# Evolutionary Approach to Discovery of Classification Rules from Remote Sensing Images

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**Abstract.** In this article a new method for classification of remote sensing images is described. For most applications, these images contain voluminous, complex, and sometimes noisy data. For the approach presented herein, image classification rules are discovered by an evolution-based process, rather than by applying an a priori chosen classification algorithm. During the evolution process, classification rules are created using raw remote sensing images, the expertise encoded in classified zones of images, and statistics about related thematic objects. The resultant set of evolved classification rules are simple to interpret, efficient, robust and noise resistant. This evolution-based approach is detailed and validated based on remote sensing images covering not only urban zones of Strasbourg, France, but also vegetation zones of the lagoon of Venice.

## 1. Introduction

The design of robust and efficient image classification algorithms is one of the most important issues addressed by remote sensing image users. For many years a great deal of effort has been devoted to generating new classification algorithms and to refine methods used to classify statistical data sets [Bock, 1999]. At the time of this writing, relatively few workers in the machine learning community have considered how classification rules might be discovered from raw and expertly classified images. In this paper, a new data-driven approach is proposed to discover classification rules using the idea of evolutionary classifier systems. The unique source of information is a remote sensing image and its corresponding classification furnished by an expert. The images have been registered by various satellites (e.g. SPOT, LANDSAT, DIAS) that use different cameras having various spectral and spatial resolutions [Weber, 1995]. These types of remote sensing images generally contain huge volumes of data. And, sometimes they are very noisy due to coarse spatial resolution or unfavourable atmospheric conditions at the time the images are acquired. In addition, data may be erroneous due to inexperienced operators of the measurement devices.

The aim of this research is to elaborate an evolutionary classification method that, in contrast to classical algorithms, will allow for supervised creation of autonomous classification. In general, classification rules are discovered from the established classifier system ([DeJong, 1988], [Wilson, 1999]). As we said, the system is data-driven because the formulated classification rules are able to adapt themselves according to the available data, environment, and the evolution of classes. In remote sensing, the initial population of classifiers is randomly created from images and given classes, and then evolved by a genetic algorithm until the acceptable solution is found.

In the remote sensing literature, several classification approaches are presented, namely:

- pixel-by-pixel: each image pixel is analysed independently of the others according to its spectral characteristic [Fjørtoft, 1996],

- zone-by-zone: before classification, the pixels are aggregated into zones, the algorithms detect the borders of the zones, delimit them by their texture, their repetitive motives [Kurita, 1993],
- by object: this is the highest recognition, the algorithms classify semantic objects, the algorithms detect their forms, geometrical properties, spatio-temporal relations using the background domain knowledge [Forsyth, 1996], [Korczak, 1999].

Our approach is based on spectral data of pixels; therefore, discovered classification rules are only able to find rather spectral classes than semantic ones. This spectral component of class description is essential to well-recognised thematic classes. It should be noted that the proposed classifier system may be easily adapted to more sophisticated object representation with further research on detailed feature recognition.

The classifier system model has been implemented in the ICU program, which has been used to validate our approach. In the ICU, we have adapted and extended previously established ideas recognized by classification experts, such as XCS [Wilson, 1999], the s-classifiers [Koza, 1992], and "Fuzzy To Classify System" [Rendon, 1997]. We have also been inspired by the works of Riolo [1988] on gratification and penalisation, and of Richards [2001] on the exploration of the space of classifiers.

The basic notion of our evolutionary classifiers is introduced in Section 2, which follows directly. Section 3 details the discovery process of the classification rules. In this Section, the behaviour of genetic algorithm functions is explained. Finally, three case studies on real remote sensing data are presented in Section 4.

## 2. Definition of a system of classifiers in remote sensing

Generally speaking, a system of classifiers integrates symbolic learning and evolution-based computing. Classification rules are symbolic expressions and describe conditions to be held and actions to be taken if the conditions are satisfied. Quality of the rules is evaluated according to their classification performance. Here, we must underscore the fact that the rules are not introduced by a programmer or by an expert.

