Toward a Multi-Temporal Approach for Satellite Image Interpretation

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Abstract: *Multi-temporal remotely sensed images have proved to be of great interest for earth resource assessment and environment monitoring. Automatic or semi-automatic interpretation of these images becomes an important and complex task in computer vision for land use change detection. However, facing the complexity of such images, many classical image interpretation techniques become inefficient. In this paper, the proposed approach, based on multi-agent system and hierarchical blackboard architecture allows an intelligent, concise and flexible control of a multi-temporal scene interpretation. It proposes the combination of semantic network representing the generic description of the scene, and a state transition diagram, modeling the possible state transitions for each one of the classes of interest. This system produces a hierarchic description of the results as well as the structural context of the identified objects including the associated attributes. We illustrate the design and implementation of our system on a set of multi-temporal satellite images SPOT4 representing a center tunisian region for different dates in order to illustrate the potential of the proposed multi-temporal approach.*

Keywords: *Multi-temporal remotely sensed images, interpretation, hierarchical blackboard architecture, multi-agent system.*

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1. Introduction

With the rapid development in remote sensing, digital image processing becomes an important tool for quantitative and statistical interpretation of remotely sensed images [16]. These images, often, contain complex and natural scenes. The constant increase in the amount of data to treat issued from satellites images, has made automatic content extraction and retrieval highly desired goals for effective and efficient processing of remotely sensed imagery. One of the main difficulties of these applications is the knowledge representation of objects, scene and interpretation strategy [1, 2, 5].

In this paper, we present an integrated hierarchical approach based on the use of blackboard and multi-agent system in order to increase the degree of semi-automatic interpretation of remotely sensed images [4, 18]. This approach makes use of four types of knowledge: *spectral*, which relates the homogeneous classes of spectral response to the correspondent classes of interest; *contextual*, indicating the relevant contexts for the discrimination of classes with similar spectral responses; *geometric*, which relates to the shape and at least the *multi-temporal* knowledge which consider both the former classification of the region and the plausible class transitions in time interval.

The sequence of interpretation was split up in two complementary processes, called top-down and bottom-up. In the top-down process, hypothesis, represented as hypothesis instance nodes, are generated from the possible occurrence of any expected object. Each one of the hypotheses corresponds to some concept of the conceptual network. The bottom-up process tries to validate the hypothesis in order generates the symbolic description of the proposed scene. During the interpretation, the generic semantic network generates an associated network of instances based on the network hypothesis.

In our approach, the blackboard system is used as a collection of intelligent agents gathered around a multi-level blackboard, looking for information written on it, thinking about the current state of the solution, and writing their generated conclusions on it. Each agent consists of special context combined with a knowledge source to contribute toward the solution in opportunistic way. The blackboard acts as a shared memory, visible to all agents and permitting communication inter-agents instead of using point-to-point communication.

The proposed architecture is composed of three levels of independent blackboards and parallel knowledge sources which are: high level, intermediate level and low level. The low level is composed from specialists and groups agents operating over image pixels proposing the possible solutions. The intermediate level is composed from tasks and treats the results furnished by the specialists to formulate new hypotheses. The High level constituted by strategies that meet all the results of the tasks to generate a new strategy.

This architecture provides a convenient way for task decomposition. Whenever a task is too complex, it can be divided into subtasks. This hierarchical architecture is motivated in order to avoid the bottleneck caused by the growing number of the knowledge sources on a single blackboard, reduce the information complexity and complex tasks and increase the system efficiency whenever the information is distributed over several blackboard levels. This paper is organised as follows: in the first step we present the different approach concerning the interpretation of different types of scenes based on the use of knowledge. In the second step, we introduce the top-down and button up interpretation process based on semantic networks. We present the proposed approach for a multi-temporal modelling for a sequence of satellite images.

During the last two decades, several works concerning the interpretation of different types of scenes using the knowledge based approach have been successful. Among these works, we can cite the sigma, kids, icare systems which based on an expert system, the aerosol and alain boucher's system which based on multi-agent system [17], the vision, messiei and skids system which based on blackboard architecture [10].

Unfortunately, none of them propose a generic architecture for a scene analysis system which can be application independent. In fact, the knowledge representation and the reasoning strategies in most of these systems are often application. This is a big drawback because that means new development have to be made for each new application [9]. But on the other hand, an important, fact emerges is the use of blackboard architecture, in most of these systems, to design scene interpretation applications. This architecture seems very adapted to model a high level vision process. Its main characteristics are based on a global data base which can be organized in different levels of representation, a highly modular structure and an easy management of various strategies and reasoning control [20]. Nowadays, many approaches tend to interpret images sensed images by using semantic networks.

