A knowledge-based system for the computation of land use mixing and the classification of a multi-spectral satellite scene

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Abstract

This paper describes the use of a knowledge-based system to manage a library of image processing programs to perform land use mixing in pixels of a multi-spectral satellite image.

This system is provided to naturalists, such as geologists, pedologists, or forester that are not specialists in computer vision, and it automatically processes the data coming from satellites.

The role of such a system is to convert the requirements of the user, expressed in terms of naturalist requests, into the correct image processing commands. Then naturalists can concentrate their attention on the interpretation of the results and not in the data management. Some examples are shown.

Keywords: Remote sensing / Knowledge-based system / Multi-spectral scene / Land use mixing / Classification

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1 Introduction

Naturalist scientists, like pedologists, geologists or foresters, need a detailed information on the ground to prepare a ground mission or a ground cartography. They don't only need the land use classification but also the ratio of the different land uses inside the same area. For this purpose, we propose a method to determine mixing of land uses inside the pixels of a satellite image.

Interpretation of pixel surface in term of land use spectral mixing have already been explored by several authors for different kinds of satellites : (N. A. Quarmby et al., 1992) for the NOAHH-AVHRR satellite and (J.B. Adams and Gillepsie, 1989; Adams and Gillepsie, 1990; J.B. Adams and Willis, 1990) for Landsat TM and aerial photography. But, in every case the choice of pure spectra is dependent on external data (like a bank of spectra) and the number of pure spectra used is also very small (maximum 2 or 3).

The library of programs we propose (named *cocktail*) doesn't need other information than those given by the satellite image.

Each program of the library computes one step of the determination of the land use mixing. Percentage computing can be followed by a land use classification associated with an entropy image. One drawback is that the user must know how to run each program and how to chain programs in the correct order to obtain a land use mixing and a classification. Different programs have to be used for different purposes. Without the knowledge-based system, the user has to select, initialize and combine manually the programs he/she needs, depending on the kind of image he has and on the kind of application he wants.

That is why we decided to manage the use of this library by a program supervision expert-system. In order to satisfy a request of a naturalist scientist, the system automatically selects, adapts and executes the most adequate programs, depending on the current images. So, the reception of a request as input, produces as output a sequence of commands (equivalent to a script). This approach provides the resulting system with extensibility (i.e it is easier to add new programs in the library) and autonomy (i.e. the user is not burden with image processing problems, the system can adapt its behavior to the data).

We begin with a description of the classification and land use mixing process, that we want to automate, its purpose and its originality. We explain the reasons why the automation of this process is necessary. We discuss the underlying concepts of program supervision, we detail the system architecture (knowledge base and inference engine) and its implementation, and eventually we analyze a real example.

2 The remote sensing process

2.1 Determination of the land use mixing

We have built a library of programs that allows interpretation of a satellite scene in term of land use mixing (see section 5). The mathematical method for the determination of land use mixing is detailed in (Mathieu, 1994).

The applied method is a linear one. Initial images are first corrected from topographic and atmospheric effects with some programs of (Ming, 1993). We apply Q-mode factor analysis, followed by a Varimax rotation to extract the principal factors of the pixel spectra (programs "Hafq6TMVarimax" for a Landsat TM image and "Hafq3XSVarimax" for a SPOT XS image). The spectra are then projected onto the plane of the two first factors (program "GreyHisto"). The reference spectra (i.e. the pure constituent spectra) could be chosen with a supervised or un-supervised method (programs "Triangulation" and "RectConvPtIn" for the supervised choice). Then, mixing proportions are calculated by comparing the position of the observed spectra with that of the reference spectra in the spectral space (programs "DiagTri2D", "DiagQuad2D", and "DiagPent2D" for $n = 3$,4 or 5 reference spectra). The output of the above processing is a set of n images, showing the percentages of n various types of land (forest, naked soil,...) in each pixel. On the basis of this set of images, we build a classification image (program "Mixing2ClassEntrop").

We can treat Landsat TM scenes as well as SPOT XS scenes. The number of final pure land uses, must be less than or equal to the number of channels of the scene. In the case of a Landsat TM scene, we can have about 6 different themes of land use, but with SPOT XS we cannot have more than 3.