A system of classifiers is called evolutionary if it is able to adapt itself to the environment. This means that it can modify its knowledge and its behaviour according to the situation. For example, in remote sensing, the size of the classes may evolve in one of two ways: (1) if, after an initial classification, there remain non-classified pixels, or (2) if there are pixels belonging to several classes (mixed pixels). When a classifier integrates one of these pixels to one or another class, it is necessary to dynamically adapt classification rules. That is, certain rules that treat only the simple cases (not mixed pixels) will be maintained as obsolete, but for other cases it is necessary to create new rules.

From a functional point of view, a classifier can be defined as a rule representing a piece of knowledge about a class, and may be a conditional expression, such as *if <conditions> then <action>*. In the early classifier systems [Wilson, 1999], each part of a rule was a binary message, encoding elementary information such as a value, colour, form, shape, etc. The "*conditions*" part described an entry message in the system, corresponding to conditions that must be fulfilled in order to activate this rule. The "*action*" part defined the action to be carried out when the appropriate conditions were satisfied. This binary encoding scheme is not well adapted to image classification rules.

One of the reasons for this is based on the domain of spectral values that may be assigned to a pixel (from 0 to 255 for 8-bit pixels, or from 0 to 65000 for 16-bit pixels). Of course, binary encoding of rule conditions is possible but the rules would be difficult to understand. Instead, we assert that the evolved rules must be rapidly evaluated and easy to interpret by any user. As a result, condition representation using the concept of an interval could be fully adequate for remote sensing image classification. In terms of machine learning, the rules have to be absolutely specific, meaning that they have to cover the extreme maximum and minimum pixels belonging to any given class.

Before rule specification is explained, recall that a pixel is encoded as a spectral vector, defining a value of reflectance for the *n* bands of the remote sensing image:

$$<pixel> := [b_1\ b_2\ b_3 \ldots\ b_n]$$

In our system, the condition for any rule is built on the concept of spectral intervals defining a given band, corresponding to a given class. Such intervals are a pair of integer numbers, between 0 and the maximum possible value for a pixel of a given band (i.e. 65536 for the pixels defined on 16 bits). This solution allows to partition the space of the spectral values in two ranges: the first containing the pixel values which corresponds to a given class, and the second containing the remainder.

To precisely specify the class definition, a set of intervals is defined for each band of the remote sensing image. Taking onto consideration all bands, one can define the condition part as follows:

$$<condition> := E_1 \text{ and } E_2 \text{ and } \ldots \text{ and } E_N$$

where $E_i$ defines a set of intervals for a band *i,* and $N$ is the total number of bands.

Each $E_i$ is defined as a set of spectral intervals: $E_i := [m_1; M_1]$ *or* $[m_2; M_2]$ *or…or* $[m_p; M_p]$ where $m_j$ and $M_j$ are, respectively, the minimal and maximum reflectance values authorised for a pixel belonging to a class *k* for the band *i.* These intervals are not necessarily disjunctive. By experiments, we have found that if we allow the genetic algorithm to create non-disjunctive intervals, instead of merging them, the results of genetic operators are more interesting. We have noticed that merging intervals significantly diminishes the number of intervals, and in the same time reduces the possibilities to create more efficient rules. The example below illustrates a concept of interval merging: $E = [11; 105]$ *or* $[138; 209]$ *or* $[93; 208]$ corresponds after merge operation to $E = [11; 209]$.

To satisfy a rule, a pixel has to match at least one spectral interval for each band. Logically speaking, to associate a pixel to a class, its values have to satisfy the conjunction of disjunctions of intervals that define a condition part of the classification rule (Fig. 1).

