

Towards an Intelligent System for Remote Sensing Monitoring

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Abstract

As issues regarding environment protection become more and more important in our life, there is an increasing need of monitoring many aspects of the environment. In this paper, we outline and discuss an architecture for intelligent monitoring that we have just started developing. By using techniques developed in the area of artificial intelligence, we are trying to develop software for environment monitoring that can replace human experts in many tasks or assist them in those tasks where they are absolutely needed. That way, we hope to reduce the cost of environment monitoring and make it available to many places where it could not otherwise be affordable.

1 Introduction

As issues regarding environment protection become more and more important in our life, there is an increasing need of monitoring many aspects of the environment. However, it is not feasible to monitor and analyze most interesting aspects of the environment by relying only on human experts. Such experts cannot be in all interesting areas at the same time. Also, some areas are not simply accessible to human experts at reasonable costs. All these constraints make remote sensing inevitable in a large-scale environment monitoring.

Remote sensing deals with the knowledge and techniques used to analyze, interpret, monitor, and manage environmental changes, using optical and microwave imagery from various kinds of sensors. The management of natural resources and the increasing challenges due to the environment monitoring make remote sensing one of the key strategic technologies of the next century.

For example, airborne and satellite remote sensing already plays a key role in monitoring and predicting climatic conditions. It has been recognized that climate models using trace gas forcing alone cannot adequately account for climate trends. In order to deal with climatic change, parameters that vary significantly in space and time must be incorporated into the models [17]. These parameters include clouds, aerosols, ocean productivity, land use, and their interactions. The prime tools for measuring and deriving these parameters are advanced remote-sensing satellites.

More efficient sensing and computing facilities become increasingly available, while there are more high-resolution satellites providing greater coverage of a large number of regions. As a result, remote sensing will play a far more important role in managing resources and the environment over the next decade. In fact, some empirical experiments with hyperspectral sensors in the visible to infrared range have already demonstrated a strong potential utility for managing natural resources [13]. However,

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for the most part, today's remote sensing tools lack sophistication to take full advantage of enhanced sensor efficiency, computing facilities, and the growing widespread use of high-resolution satellites.

To illustrate, image analysis and interpretation algorithms developed in the past for low-resolution images must be adapted or simply replaced with new ones to reap the benefits of high-resolution imagery, which should make it possible to automatically extract more information from images [6]. In addition, automatically interpreting sensor images involves a huge amount of image data and various types of image manipulations, depending on the kind of information extracted. This raises many challenging issues that need to be addressed, such as designing efficient, multisource data fusion techniques to derive more information; designing algorithms that can automatically make decisions about the kinds of images must be combined or the kinds of operations that are most appropriate for extracting specific information; and designing algorithms that can combine spectral and contextual information during interpretation, much like human experts do.

To fill in this gap, we have recently initiated a research program on the development of image-analysis software that can analyze and interpret high-resolution images; represent information derived from these analysis and interpretation processes in various formats and mapping standards useable by end-users with different profiles ranging from experts to ordinary people; and deliver such information to their intended users, directly or over the Internet.

Since we are only at the beginning of a long term research program (four years), at this stage we can only discuss our current ideas about approaching this problem and the initialization steps we have gone through so far. First of all, we have outlined a multi-agent based architecture for intelligent image analysis. Then, we are gradually developing different components of the system.

The remainder of this paper is organized as follows. The next section discusses most relevant work in remote sensing. Then, Section 3 presents our software architecture for intelligent remote sensing. Finally, we discuss preliminary results obtained by using an expert system for photo-interpretation that we have developed.

2 Related Work

The problem of remote sensing involves many issues ranging from the design and fabrication of sensing equipment to developing software for controlling equipment and analyzing imagery. As mentioned above, our project focuses on image analysis and the delivery of information derived from this analysis to end-users. Image analysis basically consists of image segmentation, classification, and interpretation. Traditionally, segmentation and classification tasks are performed with statistical, connectionist, and fuzzy-logic approaches.

Statistic approaches are founded on the theory of probability, which provides a simple and reliable understanding of the underlying algorithms. However, these methods are very sensitive to the statistical distribution of the images analyzed, so that they only yield optimal results when the grey-level distribution is known a priori and appropriate. Even when these techniques yield an approximate result, it remains difficult to judge the extent to which the result is distant from the optimal solution [4]. Furthermore, these approaches hinge on Bayesian probabilities, which assume independence between implied inferences. Consequently, it is not readily applicable to images from many different sources.