Before the knowledge-based system was implemented, the user had to perform all the different steps, before he could obtain the images he wants to interpret. Now, thanks to the supervision system these steps and their correct chaining are automatic. The only manual action refers to the most important point: the determination of the reference spectra. Default reference spectra are automatically chosen, but the user has either to acknowledge the choice or to choose other reference spectra that he wants to work with. This point hasn't been automated because of its importance in the determination of the land use mixing values; a specialist acknowledgment is necessary to continue the process.

The final product is a set of n images, as many images as land use themes, as shown in figure 1. The intensity of the grey level of a pixel inside a theme-image is equal to the percentage of the theme inside the pixel. Examples of theme-images can be shown in (S. Mathieu and Berthod, 1994)

The user can work with this set of theme-images. Nevertheless, a naturalist also needs a synthetic view of the land he's going to study. For this kind of use, we have added to the mixing information a land use classification (cf. section 4).

Such a process, from the original scene to the classification and entropy image, is heavy to run if you have to handle all the data transferred from a program to another. The fact that the user has to choose the programs to run depending on the application and the kind of images, may introduce many unnecessary problems. The role of the knowledge-based system is to help the user in this phase, and to leave him focus on the most interesting part of the job. The system asks the user what kind of image he wants to treat (SPOT XS or Landsat TM) and what is his goal (to get a land use mixing image, a classification image, an entropy image or all). Then the knowledge-based system works alone, and only asks the user for acknowledgement.

3 Supervision of programs

The basic idea in automatic program supervision is to automate the choice and execution of algorithms from a library to accomplish the desired processing objective. This is done by emulating the strategy of an expert in the use of the algorithms. Artificial intelligence techniques have been developed for this purpose, notably in the domains of image processing (Clément and Thonnat, Mar. 1993), (Aerospace, 1991), signal processing (Nawab and Lesser, 1992) and automatic control (Favier et al., Sept. 1991).

The objective of supervision of programs in general is to facilitate the automation of (or even to automate completely) an existing processing activity, independently of any application, for example the sequence of programs to trigger in order to extract some shape in an image.

This task can be decomposed into two sub-tasks: to select and schedule the programs, which corresponds to a *planning* process, and to compute the parameter values, to run the programs and to control their results, which corresponds to a *control of execution* process.

Planning is the process of finding an ordered list of *actions* to achieve a goal w.r.t. a given complex *state of the world*. Planning is based on the description of the actions (not on the state of the world), and because the knowledge exists at several levels of abstraction, the planning processus uses *skeletal plans* with *refinement mechanisms*.

Control of execution consists in an optimisation of the original plan. Since the action results are unpredictable (it is impossible to predict the results of vision programs on the data), a good solution is to use a *predict and correct* strategy with possible re-tuning of program parameters or even re-planning.

The optimal selection of a method at a given step needs the results of the previous steps, that why planning and control of execution have to be interleaved.

In order to accomplish a given perceptual processing goal, a number of programs have to be selected, initialized, scheduled, linked, executed and monitored, with possible time and resource constraints. This job is done by a knowledge-based system, the knowledge base of which contains the necessary knowledge about the library of programs to supervise. This knowledge may be roughly divided into *planning knowledge*, which pertains to the choice of programs and their composition into processing sequences, and *execution control knowledge*, which is concerned with the setting of parameters, the evaluation of program results, and the remedial actions to be applied if the results are not satisfactory.

In our context, we do not generate new plans, we just select a best solution in an existing set of plans and programs, and we schedule the data flow. The control of execution in this application is rather simple: usually its role is to run dynamically program plans, using defaults values of parameters. Should problems occur, the hand is given back to the user. We intend to add some methods to tune the parameters values.

Based on a generic tool, we have implemented a module for these planning and control of execution requirements. This module requires some information on:

- Individual description of programs: forms describing: I/O arguments, types and (default) values of parameters, syntax to call the code,
- Skeletal plans of programs: sequencing of programmes and data I/O flow

4 Example of supervision of programs: the classification of land use

Our classification images derive from the results of the determination of the land use mixing. There are several ways to compute a classification. We choose to give to each pixel the label of the dominant land use on its surface. Land use mixing classification have been compared with maximum likehood classification of the same images. The use of ground truth and vegetation map allows us to conclude that our method is better than the maximum likehood one.

