuzzy system.

The *expert fuzzy rule base* (EFRB) represents the knowledge of an expert, which can be formulated quite easily as fuzzy rules with suitable membership functions. Features used in our experiments for the EFRB are: the area of segments enclosed by edges found by a standard bandpass filter, the distance to local intensity maxima and the fuzzy entropy [5] of a region around each pixel. Rules in the EFRB are typically of the form:

$$\textit{IF feature } A \textit{ is } \widetilde{A} \textit{ with } \alpha \;\; \textit{THEN class is } X$$

where α or more generally $\alpha_i \in [0,1]$ represents a certainty factor for each feature i defined by an expert to express the confidence in these features in the context of the concerned class concept and $\widetilde{A}$ a fuzzy term like *high* or *near* dependent upon the context the considered feature is used. To integrate the certainty factor within the rule base in our experiments the algebraic product was chosen.

An example of linguistically described knowledge used in the EFRB is:

"A pixel near a local intensity maximum
could belong to the class house"

which is transformed into the rule:

$$\textit{IF [distance to local intensity maximum (pixel } p\textit{) = near]} \cdot \alpha$$
$$\textit{THEN class (pixel } p\textit{) = house}$$

If it is more difficult to find the basic rule parameters or to explicitly express the relationship between features and classes, the rules are generated automatically using a second fuzzy rule base (*automatically generated fuzzy rule base*, AFRB). The automatic extraction of the rules is done using a modified neural network approach according to [6]. In this approach multilayer perceptrons are used to find redundant features and to learn appropriate aggregation operators as well as the rules themselves by applying a backpropagation algorithm (see [7]). The neural network structure employed to learn the fuzzy rules is shown in Fig. 2, which in contrast to the original one presented in [6] is extended by a second inner layer.

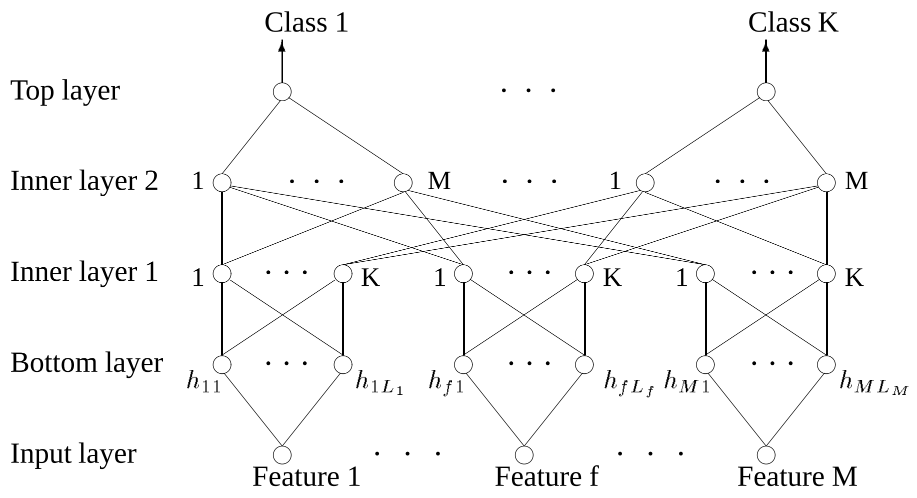


Figure 2: Structure of the neural network used in the AFRB.

The input layer takes the applied feature values as input values. The h_{fl} in Fig. 2 are estimated linguistic terms for the non-redundant features approximated by Gaussian distributions. They serve as activation functions in the bottom layer and fuzzify the feature values. In the first inner layer there exist as many nodes as classes for every feature. The important fuzzy terms for each class are extracted in this layer. The generalized mean operator serves as activation function for the nodes of the inner layers and the top layer [6, 7]:

$$g_p(x_1, ..., x_n; w_1, ..., w_n) = (\sum_{i=1}^{n} w_i x_i^p)^{\frac{1}{p}}, \quad \text{where} \quad \sum_{i=1}^{n} w_i = 1 \tag{1}$$

where x_i represents the activation of the former node i, w_i the weights for the relative importance of node i and p a parameter for the specification of the type of aggregation operation. Throughout the training process not only the weights w_i but the parameter p is learned, too. Thus the relationship between the different features is also determined. Positive values of p are interpreted as OR, negative values as AND.

The new introduced inner layer consists of $K \cdot M$ nodes according to the M features and K classes which are combined in the top layer. Each node in the second inner layer has M inputs which represent the combination of all features of one class. There are M nodes for each class k which all possess the same connections as input. But all these input connections each own a different given initial weight. Every node has another feature f as centre of gravity realized through the initial weight of 1. All other connections to this node get a lower initial weight (found with the help of test series): small enough to put sufficient emphasis on the feature f and large enough to allow a strenghtening of the weaker weights during the training process to the same degree as the former centre of gravity.