In contrast, fuzzy approaches rely on a different mechanism for combining inference fuzzy rules, making it easier to analyze images from different sources [3]. Another advantage of fuzzy methods is that they are not sensitive to the probability distribution of images. However, the effective application of these methods requires the definition of *membership functions*, which are used to interpret basic facts about image properties. The problem is that the definition of these functions is empirical, which makes it hard to analyze or predict the results yielded by the overall image analysis process.

The connectionist approaches rely on the neural network model of computation, which makes it inherently parallel in the sense that the analysis function is spread across the network different nodes. In most cases, the computation is more efficient than the other two approaches. Network performance depends, however, on its architecture (layers of nodes, number of nodes in each layer, and connections between them). The problem is that there is no clear theory for establishing the appropriate architecture for given image analysis tasks [18].

Obviously, each of these approaches has its own advantages and limitations. This has prompted approaches built on combinations of all or some of the three [18]. This also raises the question of planning image processing actions [11]. Each possible operation on an image is considered as a basic action executable by the system (e.g., application of a particular filtering or segmentation algorithm to the image). Given a particular task specified by the user (e.g., “determine the vegetation content on the ground for each pixel of this image”), knowledge about the different basic image processing algorithms together with rules about combining them to achieve goals, a *planner* constructs a program made of carefully selected basic operations which, after being executed, produces the intended result.

Many planning algorithms have been proposed in the area of artificial intelligence. Lansky, among others, demonstrated the effectiveness of using such algorithms to automatically generate image processing flows that are, in fact, plans of actions, where the actions are in turn basic image processing operations [11]. However, these experiments were made in a framework less general than the one we are proposing here. In particular, they use a system with a single reasoning component, while ours involves many of them running concurrently, as explained below.

In their traditional formulations, statistic, fuzzy, and connectionist approaches perform spectral analysis on a per-pixel basis. However, the analysis of some spatial properties requires considering pixel and its neighborhood, while the analysis of temporal changes may require the analysis of multisource images [2]. Because of spatial units heterogeneity due to high-resolution image, interpretation tools must include textural, fractal, and multiscale analysis on both the local and global bases [10]. This accounts for the important role of data fusion techniques. These techniques present three major constraints: the high number of data sources, data heterogeneity, and the complex management of data imprecision and uncertainty. One approach for overcoming these constraints is to use fuzzy logic or evidence theory extended by mechanisms that take context into account [14].

On the other hand, many image interpretation tasks may require contextual information not in the image itself. For example, a human expert in photointerpretation of forest imagery could use varied knowledge to facilitate his task and, most importantly, to understand how the combination of these factors affects forests. These tasks can be based on physical criteria (texture and spatial neighborhood of trees, such as shape and structure, species identification, species health state) and ecological criteria (terrain relief, soil type, chronosequence of perturbations, precipitation) [5].

Different attempts have been made to overcome these limitations. In particular, some approaches combine supervised and unsupervised analysis, while others include spatial or temporal information in the image analysis [2]. On the other hand, expert systems have been proposed to reason about contextual information that cannot be represented numerically [16]. Many of these expert systems rely on a single inference engine that reasons on one or more knowledge bases. Single reasoning components, however, are limited to knowledge represented in the same manner. This implies that all knowledge in the system must have the same representation. Yet, photo-interpretation is inherently based on many different types of knowledge, which is generally represented differently.

3 Our Multi-Agent Approach

A sound alternative to a traditional expert system that could replicate the work ordinarily carried out by human image interpreters would involve several concurrent interpretation processes that operate independently yet co-operatively to some extent in order to derive a conclusion. These processes may operate independently, but have some form of intelligence for communicating or planning some of their own actions. To our knowledge, no such image interpretation system exists today.

The architecture discussed in this paper and that we are developing proceeds along these guidelines. The abstract design of our system comprises three major components: 1) data and program selection; 2) image analysis; and 3) interface. Each component is, in turn, composed of several software agents as shown in Figure 1. Before elaborating further on this architecture, it may be important to explain a little bit more the concept of software agent.