The goal of our work is to propose a generic scene analysis system in term of application independent architecture and world modeling. The main characteristic of such system is its reasoning ability in order to find the best strategy to extract visual information needed for this goal. To do this, it needs two kinds of knowledge which are descriptive and operational knowledge [19]. The descriptive knowledge used to describe the scene and the objects within. The operational knowledge used to describe how to combine different information to deduce new facts [8].

While segmentation the system extract a large scale of information from multi-temporal images and the main problem of a scene interpretation system is to select and process only the relevant information, to avoid problems like combinatorial explosion and very long processing time.

2. Semantic Network

A semantic network contains two different types of knowledge: declarative and procedural knowledge. Declarative knowledge consists of concepts and links, while procedural knowledge contains methods for determination of attributes of concepts as well as for valuation of concepts and relations. The declarative knowledge can be described by a marked and directed graph, where the nodes are attributed. Therefore, graph-theory can be applied for the control and analysis process within a semantic network [14].

Semantic networks consist of nodes and links, and are defined as directional acyclic graphs. Specifically, in our system, nodes represent the objects expected in the scene, whilst links describe the relations between the objects. In this context, the initial description of the scene contents, including nodes and links, is called conceptual semantic network. We define three different sorts of nodes: the class nodes represent classes of objects, the compound nodes represent objects detected in the scene and end nodes represent sets of attributes and characteristics for each object.

The sequence of interpretation can be split up in two complementary processes, called top-down and bottom-up. In the top-down process, hypothesis, represented as hypothesis instance nodes, are generated from the possible occurrence of any expected object. Each one of the hypotheses corresponds to some concept of the conceptual network. The bottom-up approach tries to validate the hypothesis. In this way, the interpretation process generates the symbolic description of the proposed scene [21].

2.1. Top-Down Process

The top-down process has the task to separate a region into sub-regions and to build hypothesis for the expected objects. The task is realized recursive from the upper nodes in the semantic network to the lower nodes [21]. For this purpose any proposed agent can be integrated, which creates hypothesis for the sub-regions by means of four view points which are geometric, radiometric, spatial context and functionality. During the top-down-analysis the restrictions of the concepts are checked and hypothesis, which are not conform are deleted.

The depicted process chain is shown in Figure 1. The top-down step generates a hypothesis network; the bottom-up-step generates an instance network. Each semantic object specialist has its own detection strategy. In general way, a semantic object specialist starts by asking a low-level feature extraction according to one of the semantic, object view point (geometry, radiometry and spatial context) and uses the others view points to validate the selected features. Therefore after the validation step, the scene could be described as a collection of different types of objects and each object as a collection of samples with different description and parameters as in Figure 2.

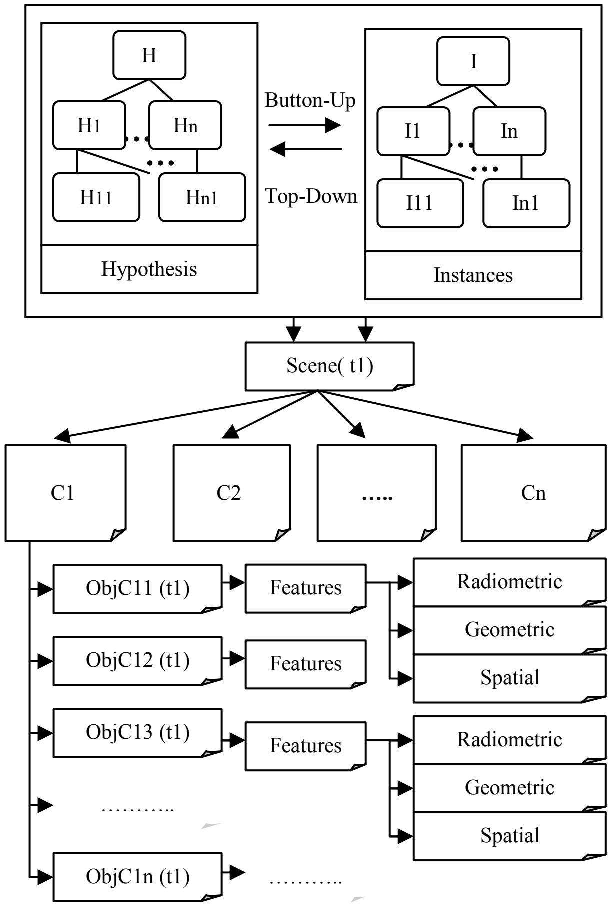

Figure 1. Semantic scene description top-down and botton-up process.