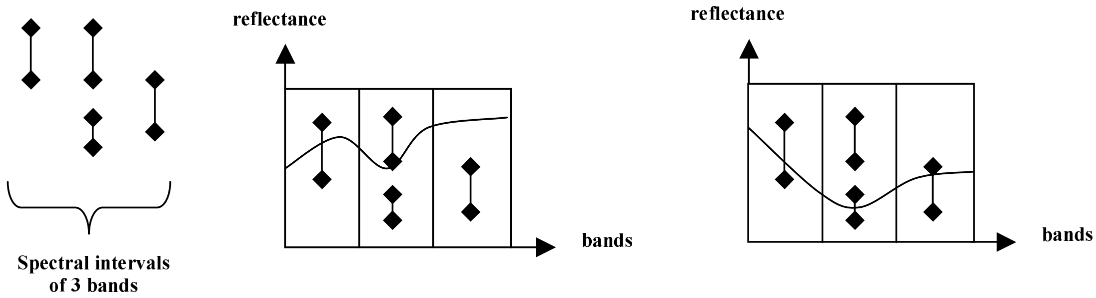


**Fig. 1.** Matching spectral bands and spectral signature of pixels

The figure on the left shows the spectral intervals defined in a rule for a class C. The second figure shows the spectral signature of a pixel in the image. If we apply the rule, the intervals do not match the pixel spectral signature, so this pixel is not classified in C. The third figure illustrates a case when the spectral bands match the spectral signature of the pixel; therefore the pixel is assigned to the class C.

This representation of the rule has been chosen mainly because of its simplicity, compactness and uniform encoding of spectral constraints. During experimentation, this representation has demonstrated rapid execution of genetic operators and efficient computing. Of course, one may specify more complex structures using spatial properties of the pixel, with respect to the pixel neighbourhood. Also, one may include features resulting from thematic indices or mathematical operators applied to pixel environment. We may also apply a genetic programming to identify new characteristics. These semantically extended formalisms are interesting, however they not only require more sophisticated genetic operators, but also more powerful computers to perform the calculation in an acceptable amount of time.

## 3. From the rule creation to the evolution

### 3.1. Genetic algorithm

In order to efficiently develop the classification rules, a genetic algorithm initialises interval values according to spectral limits of the classes designated by an expert, for valid zones of the remote sensing image. Initial classification rules are created based on the extreme maximum and minimum values for defined spectral intervals, taking into account every class. It should be noted that by this initialisation, rule searching is considerably reduced, and initial intervals are very close to the final solution. During this process, the initial spectral limits are slightly perturbed by adding a random value to lower and upper spectral limits. At the same time, the initial population of classification rules is quite diversified.

This initial pool of classifiers is evolved from a genetic algorithm. Our system searches for a best classifier for each class, independently. A major reason for choosing this procedure is the efficiency of computations; that is, the process of rule discovery is not perturbed by other rules.

The quality of classification rules is based on a comparison of these results with the image classified by an expert. If pixels covered by the classifier perfectly overlap those indicated by an expert, then the system assigns the highest quality value to the classifier; otherwise, in the case of some mismatching, the quality factor is reduced (between 0 and 1). An associated fitness function will be detailed in the next section. During the evolution process, the rules are selected according to the quality for a given class. It should be noted that it is also possible to define global system quality based on individual rule classification qualities. The process of rule evolution is defined in the algorithm below.

**ALGORITHM: Process of rule discovery**

```
R is a classification rule and P, P' and P" populations of classification rules
R: = INITIAL_RULE (images)          // Creation of a rule according to the remote sensing images
P: = INITIALISATION(R)              // Creation of an initial population of rules
EVALUATION(P)                       // Calculation of the fitness function for each rule
WHILE termination_criterion is not satisfied(P) DO
P' : = SELECTION_X(P)               // Selection of rules for crossover operation
P' : = CROSSOVER(P') U COPY(P)
P" : = SELECTION_MUT(P')            // Selection of rules for mutation operations
P" : = MUTATION(P') U COPY(P')
EVALUATION(P")
P: = REPLACEMENT(P,P")              // New generation of rules
```

As mentioned before, this algorithm must be designed to run independently for each class. This allows for obtaining classifiers according to user requirements without the necessity of carrying out computations for all classes with the same level of quality. This also allows for the maintenance of previously generated classifiers, as well as for the introduction of new ones. Further, the user may define a hierarchy of classes and specialise some classifiers while respecting newly created sub-classes with different levels of classification quality.