3.1 Software Agents

This concept is directly borrowed from the area of artificial intelligence [15]. Generally speaking, a *software agent* (or *agent* for short) is a software that has some delegation capabilities. This means that the software can accomplish various tasks on behalf of human users or of other systems. This is in accordance with the notion of an agent in everyday life such as bank tellers or mutual fund brokers.

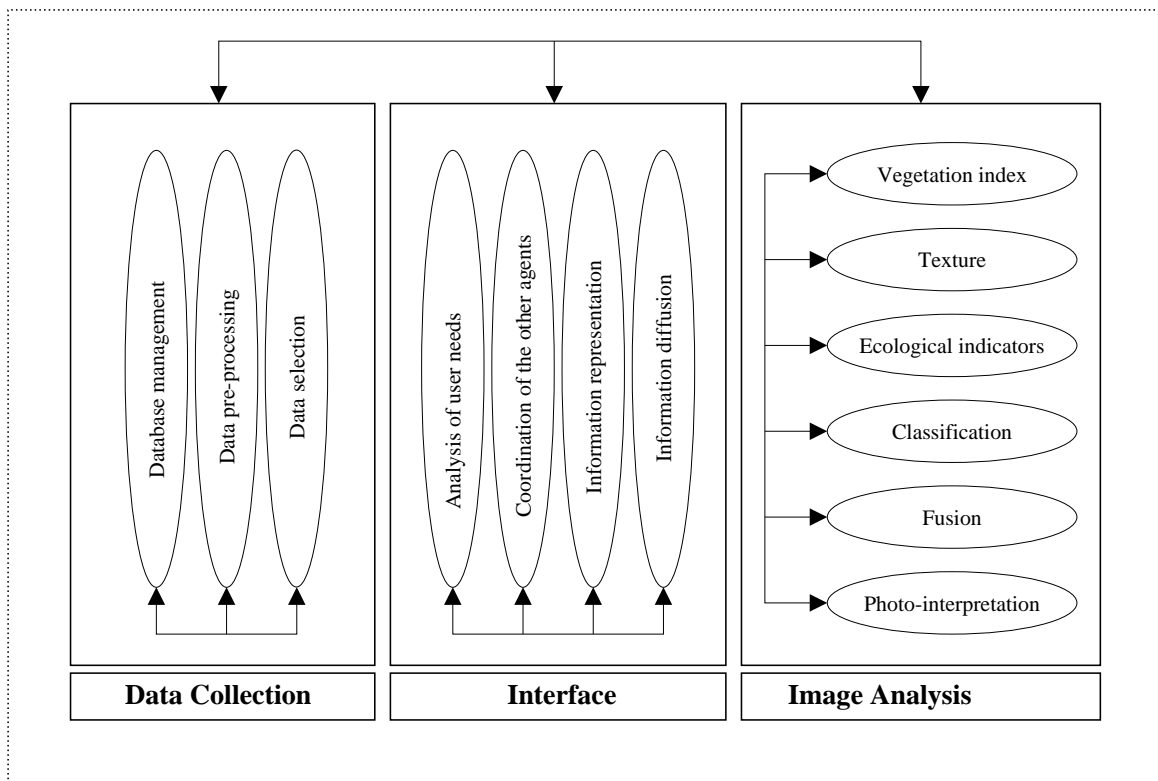


Figure 1: System architecture

An agent is said to be *intelligent* if its way of doing things involves one or more abilities that are usually associated with human intelligence. Now the question is, how do we define human intelligence? There is no single answer to this question. Ask this question to four different outstanding philosophers,

and you will get four different answers. In fact, we all agree that human intelligence exist, but the difficult is to agree on a well defined notion of intelligence. The situation is similar in computer science. Computer scientists generally have no problems in recognizing intelligent software agents, but there is no commonly agreed definition of artificial intelligence.

To avoid any debate about the correct definition of intelligence, let us simple state our meaning of intelligent software agent. We say that a software agent is intelligent if it can achieve tasks for which it has not been explicitly programmed. Most researchers in the area of artificial intelligence or software engineering will agree with that definition. In particular, this means that an intelligent software agent effectively has some delegation capability and it can also automatically adapts its own behaviors to different environments.