2.2. Bottom-Up Process

The bottom-up process has the following tasks [21]:

- Extraction of object attributes and measurement of single objects.
- Grouping of objects with guidelines of the user.
- Adaption of the label images to the new obtained interpretation.

Measurement of the new group, generated by the bottom-up-step. If the top-down-analysis reaches the leaf nodes, the analysis turns from model based interpretation to data based interpretation (bottom-up). The bottom-up process can also be extern programs, designed by the user. The top-down path can generate different hypothesis for one region. The bottom-up-step has to decide for an explicit interpretation for a region, as shown in Figure 1.

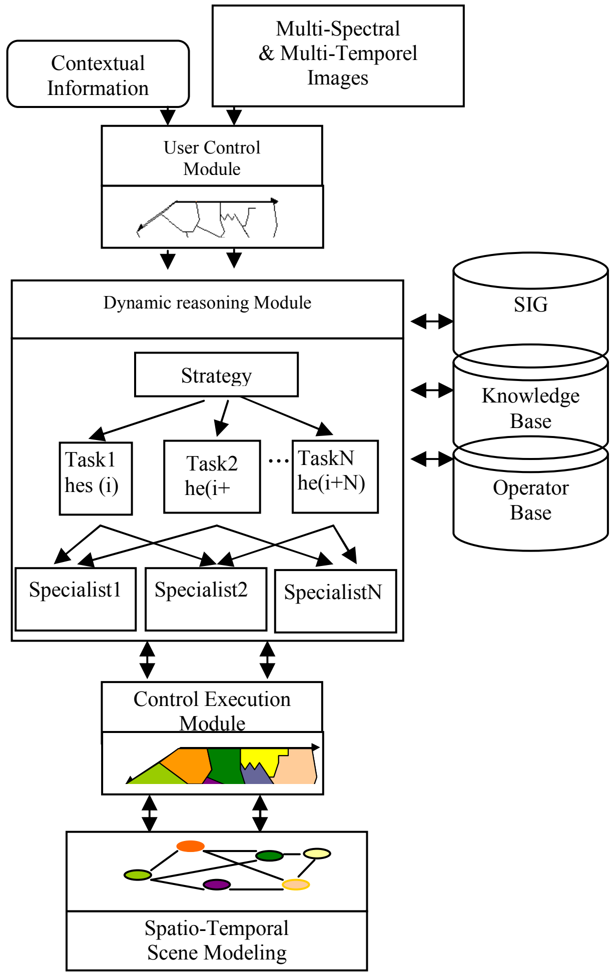

Figure 2. The proposed architecture.

3. The Proposed Architecture

This system has distributed hierarchical blackboard architecture, as shown in Figure 3, and based on a set of knowledge sources communicate through o multi-level data structure. The knowledge sources are structured in a three level hierarchy: Strategy, tasks and specialists [10].

Our system in Figure 2, is composed of three modules which are the user control module, the dynamic reasoning module and the execution control module. Each level represents a different view of the goal resolution space. The hypothesis is the basic data unit of the blackboard and represents a partial solution. The agents are invoked by the control mechanism in response to a particular change on the blackboard which is the event [3, 6, 12].

The user control module is in charge of supervision and interaction with the operator. The blackboard structure of this module contains a symbolic description of the scene. The dynamic reasoning module is the center of intelligence of the intelligent control system. Strategies are received from the user control module. The blackboard structure of this module consists on three abstraction level hierarchy: strategy, tasks and specialists.

The execution control module is responsible for the execution of actions specified by the dynamic reasoning module. On each level the agent control is responsible of the management of the structure and for scheduling of the agents. Each level receives events from other levels or from other modules. On each level, a control agent identifies the event type and processes it. Types of events can be modifications of the blackboard data or signals of agent termination [13, 15].

The evolution and change of system agents is supported by the architecture. The architecture of the multi-agent systems is able to cope with evolution of the system. New agents are able to enter the systems as knowledge source or control, whereas old agents may leave the systems [7, 11]. Agents are also adaptable to different environment. In this situation, agents are reusable in different systems and environments [22].