This section describes, on two particular examples, the different steps, necessary to compute a classification, from a superposition of scenes, through a superposition of theme images to a classification.

The first example consists in the classification of a Landsat TM image from South-West of France (figure 3). For this classification, the user asks for a determination of land use mixing and a classification of Landsat TM images, the knowledge-based system runs the process and the user acknowledges the machine choice for the reference spectra.

The comparison with the vegetation map (figure 4) shows that the change from fir trees to holm oak in the Nord-West South-East direction is not visible on the maximum likehood classification (figure 3 right) . The spectral difference between those two vegetations is not sufficient to be exploited by the maximum likehood method (figure 3 left). Our spectral definition of the pure land use is more accurate and we succeed in separating those two land uses. This separation is important because this kind of change in the vegetation (from fir trees to holm oak for example) is the witness of a change in the relief or in the humidity of the ground. In our case it is due to a variation of elevation. This phenomenon is hidden in the classification with the maximum likehood criterion.

The land use mixing classification is also able to find some clives labelled as naked soil and visible in the North-West of the image (red pixels). Those clives don't exist in the maximum likehood classification image.

The second example concerns a Landsat image of an area situated in the North of Spain, in a region called Logrono. The main problem of this classification is that water and pines in the shadow got about the same reflectance, as it can be seen in the Landsat TM 4 channel, figure 5. The user knows that the interesting point of the study is the separation of these two different kinds of land use. So he refuses the system choice for the reference spectra and replaces it by the spectra he wants ("S1" and "S2" in figure 5)

Figure 5 shows the cloud of spectra of the scene projected on the two dimentional space of the principal factor. Those factor are calculated by the factor analysis we use for the determination of the land use mixing. In this cloud of spectra we can see that the respective spectra of the pines in the shadow and of the water are very close ("S1" and "S2" spectra in figure 5). A classical classification can't separate them. Figure 6 shows the maximum likehood classification (right).

For this application we took five reference spectra: water ("S2"), pine in the shadow ("S1"), naked chalk soil ("S4"), naked non chalk soil ("S5"), and grassland ("S3"). The result of the classification based on the theme-image (figure 6), gives a good idea of the real repartition of the pines in the shadow and the water.

As a classification tool, the COCKTAIL librairy is very efficient, due to its accurate choice of the reference spectra and because pixels are not obliged to have labels, but can be expressed by a sum of percentages of different land uses, associated with an entropy value.

5 Implementation of the system

As said previously, the system has been implemented as a knowledge-based system, the knowledge base of which contains squeletal plans of the possible chaining of programs and a description of each program, its arguments, its semantics, and so on. These descriptions and plan squeletons are used by the knowledge-based system, to choose and adapt the programs.

For example the "Hafq3XSVarimax" program is described as follows:

Name	Hafq3XSVarimax
Input Data	*xs1*, type: SpotImage
	xs2 , type: SpotImage
	xs3 , type: SpotImage
Input Parameters	*list* , type: Integer, default: 0
Output Arguments	*fact1*, type: Image
	fact2, type: Image
	fact3, type: Image
	frq, type: Image
Preconditions	Data Files *xs1,2,3* must exist
Postconditions	Data Files *fact1,2,3* and *frq* exist
Calling Syntax	Hafq3XSVarimax -XS1 xs1 -XS2 xs2 -XS3 xs3 -list list
Language	C
System	Unix

The squeleton of possible plans is shown in figure 7.

The programs of the library are written in C. The expert-system shell and the knowledge base have been prototyped in Lisp and are currently implemented in C^{++}.

We have tested this system on a set of 30 images with the prototype in Lisp. We have obtained the following average execution times : the CPU time is 1'25" for a 400x400 image Spot XS, which is about the sum of all the computation times of the programs. The expert-system intervention adds no significant delay.