The agents involved in our remote sensing system will be able to plan image processing flows, help end-users to select image data that fits their needs and interpret images by using not only raw data images but also background information, much like human expert do.

3.2 Data Selection Agents

The data selection agent comprises a database of images and auxiliary data (existing data and ground truth measurements), a database of programs for image analysis, a planning process for selecting images, and a planning process for generating image data flows. The image analysis agent comprises a number of auxiliary agents involved at various levels of an image analysis task: generating vegetation indexes, analyzing textures, generating ecological indicator metrics, classifying images, fusing data, and interpreting images. The interface manages external interaction between the user and the system as well as internal interactions between the different agents of the system.

The image database may contain processed or partially processed images for certain regions. For example, it may already contain images with vegetation indexes that were created during previous interactions with users and then memorized. Thus, if no appropriate image is available, the image process flow planner includes appropriate processing actions so that the image can be imported into the database. On the other hand, when processed images are created during a particular task (e.g., segmented or classified), they are stored in the database for later reuse, if required. The memorization of processed images involves artificial intelligence deductive reasoning techniques (much like in expert systems), by taking into account many factors such as the likelihood of reutilization of imagery and by querying the user if advice on saving the imagery is required.

3.3 Image Analysis Agents

The agent for generating vegetation indexes uses spectral signatures database to adapt existing or create new indexes consistent with high spatial and spectral resolution images. This agent also analyzes spectral signatures to determine vegetation stress, the topography impact on object reflectance, multi-resolution effects (sub-pixel information), and the role of auxiliary data in vegetation discrimination [19].

The texture agent is based upon the integration of fractal and multiscale analysis, wavelet transform, and random Guassian-Markovian fields [18].

The ecology indicator agent is based on existing metrics. Various landscape ecology metrics have been developed and used throughout the landscape ecology community, such as contagion, dominance, and fractal dimension. These indicators have been successful in quantifying different features of spatial patterns, such as fragmentation, patch shape, and complexity. These features are, in turn, related to ecological and environmental processes, such as wildlife habitat, biodiversity, and landscape changes.

Since metrics vary with spatial resolution, some existing metrics will have to be improved in order to make them fit the fine scale of remote sensing data.

The classification agent is based on existing algorithms developed by Bénié *et al.* [2]. They are being adapted to make them fit high-resolution images. An algorithm based on other approaches will be developed so that the system can dynamically select those appropriate for the task at hand. Approaches that will be considered include: Markovian, fuzzy, probabilistic, and fractal functions.

The fusion agent uses weak fusion (exploiting high correlation of data images for each theme) and strong fusion (exploiting the complementarity between data spectrum, space, time, and scale) [12]. The system dynamically selects the data that must be fused.

The interpretation agent emulates a human photointerpreter by using deductive reasoning much like that in an expert system. The difference is that the agent interacts with a user and with the other system agents. Moreover, the agent contains knowledge bases and deductive reasoning components, each geared towards a specific type of knowledge. In particular, we have a subagent that reasons about the global view of the environment (maps of different landscapes) and agents that reason about local views for extracting specific objects from the scene (artificial impacts caused by anthropic actions, animals, or natural events). A typical information yield is: “vegetation cover (result of optical image, date one), cut (result of optical image, date two), on humid soil (result of radar image, date one or two)”. The knowledge base can contain a variety of information ranging from soil type and area topography to the spatial organization of scene objects. The photo-interpretation agent is further discussed later to illustrate preliminary experimental results.

3.4 Data Collection Agents

Many researchers, including Lansky at NASA Ames Research Center, have demonstrated the usefulness of planning techniques in generating image processing flows [11]. On the other hand, Bacchus and Kabanza have developed an innovative planning system called TLPLAN and have demonstrated its remarkable efficiency with comparative benchmarks against the most efficient planning systems publicly available [1]. The process flow planning agent is based TLPLAN and make use of ideas from the applications of planning to image processing mentioned above.

An agent for planning the selection of data images are built on similar ideas. In fact, the basic problem in both cases deals with the decision about what action to do and when in order to achieve a particular goal. In the case of image selection, a basic action is to select a particular image; the goal is to have a set of images consistent with a particular fusion action. In the case of process flow, a basic action is a particular image processing function; the goal is to have a sequence of image manipulations that produce a desired result.