With the additional layer it is possible to realize more complex AFRB rules such as:

$$\textit{IF [(feature A is } \widetilde{A}_1 \textit{ OR } \cdots \textit{ OR } \widetilde{A}_{r_A}\textit{) OR (feature B is } \widetilde{B}_1 \textit{ OR } \cdots \textit{ OR } \widetilde{B}_{r_B}\textit{)]}$$
$$\textit{AND (feature C is } \widetilde{C}_1 \textit{ OR } \cdots \textit{ OR } \widetilde{C}_{r_C}\textit{) THEN class is X}$$

$$\textit{IF [(feature A is } \widetilde{A}_1 \textit{ OR } \cdots \textit{ OR } \widetilde{A}_{r_A}\textit{) AND (feature B is } \widetilde{B}_1 \textit{ OR } \cdots \textit{ OR } \widetilde{B}_{r_B}\textit{)]}$$
$$\textit{OR (feature C is } \widetilde{C}_1 \textit{ OR } \cdots \textit{ OR } \widetilde{C}_{r_C}\textit{) THEN class is Y}$$

where $r_A/r_B/r_C$ denotes the number of fuzzy terms for feature $A/B/C$ within the considered rule. To produce the experimental results in chapter 3 within the AFRB intensity-based as well as texture-based features (using cooccurence matrices) were used.

Finally, the results of the EFRB and AFRB are fused together using another manually generated rule base (*fusion fuzzy rule base*, FFRB). In the FFRB the relative importance for the decision process of the EFRB and AFRB with their features are weighted with certainty factors, as it was done in the EFRB. As an example the applied features in the AFRB may be optimal for the classification of houses but may be suboptimal for the class street. On the other hand the features used in the EFRB could be useful to detect houses but much better in classifying streets. This can be taken into account by the certainty factor for each rule base within the rule for each class. Additionally, context information about the class concept, e.g. the grade of isolation of segments of class X with respect to other segments of class X or the distance of class X segments to segments of class Y, can also be employed.

Therefore a typical FFRB rule used in our tests (where the logical operators *AND* and *OR* were modelled as min and max) was:

$$\textit{IF [(result of the EFRB (pixel } p\textit{) = house)} \cdot \alpha_1 \textit{ OR (result of the AFRB (pixel } p\textit{) = house)} \cdot \alpha_2\textit{]}$$
$$\textit{AND degree of isolation (pixel } p\textit{) = not isolated}$$
$$\textit{AND count(class(neighbours of pixel } p\textit{) = street)} \leq 1$$
$$\textit{THEN class (pixel } p\textit{) = house}$$

2.2 The Classification Process

The structure of the whole classification system is shown in Fig. 3. First, the user declares one of the class concepts introduced in the system as *class of interest* (e.g. *house*, *street*, etc.). Then, a fuzzy clustering technique is used as an unsupervised segmentation method to divide the image coarsely into some clusters. Within this and the following step information about the colour space is used to reduce the number of pixels in the actual classification process. In the next step it is verified whether or not the requirements of a certain class are met by pixels of the clusters using the rule-based fuzzy system. If there is enough evidence that a cluster contains pixels of the class of interest (e.g. the class house), this cluster is declared as *cluster of*