4. Multi-Temporal Scene Modeling Using Graph

Applications like change detection and environmental monitoring require the analysis of images from different acquisition times. By comparing the current image with the latest interpretation derived from the preceding image, land use changes and new objects can be detected.

The temporal approach proposed employs a transition graph, as shown in Figure 3, to describe the temporal dependencies between the classes of interest. The transition graph models the expected transition of objects in the scene. Temporal changes can be formulated in a so called state transition graph where the nodes represent the temporal states and the edges model the state transitions. To integrate the transition graph in a semantic net the states are represented by concept nodes which are connected by a new relation: the temporal relation. As states can either be stable or transient, the corresponding state transitions differ in their transition time which can be also specified in the temporal relation. The start and end node of temporal relations may be identical forming a loop to represent that the state stays unchanged over time.

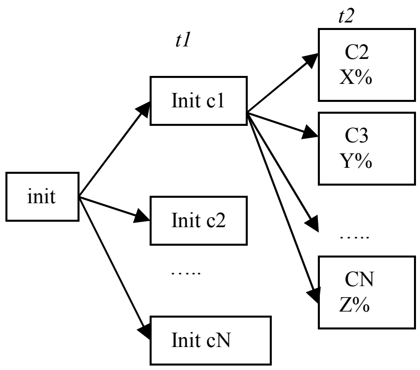

Figure 3. Sample evolution model using graph.

During the interpretation process, the state transition diagram is used by a new inference rule. Analysis starts with the first image of the given sequence marked with time t1. If a state of the state transition diagram can be instantiated completely, the temporal knowledge is used to hypothesize one or more possible successors of this state for the next image in the chronological order (time t2). The system selects all successor states that can be reached within the elapsed time *t2–t1* according to the transition times defined in the temporal relations.

5. Validation

In order to validate our approach, we are carrying out the pre-processing of SPOT images with different filters. The study area is situated in center tunisia (north africa).

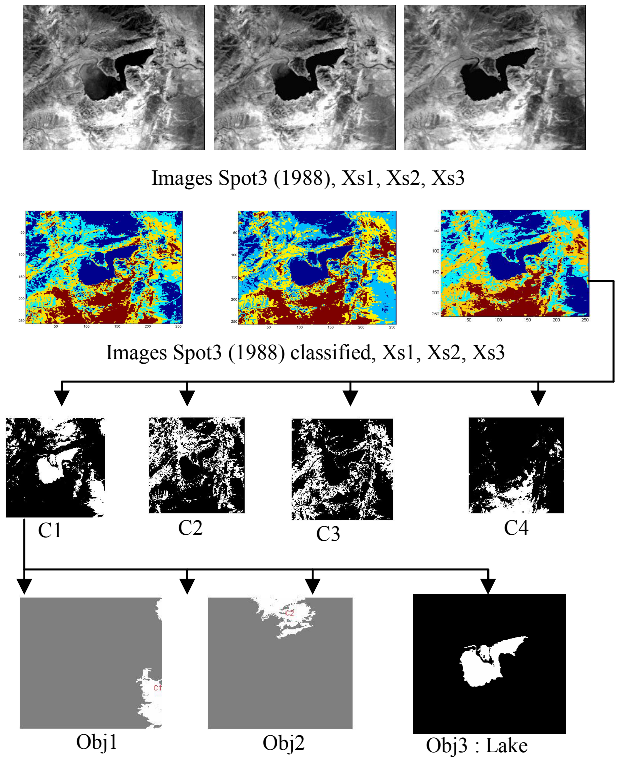

Figure 4. Spot images 198.

The basic system implemented by a multi-agent system was each agent associated to an operator located in the operator base and provided by the dynamic reasoning module. As an input, the satellite images (as shown in Figure4 and Figure5) used in our application is provided from different sensor like XS1, XS2 and XS3.

The first agent was an agent classifier using unsupervised operators for classification provided by the operator base and evaluated by a multi-agent engine which combine facts and rules provided from knowledge base [6]. The output classified images, as shown in Figures 4 and 5, represent for classes (humid zone, stony soil, bare soil, vegetation). These classes allow the extraction of principal objects by means of radiometric, geometric and spatial features. This information was given as an input to the agent change detection in order to compute the similarity between objects and detect the change occurred since 1988 in our zone of interest, as shown in Figure 6. In our example, we cope with the transition occurred in the lake and specially the transition from humid zone to other classes, as shown in Table 1.