3.5 Interface Agents

While interesting in itself, analyzing images and extracting information from them are valueless if the information cannot be delivered to users in a format they can use and in a timely fashion. With the widespread availability of commercial satellites, the profile of end-users has changed drastically ranging from experts to ordinary people, who have the barest knowledge about image representation conventions. On the other hand, the Internet makes it possible to link end-users via the World Wide Web. Users may also require information for specific deadlines, which reduces the benefit of information delivered later. For example, a farmer may need specific information within a hard timeframe in order to take decisions regarding farming activities. Thus, there is a need for more smart interfaces that can take into all these issues into consideration and yet remain user-friendly.

Our system’s interface will use artificial intelligence techniques (such as planning, machine learning,

and data mining) in order to interact intelligently with users. Users will be able to dialog with the system, specify their profiles, provide their needs (such as the type of images or information from images they want), and how system results should be returned. In turn, the system will be able to analyze user profiles, needs, and other input, on which to apply intelligent decision making processes to decide on appropriate treatment, such as activating a particular thread of image processing, suggesting a map projection system to the user, or generating a map annotated with relevant statistical data.

The interface will not only manage external interactions between users and the system, but also internal interactions between the different processes of the system. For example, given user deadlines for image processing, the interface will propagate this information down to the planning processes, which will be able to produce plans that make tradeoffs between user deadlines and the complexity of generated plans. The idea is that more complex plans yield more accurate results but take a longer time to compute.

3.6 Coordinating the Agents

All the agents operate concurrently and independently one from another, but can communicate to achieve the system goal. For example, given the goal of creating a map of the vegetation of a specific area of Labrador, the system interface will trigger events that activate the planning for selecting of appropriate data for the specific area and the planning of the appropriate process flow for these data. Assuming that no imagery with vegetation indexes exist for the area, the process flow will include analysis of images for the region in order to add vegetation indexes. The process flow may also include texture analysis to determine the structural and spatial arrangement of different vegetation elements. Along the way, the system may realize that it is necessary to retrieve additional data to be fused into current data in order to extract more accurate information. To make all this possible, each agent can communicate its needs to others or to the interface.

4 Preliminary Results

The testbed for our system is set to be Labrador's environment (in Northern Canada). This region is characterized by huge biological diversities, which include fauna and vegetation resources of great importance for the local population, water resources and peat fields, primitive areas, and interaction between human beings and their environment. In spite of the biological diversity, very few geoscientific studies on Labrador have been undertaken because of its harsh climate, its low population density, limited access to its land, and limited development of its natural resources to date. The basic database includes satellite and airborne imagery (SPOT, LANDSAT, RADARSAT, CASI), videographs, aerial photos, topographic base maps, 35-mm photos, habitat maps, forestry classification maps, digital terrain models, GPS data, and ground proof measurements from that region.

The bulk of our system is still under the stage of specification, but we already have a partial implementation of the interface and image analysis module. The current interface is shown on Figure 2. The user can display an image and select an area by dragging a mouse or by entering the coordinates on the keyboard. Then he can perform an image processing task, such as photo-interpretation.

The photo-interpretation agent is basically an expert system with a library of basic image processing functions, an image database, and a knowledge base for photo-interpretation rules. The expert system shell is Java Expert System Shell (JESS) from Friedman-Hill at Sandia National Laboratories [8]. The image processing library is the Java Advanced Imaging Application Program Interface (JAI) from Sun Microsystems [9]. We designed an internal interface for integrating JESS, JAI and our image database. With this interface, JESS can call JAI functions to assert facts about images in the database, by accessing individual pixel values or determining characteristics.