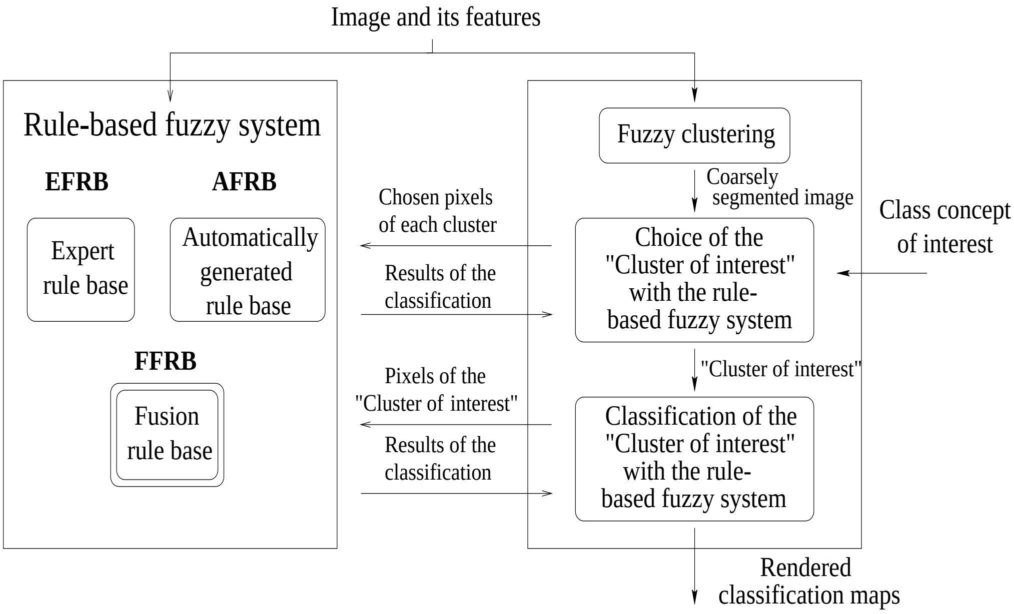


Figure 3: Illustration of the classification process.

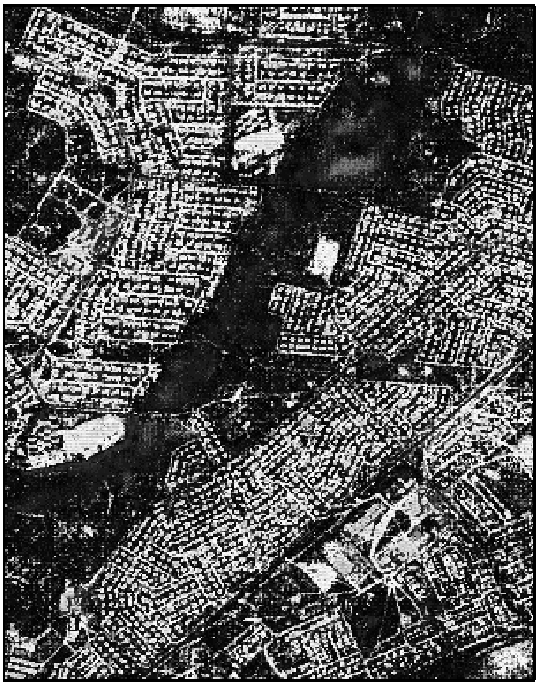
interest. In a final step all those pixels of the clusters of interest which belong to the cluster with a certain minimum membership value are classified by the rule-based system. Remaining pixels are marked as not belonging to this class and the classified pixels are rendered for visualization.

3 Experimental Results

The system has been tested on images taken by the German MOMS-02 sensor (see e.g. [8]). As an example results are presented here that were obtained using the class concept *house* and the test image shown in Fig. 4. Two clusters were initially extracted by making use of the well known *Fuzzy c-Means Algorithm* [9]. The results of the clustering are given in Fig. 5, where a darker intensity value of a pixel indicates its higher membership in the cluster. Utilizing the rule-based fuzzy system the cluster in Fig. 5b was labeled as the cluster of interest for further classification.

In Fig. 6 the classification results are shown that were received by applying the AFRB and the EFRB individually as well as the whole classification system to the cluster of interest. (In Fig. 6a…c darker pixel intensities represent higher membership values of the pixels to the class *house*.) It can be observed that application of the single AFRB produces reliable results (Fig. 6a), but suffers from deficiencies at the edges of the considered settlements where houses are often not found. Furthermore pixels having a high intensity in agriculturally used fields are misclassified as houses. The employment of the single EFRB instead does not lead to these difficulties, however, probably in particular caused by having specified the EFRB too coarse or incomplete, the generated results are often very vague (Fig. 6b). Both results combined in the FFRB overcome these indiviual problems as is shown in Fig. 6c. The same results are also displayed in Fig. 6d but only pixels with a certain minimum membership value (exemplary a membership of 0.6) to the class *house* are registered in the map as dark pixels.

Figure 4: The test image.



(a) Cluster 1

(b) Cluster 2

Figure 5: Results of the Fuzzy c-Means clustering ($c = 2$).

(a) Results of the AFRB

(b) Results of the EFRB

(c) Results of the FFRB

(d) Results of the FFRB (≥ 0.6)

Figure 6: Classification results.

4 Conclusions and Future Research

A rule-based fuzzy system has been successfully applied to the classification of satellite image data. Vagueness and uncertainty of both the class concepts and the expert rules were taken into account. Because of the usage of fuzzy methods throughout the whole process of classification there is no loss of information until the fusion fuzzy rule base takes its final decisions. Maps indicating the membership values of all pixels with respect to one class allow for a more flexible analysis of the underlying situation shown in the image. Not only does the fusion fuzzy rule base permit a flexible fusion but it also makes the application of additional context information about the classes possible. In future projects our work will be aimed at an automatic adaptation of the extracted and formulated rules or membership functions to new situations in different image data.

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