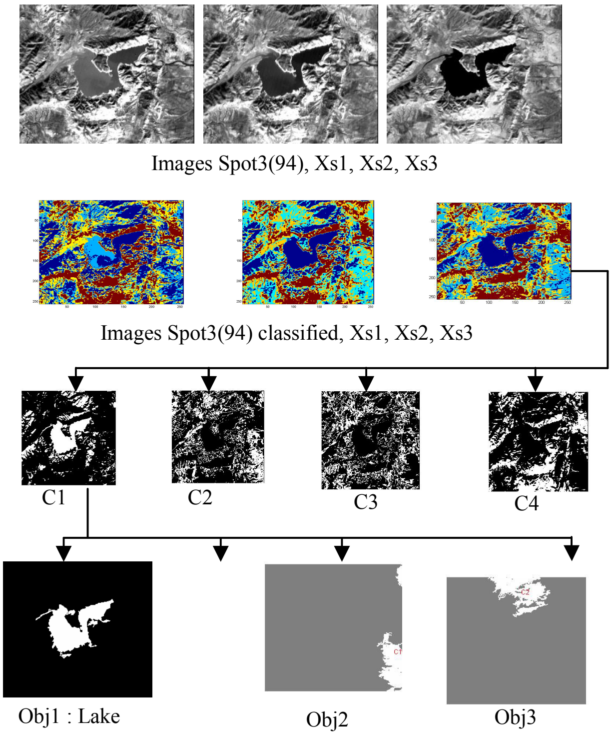

Figure 5. Spot images 2001.

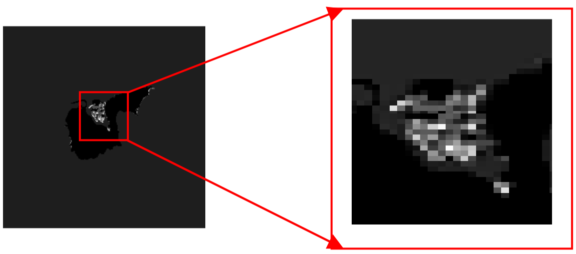

Figure 6. Change detected in the lake between 1998 and 2001.

Table 1. Humid zone transition.

	C1 : Humid Zone	**C2 : Stony Soil**	**C3 : Bare Soil**	**C4 : Vegetation**
C1(%) : Humid Zone	92.76	4.75	1.80	0.68

This transition was expanded with a state transition diagram to handle temporal dependencies to model relevant changes in the data. The Figure 7 explain the transition occurred in the object (lake): 92.76% of surface stills a humid zone, 4.75% of the total surface changes to stony soil, 1.8% of the total surface changes to bare soil and 0.68% of the total surface changes to vegetation.

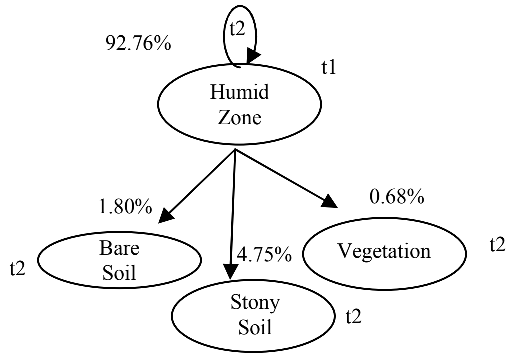

Figure 7. Graph transition.

6. Conclusion

The conception of an application specialized in image processing and analysis consists in configuring the graph of the adequate operators. This configuration results from the auto-organization of a system composed by agents, representing operators and having essentially a cooperative and a social attitude. That system organizes itself and stabilizes according to the reactions coming from its environment. In this approach, one doesn't construct an application while asking a system to solve a completely specified problem but the application will result from the adaptation of a system conversing with the user to put his own concepts in adequacy with those of the studied domain.

The semantic net models relation-ships between objects and primitives extracted from images. The system was expanded with a state transition diagram to handle temporal dependencies. The temporal dependencies were used to find relevant changes in the data. By modelling an older state of the data and following change detection a good correspondence to the present day situation was achieved. The state transition diagram may also be used to perform a detection of temporal changes of objects as found in monitoring tasks.

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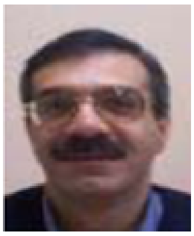

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