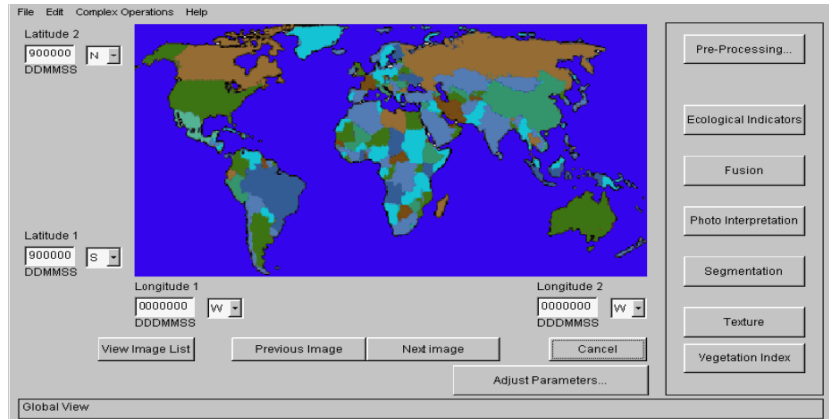
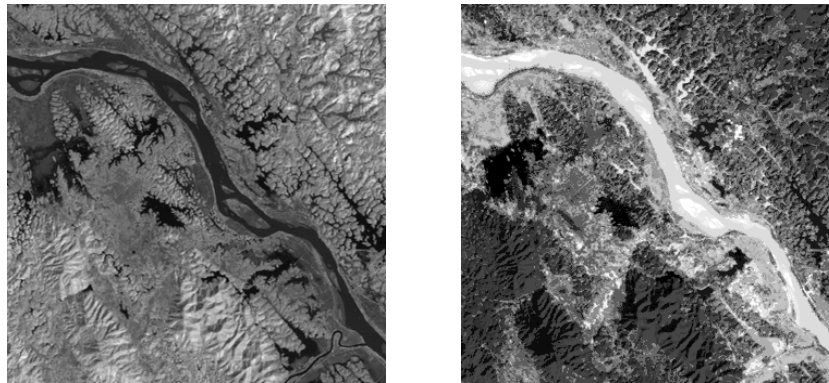


Figure 2: Image Analysis Interface



(a) Near-infrared Picture

(b) Classified picture

Figure 3: Images from the database

To illustrate, Figure 3 shows two different images from our database. The first one is a raw near-infrared picture and the second one is its corresponding classification obtained using specific functions in our image processing library. Figure 4 shows examples of two rules among several many recorded in a knowledge base for recognizing water, forest and other features. Finally, Figure 5 shows the result yield by our photo-interpretation when asked to interpret the raw picture in Figure 3(a).

In a typical interaction, when the user pushes on any of the image processing buttons, the system checks if there exist pre-processed images for the selected area sufficient for processing the image. If not, the required images are computed using the image processing library and then stored in the database. Then, the expert system is ran on both theses images, using its knowledge base. In the previous example, the expert system only needs the raw picture and a corresponding classified image.


```

(defrule threshold-muddy-water
  (can-detect-water ?picture1 ?picture2 ?year1 yes)
  (muddy-water yes)
  =>
  (assert (threshold-for-water 50))
  (printout t "Water is muddy in this area. \
              Thresholding changed for 50." crlf)
  (detect-water ?picture1 ?picture2 0 50)
  (assert (water-treatment finished ?year1)))

(defrule can-detect-vegetation
  (water-treatment finished ?year4)
  (near-infrared-image ?picture1 set-nbr ?year1)
  (red-image ?picture2 set-nbr ?year2)
  (classified-image ?picture3 set-nbr ?year3)
  =>
  (if (and (= ?year1 ?year2) (= ?year1 ?year3) (= ?year1 ?year4)) then
    (printout t "We can detect vegetation and forest \
              with " ?picture1 " and " ?picture2 crlf)
    (detect-forest ?picture2 ?picture1 ?picture3)
    (detect-vegetation ?picture2 ?picture1 ?picture3)
    (print-pixel-class ?picture3)))

```

Figure 4: Examples of rules from the knowledge base

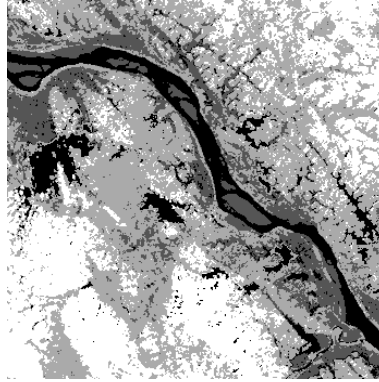
5 Conclusion

As basic image processing algorithms are becoming more efficient thanks to intensive research in the area of image processing, the main goal of this research is to develop a tool that integrate to perform environment monitoring. The integration relies on quite well defined artificial intelligence methods, such as deductive reasoning (as implemented in our current expert system) and planning (currently under implementation). We test these methods in the field of remote sensing monitoring and at the same time find adjustments for cases where they do not fit. This is a four year research project, but as illustrated by the current prototype, we will have a working system at different stages, with an increasing level of sophistication.