### 3.2. The evaluation function

The evaluation function serves to differentiate the quality of generated rules and guide genetic evolution. Usually, this function depends strongly on application domain. In our work, evaluation is based on the classification obtained by the classifier ($I_{rule}$) and the expertly given classification ($I_{expert}$). Table 1 defines the values necessary to compute the evaluation function.

**Table 1.** Characteristics of the evaluation function

| | | Image classified by the classifier $R$ ($I_{rule}$) | |
|---|---|---|---|
| | | No. of pixels activating $R$ | non activating $R$ |
| Pixel classified by the expert $E$ ($I_{expert}$) | True | $P_{\exp}^{rul}$ | $P_{\exp}^{\overline{rul}}$ |
| | False | $P_{\overline{\exp}}^{rul}$ | $P_{\overline{\exp}}^{\overline{rul}}$ |

In any given system, the evaluation function is computed as follows:

$$N_{final} = C_{class} \cdot N_{class} + C_{\overline{class}} \cdot N_{\overline{class}} \tag{1}$$

where $N_{class} = \frac{P_{\exp}^{rul}}{P_{\exp}^{rul} + P_{\exp}^{\overline{rul}}}$ and $N_{\overline{class}} = \frac{P_{\overline{\exp}}^{\overline{rul}}}{P_{\overline{\exp}}^{rul} + P_{\overline{\exp}}^{rul}}$. $C_{class}$ and $C_{\overline{class}}$ are called the adjusting coefficients, which are used for certain classes that are under- or over-represented. By default the value of these coefficients is equal to ½.

The proposed function has a number of advantages; it is independent of the pixel processing sequence, invariant of the size of classes, and efficient for class discovery with a highly variable number of pixels.

The evolution process converges according to some statistical criteria indicating if the current classifier is near to a global optimum or if the population of rules will not evolve anymore. The termination criterion of the algorithm leans on the statistics of classifier quality evolution. In our system, we take into consideration not only the evolution of quality of the best and the average classifiers, but also the minimum acceptable quality defined by a user and a maximal number of generations to run. If one of these criteria is satisfied, then the process is stopped.

The most difficult determination to make is whether the quality of a classifier is not continuing to evolve. To detect stabilisation of the quality evolution, we have based our heuristics on statistics regarding quality evolution of the best classifier. For example, let $Q_k$ be the quality of the best classifier obtained during the last $k$ generations, and $Q_o$ be the quality of the best classifier of the current generation. The algorithm is interrupted if the following equation is satisfied:

$$\left| \frac{\sum_{k=1}^{P} Q_k}{P} - Q_0 \right| \leq E \tag{2}$$

where $P$ represents the maximum period of quality stabilisation, and $E$ is a maximal variation of this stabilisation compared with the current quality.

It is important to have an initial population of classifiers within the vicinity of the solution to be found. We have proposed two algorithms allowing for the generation of a diversified pool of classifiers close to the expert hidden classification rule. The first, called MinMax, creates maximum intervals covering the expert rule, and the second algorithm, called Spectro, integrates the spectral distribution density and interval partitioning.

### 3.3. Genetic operators

One of the most important tasks while designing a genetic algorithm is to invent operators that will create new potential solutions. All of our operators have been specialised on classifier representation, and they have been validated on remote sensing images. With respect to software engineering, the genetic algorithm has been structured into layers corresponding to genetic operations (e.g. selection, mutation, crossover and replacement). The system is viewed as a collection layers with data passed from layer to layer. Layer execution follows from one to another, and genetic operations are invoked in the same sequence. This modular approach makes program maintenance and future extensions much easier.