The user time has dramatically decreased from more than 20' manually, to 2' or 3', depending if the user acknowledges the system choice or not. The expert-system use saves user's time, because the user gets rid of the input/output management. For example to process a SPOT image the final script is a chaining of Hafq3XSVarimax, HistoGrey, Triangulation, LocalNSpectr, DiagTri2D, and Mixing2ClassEntrop. In this series, the user must manage the input/output data, for example he/she has to remember that the intensity file produced as output of Triangulation has to be given as input both to LocalNSpectr and to DiagTri2D.

6 Conclusion

The *cocktail* library included in a knowledge-based system gives an automatic spectral decomposition of pixels from a multi-spectral satellite image. From the AI point of view, this experiment shows that AI can be used as a complement of other classical software tools, and that it does not implies a tremendous time cost. The program supervision approach leads to transparency of use of image processing programms for non specialist end-users. The principles developed here are quite general, and applicable to a variety of situations requiring the autonomous use of complex programs.

From the naturalist point of view, there are several advantages. First, apart from the knowledge-based system, the possibility to express pixel in a land use mixing way is close to the real ground, it also allows interpretation of land use ratio in a small area. The knowledge-based system added to the *cocktail* library makes the process easier to compute and asks the naturalist only what is really important, all the ancilliary processes are automatic and don't need a human intervention. The naturalist user can focus on accurate, important and interesting points that really need his interpretation.

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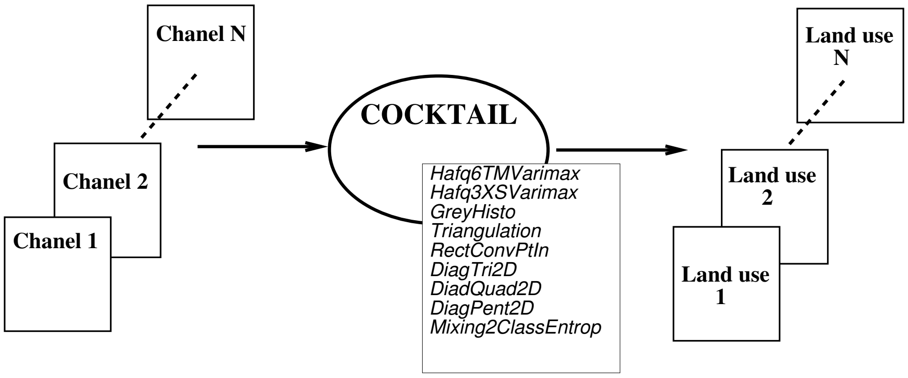

Figure 1:

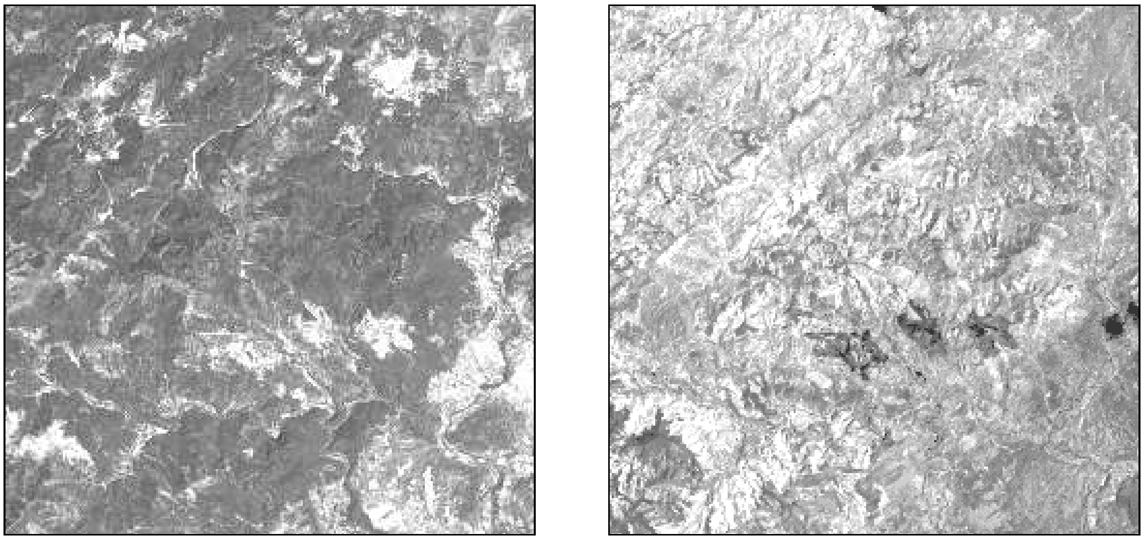

Figure 2:

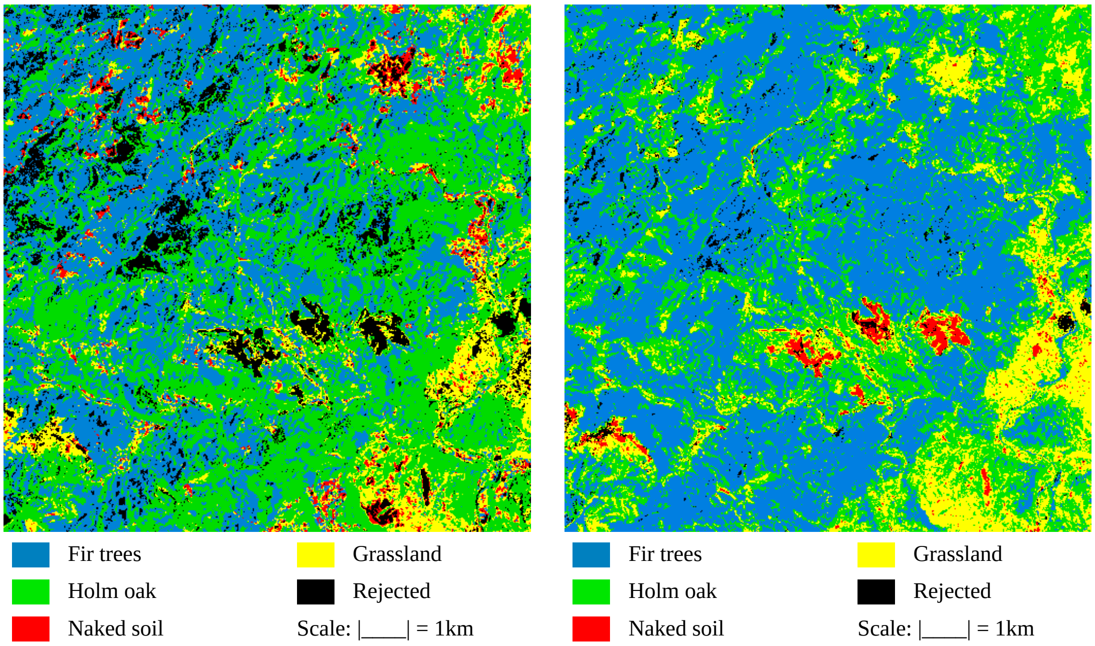

Figure 3:

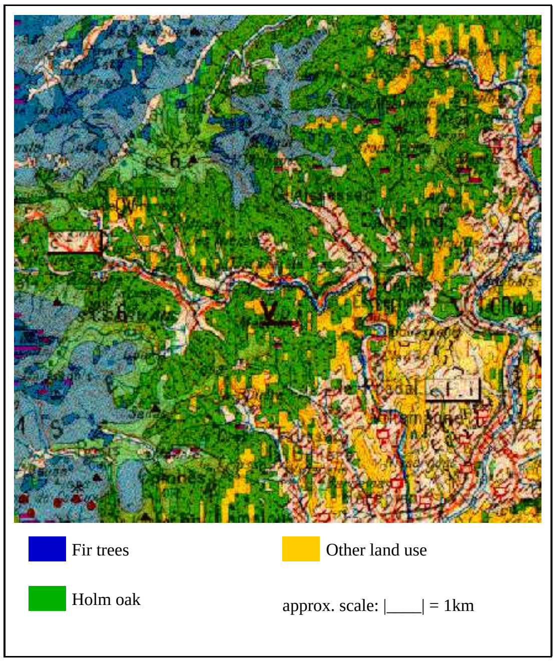

Figure 4:

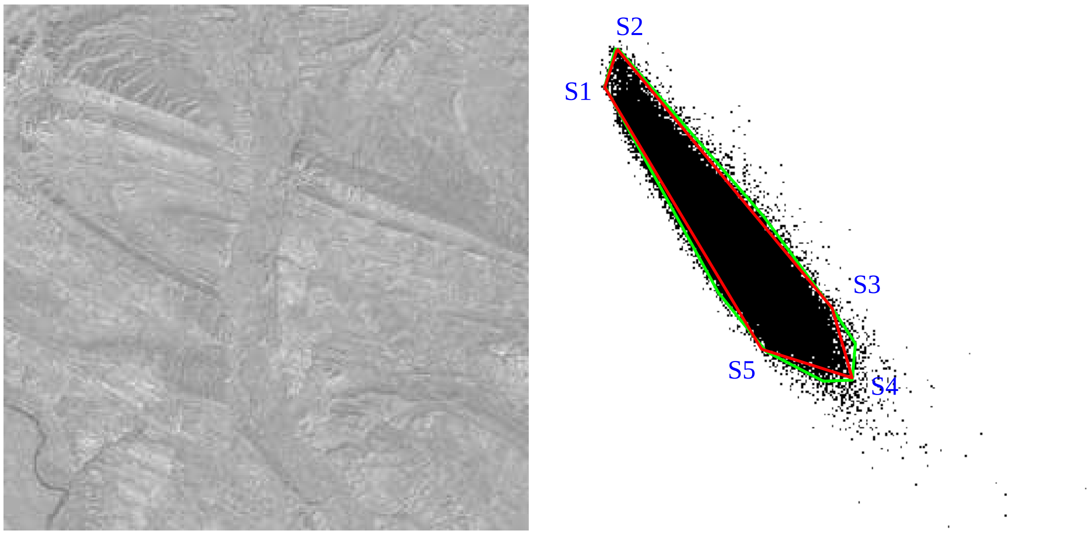

Figure 5:

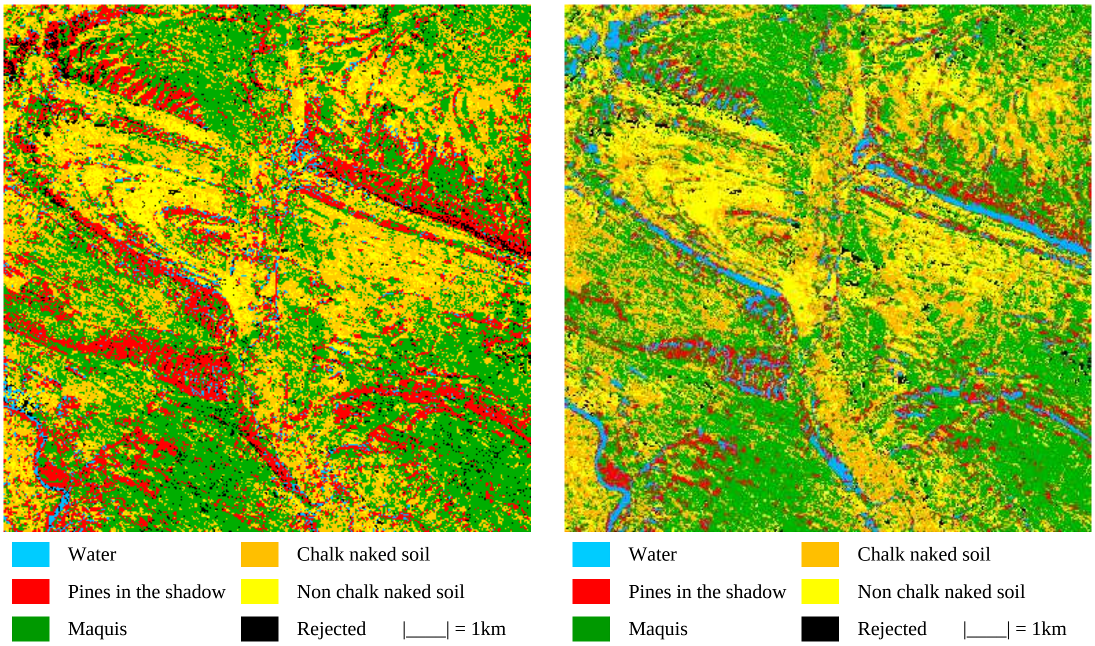

Figure 6:

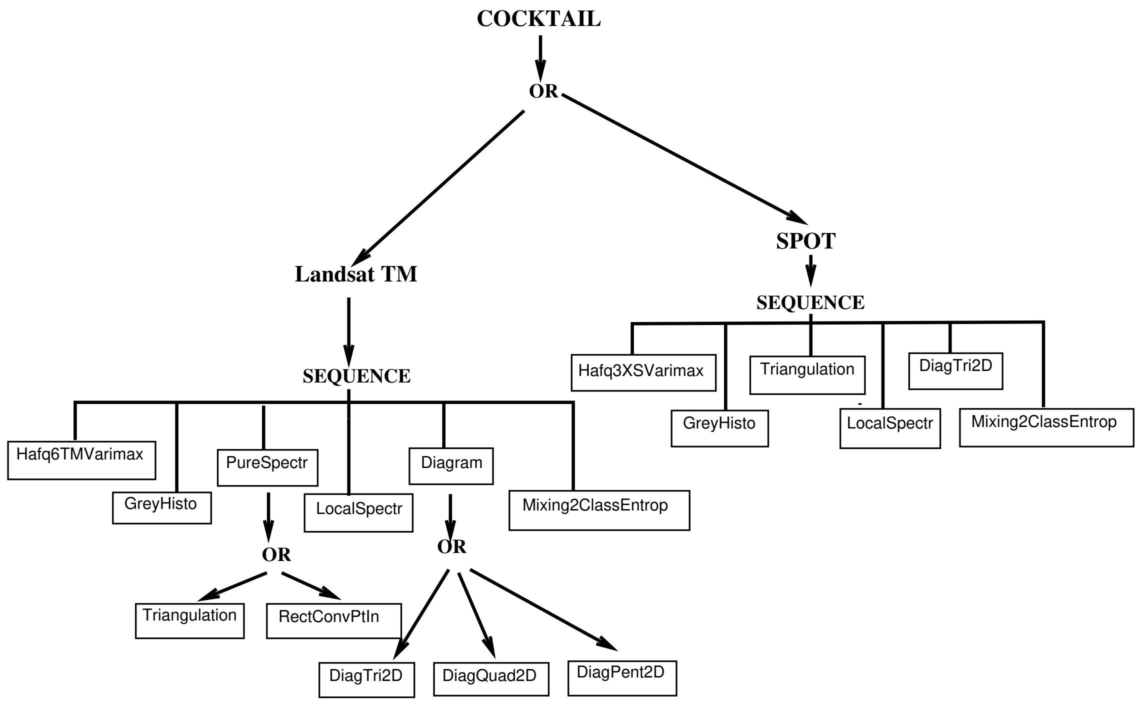
COCKTAIL
OR
Landsat TM
SPOT
SEQUENCE
SEQUENCE
Hafq3XSVarimax
Triangulation
DiagTri2D
GreyHisto
LocalSpectr
Mixing2ClassEntrop
Hafq6TMVarimax
GreyHisto
PureSpectr
LocalSpectr
Diagram
Mixing2ClassEntrop
OR
OR
Triangulation
RectConvPtIn
DiagTri2D
DiagQuad2D
DiagPent2D

Figure 7:

Figure captions

Figure 1: Scheme of the use of the land use mixing programs library

Figure 2: TM3 and TM4 channel of one of the studied scenes

Figure 3: Classification from the land use mixing values (left) and Maximum likehood classification (right)

Figure 4: Vegetation map

Figure 5: The TM4 channel, and the cloud of spectra

Figure 6: The Maximum likehood classification (left) and the classification from the land use mixing values (right)

Figure 7: Squeletal plans in the knowledge base