The above simple experiment illustrates what our system can currently do, but this is still far from the objectives outlined in this paper. For instance, we have mentioned that image processes (such as classification) usually take time. Thus, the system should be able to anticipate the image processes that will be required by the expert system in order to perform them in advance. This relates to planning image process flows.

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Forest
 Vegetation
 Water
 Unknown

Figure 5: Photo interpretation result

References

- [1] F. Bacchus and F. Kabanza. Using temporal logic to control search in a forward chaining planner. In M. Ghallab and A. Milani, editors, *New Directions in AI Planning*, pages 141–153. ISO Press, 1996.
- [2] G.B. Bénié, Y. Voirin, S. Foucher, M. Germain, R. Diébré, J. Boisvert, and A. Devost. Cartographie du parcellaire à l’aide d’images radarsat : essai d’algorithmes de classification spectrale et contextuelle. In *Synposium ADRO*, 1998.
- [3] E. Binaghi. Fuzzy contextual classification of multisource remote sensing images. *IEEE-GERS*, 35(2), 1997.
- [4] I. Bloch. Incertitude, imprécision et additivité en fusion de données : point de vue historique. *Traitement Signal*, 13(4):267–288, 1996.
- [5] T. Brandtberg and F. Walter. Automated delineation of individual tree crowns in high spatial resolution aerial images by multiple-scale analysis. *Machine Vision and Applications*, 11:64–73, 1998.
- [6] *Canadian Journal of Remote Sensing*, 24(2), 1998.
- [7] R.C. Frohn. *Remote sensing for landscape ecology - New metric indicators for monitoring, modeling, and assessment of ecosystems*. Lewis publishers, 1997.
- [8] E. Friedman-Hill. *JESS, the Java Expert System Shell*. Sandia National Laboratories, <http://herzberg.ca.sandia.gov/jess/>.
- [9] *JavaTM Advanced Imaging API*. SUN Microsystems, <http://java.sun.com/products/java-media/jai/>.
- [10] S. Krishnamachari and R. Chellappa. Multiresolution gauss-markov random field models for texture segmentation. *IEEE-IP*, 6(2):251, 1997.
- [11] A. Lansky. Web-based planning for image processing. In *Proceedings of the 1996 AAAI Spring Symposium on Acquisition, Learning, and Demonstration: Automating Tasks for Users*, Stanford University, 1996.
- [12] R.S. Lunetta, J.G. Lyon, B. Guindon, and C.D. Elvidge. North american landscape characterization dataset development and data fusion issues. *PERS*, 64(8):821–829, 1998.
- [13] H.L. Qiu, N.S.N. Lam, D.A. Quattrochi, and J.A. Gamon. Fractal characterization of hyperspectral imagery. *PERS*, 65(1):63–71, 1986.
- [14] G. Shafer. *A Mathematical Theory of Evidence*. Princeton University Press, Princeton, NJ, 1976.
- [15] K.P. Sycara *et al.* Intelligent agents. *AI Magazine*, 19(2):11–92, 1998.
- [16] A. Taylor, A. Cross, D.C. Hog, and D.C. Mason. Knowledge-based interpretation of remotely sensed images. *Image and Vision Computing*, 4(2):67–83, 1986.
- [17] D.L. Versegny, N.A. MacFarlane, and M. Lazare. Class: a canadian land surface scheme for GCMs, ii. vegetation model and coupled runs. *International Journal of Climatology*, 13:347–370, 1993.
- [18] D. Wu and J. Linders. A new texture approach to discrimination of clearcut, canopy, and burned area using airborne c-band SAR. *IEEE-GERS*, 37(1):5–53, 1999.
- [19] M.A. Wulder, E.F. Ledrew, S.E. Franklin, and M.B. Lavigne. Aerial image texture information in the estimation of northern deciduous and mixed wood forest leaf index (lai). *RSE*, pages 64–76, 1998.