*Selection of classifiers*

In general, selection is the operation of allocating reproductive opportunities to each classifier. The reproductive force of a classifier is expressed by a fitness function that measures relative quality of a classifier by comparing it to other classifiers in the population. There are many methods for selecting a classifier [Blikle, 1995]. In our system, the selection operator is applied in the following cases:
- choosing the classifier to be reproduced for crossing, or muting;

- repetition of the classifier, depending on whether it completes the genetic pool after having completed the crossover;
- preservation of a classifier from the former genetic pool for the next generation;
- elimination of a classifier in a newly created genetic pool based on an assigned rank.

Selection strategies are well known: the roulette wheel, ranking, elitism, random selection, the so-called tournament, and eugenic selection. Our experiments have shown that roulette wheel selection is most advantageous for the reproductive phase, but the tournament strategy with elitism is best for the generational replacement scheme.

*Crossover of classifiers*

Crossover requires two classifiers, and cuts their chromosome at some randomly chosen positions to produce two offspring. The two new classifiers inherit some rule conditions from each parent-classifier. A crossover operator is used in order to exploit the qualities of the classifiers.

Each result of the crossover process has to be validated. Validation of the various rule attributes (border limits violation, overpassing, ...) is carried out by a process of interval merging, as shown in Figure 2.

| | | After crossover | | After merging |
|---|---|---|---|---|
| $[10;13] \vee [24;36] \vee [55;67]$ | $\longrightarrow$ | $[10;13] \vee [48;53] \vee [55;67]$ | $\longrightarrow$ | $[10;13] \vee [48;53] \vee [55;67]$ |
| $[7;27] \vee [48;53] \vee [81;93]$ | | $[7;27] \vee [24;36] \vee [81;93]$ | | $[7;36] \vee [81;93]$ |

**Fig. 2.** Interval merging after crossover operation

However, merging not only decreases the number of intervals in the rules, but also generates some information loss. In fact, in order to avoid a premature convergence of rules, it is generally important to preserve for the following generation two distinct intervals instead of a single aggregated one. On the other hand, it is interesting to note that the positive or negative effects of an interval on the quality of the rule can be related to other intervals encoded in the classification rule.

*Mutation of classifiers*

The mutation operator plays a dual role in the system: it provides and maintains diversity in a population of classifiers, and it can work as a search operator in its own right. The mutation processes a single classification rule and it creates another rule with altered condition structure or variables. The mutation operator to several may be applied on three levels: band level, interval level and border level. Figure 3 shows the different variants of mutation applied to remote sensing images.

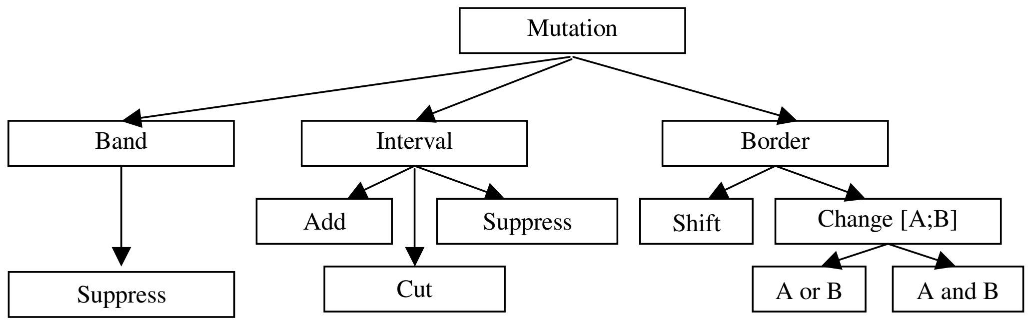


**Fig. 3.** Mutation operators

Band mutation consists of a deletion of spectral bandwidth in a chosen classification rule. Its interest is twofold; firstly, the band mutation type allows for simplification and generalization of a rule; secondly, it allows for the elimination of noisy bands that frequently appear in hyper spectral images. The existence of noisy bands significantly perturbs the learning process, as well as the process of evolution convergence.

Interval mutation allows for a chosen band to add, eliminate or cut an interval in two spectral ranges. In case of addition, the new rule is completed by a new interval centred randomly with a user-defined width. The cutting of an interval is done by random selection of a cutting point within the interval (for example, the cutting of *[10;100]* can generate two intervals: *[10;15]* and *[15;100]*). Mutation such as this allows for breakage of continuous spectral ranges. And, this allows for the definition of a spectral tube in which spectral values of the pixels can be assigned to a given class.

Finally, border mutation modifies both boundaries of an interval. This mutation refines the idea of targeting spectral tubes carried out by the other types of mutation. It is worthwhile to note that the mutated rules are systematically validated.

In our system, mutation operators are dynamically adapted. Adjustment is related to the probability of each mutation operator according to its current effectiveness.

*Generational replacement*

The generational replacement is an operation that determines which of the current classifiers in the population is to be replaced by newly evolved classifiers. According to Algorithm 1, the new generation of classifiers is created from a generation of parents (P) and their children after the crossover and the mutation operations (P"). There exist several strategies for producing a new generation, notably:

- the revolutionary strategy in which only the population of the children completely replaces the parent selection,
- the steady state strategy in which new classifiers are inserted in the new population by replacing the worst, the oldest member, the most similar, or by preserving the best classifiers (elitism).

We can also imagine other replacement strategies integrating for instance the strategy where the best individual of the previous population replaces the worst one of the current population. However, both this strategy generate a risk with respect to individuals over long periods of time. This is not a priori perturbation, except in the case of a poor genetic pool in which some individuals of average performance would profit from absolute immunity.

## 4. Case studies and experiments

In this paper, three case studies involving the remote sensing images of Strasbourg and San Felice (lagoon of Venice) have been chosen. Using these examples, we have addressed the main issues of remote sensing image classification using the evolutionary approach. The first case study, classification of high-resolution SPOT images (3 bands, 8 bits per pixel, resolution 1.3 m), demonstrates a typical problem of classification for urban zones including mixed pixels. The second case study illustrates the problem of noisy bands within a hyper spectral image (80 bands, 16 bits per pixel, resolution 3m). The third case demonstrates the performance of classifiers on very noisy hyperspectral images, such as DAIS (80 to 100 bands, 16 bits per pixel, resolution 3m, [DAIS, 2001]). Experimental results for each case study contain an extract of the discovered classification rules, the classified image according to these rules, the table of parameters, as well as a few comments. More detailed reports on the experiments can be found in the report by [Quirin, 2002].

*Classification of image of Strasbourg, Stadium Vauban*

**Fig. 4.** Classification

**Table 2.** The obtained classification rules

| Class | Rule |
|---|---|
| *Water* | [20;34] [0;26] [2;16] |
| *Shadow* | [8;35] [1;23] [11;26] |
| *Vegetation* | [6;32] [9;29] [18;50] |

**Table 3.** Parameters of rule discovery

| Parameter | Value |
|---|---|
| No. Classifiers | 1500 |
| No. Generations | 200 |
| Stabilisation Period | 20 |
| Stabilis. Tolerance | $10^{-4}$ |
| Crossover Rate | 80% |
| Mutations Rate | 5% |
| % Eugenic | 1% |
| No. Class Learned | 11 |
| Performance | 90,74 % |

*Comments:* For this complex remote sensing image relatively good rule qualities have been obtained; the classes WATER and SHADOWS are usually difficult to distinguish. The obtained rules correctly distinguish between these two classes.

*Classification of hyperspectral image of Strasbourg, Stadium Vauban*

**Fig. 5.** Classification

**Table 5.** Parameters of rule discovery

| Parameter | Value |
|---|---|
| No. Classifiers | 1500 |
| No. Generations | 250 |
| Stabilisation Period | 20 |
| Stabilis. Tolerance | $10^{-4}$ |
| Crossover Rate | 80% |
| Mutations Rate | 5% |
| % Eugenic | 1% |
| No. Class Learned | 11 |
| Performance | 86,06 % |

**Table 4.** The obtained classification rules

| Class | Rule |
|---|---|
| *Water* | [460;1236] ... [7262;8411] |
| *Shadow* | [209;2182] ... [6949;8726] |
| *Vegetation* | [168;2998] ... [7166;9382] |

*Comments:* Amongst 80 bands, the half was noisy. The algorithm has demonstrated its robustness.

*Classification of hyperspectral image of Venice, lagoon San Felice*

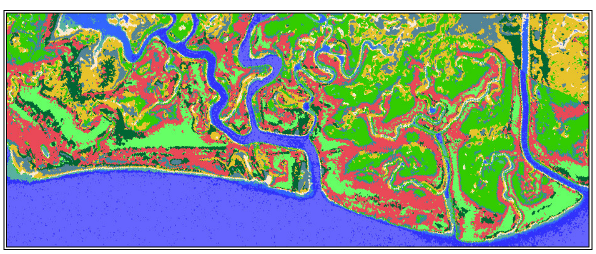

**Fig. 6.** Classification

**Table 7.** Parameters of rule discovery

| Parameter | Value |
|---|---|
| No. Classifiers | 100 |
| No. Generations | 100 |
| Stabilisation Period | 10 |
| Stabilis. Tolerance | $10^{-4}$ |
| Crossover Rate | 75% |
| Mutations Rate | 15% |
| % Eugenic | 1% |
| No. Class Learned | 12 |
| Performance | 96,13 % |

**Table 6.** The obtained classification rules

| Class | Rule |
|---|---|
| *Water* | [288;1288] ... [223;1451] |
| *Sarcocornia fr.* | [409;1017] ... [1266;2724] |
| *Spartina ma.* | [289;1082] ... [461;1716] |
| *Juncus ma.* | [435;1647] ... [668;4413] |

*Comments:* The initial classified image was very coherent; therefore the performance obtained on the 80 band hyperspectral image is very high. The algorithm eliminated some noisy or redundant bands.

The three case studies have demonstrated the high capacity of the evolution-based classifiers to interpret and classify heterogeneous and complex images (e.g. high dimension, large number of bands, noise data). The quality of classification is very high even if there were a high number of noisy bands and mixed pixels. It must be noted that the quality of learning is highly related to the quality of the classified image used for rule discovery. The discovered classification rules are simple and easy to interpret by remote sensing experts. They are also mutually exclusive and maximally specific. The learning time was relatively long due to the large image size and the chosen parameters for the evolution process.

Finally, we must mention the high correlation between obtained results and statistics carried out on the remote sensing image (spectrogram statistics, excluding noisy bands). Classified images by the discovered rules have shown that the evolution-based classifier is able to faithfully reproduce the human expertise.

## 5. Conclusions and perspectives

This article has described the evolution-based classifier system applied to remote sensing images. The system has discovered a set of *if ... then* classification rules using the fitness function based on image classification quality. These rules, which were proven robust and simple for the user, are sufficiently generic for reusing them on other portions of satellite images.

Taking into consideration image complexity and noisy data, the results of our experiments are very encouraging. Case studies have demonstrated that the obtained classifiers are able to reproduce faithfully the terrain reality. The rules are well adapted to recognise large objects on the image (e.g. sport lands), as well as the smaller ones (e.g. trees, shadows, edges of the buildings). The redundant or noisy bands have been successfully identified by our rule representation. The formulation of rule representation has allowed for the modelling of a spectral tube adapted to the granularity of spectral reflectance.

The potential of evolution-based classifiers in remote sensing image classification is just beginning to be explored. Further investigation of ICU's learning efficiency are necessary. Currently, we are starting to work on a more powerful representation of rules including spatial knowledge, temporal relations, and hierarchical representation of objects. We are also trying to optimise system performance, in particular the genetic process implementation and its initial parameters. The classifier system developed by this research work, called ICU, is currently available on our web site, which is `http://hydria.u-strasbg.fr`.

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