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Survey on the Utilization of Artificial Intelligence in Remote Sensing

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ABSTRACT

This manuscript reviews current research on the usage of artificial intelligence in remote sensing and related sub-fields. Remote sensing is a geographic analysis tool capable of producing large quantities of data in the spectral, temporal and spatial domains. Artificial intelligence (AI) is the field of research which develops computer programs to solve problems in ways that appear to emulate human intelligence. Techniques for automating the image analysis process would be advanced by the inclusion of artificial intelligence techniques in the design of image processing systems. The remote sensing applications which show promise for successful implementation of artificial intelligence techniques are intelligent onboard processing, advanced database interrogation, and the automated analysis of multispectral imagery. While general purpose programs for AI have proven too difficult to develop, it was found useful, at times, to store separately information that could be used to make a computer program behave intelligently. Various knowledge-based systems have been built for processing images in the fields of robotics, natural language interface, computer vision and geographic information systems. Intelligent classification is a hot topic in remote sensing study. Traditional approaches of classification may have some limitations in constructing proper classifiers when the study area is complex. Therefore, it is necessary to introduce intelligent methods to improve the accuracy of classification.

Key words: remote sensing; artificial intelligence; image classification; expert systems

1. INTRODUCTION

During the past few years, a new attention has been paid to the application of artificial intelligence (AI) in the remote sensing field. Several papers were published introducing the basic concepts of AI and expert systems to the remote sensing and earth science community [1]-[3]. General background material on artificial intelligence will be presented including a discussion of "expert systems," an area of AI which is believed has great potential for direct application to a variety of remote sensing tasks, particularly in computer-assisted image analysis. Applications of AI to remote sensing will be reviewed including onboard processing, database interrogation, and the potential of AI techniques for improving our capability to perform automated analysis of multispectral imagery. Some issues involved in the development of an AI-assisted image analysis system are also discussed. The impacts of AI techniques on the acquisition, processing, and analysis of remotely sensed data can be profound, however their successful implementation will require substantial effort.

AI is the art and science of making machines perform tasks which would require intelligence if done by humans. The field encompasses a wide range of applications from the modeling of sensory capabilities such as speech and vision to the more cognitive activities of planning and decision-making. The classification of what constitutes an AI program is evolving along with the field of AI. As such, there is no single characteristic of an AI system that can distinguish it from more conventional systems. There exists a set of characteristics which typify the AI approach, but AI techniques can easily be integrated with non-AI techniques to develop a specific program. Thus, there is a continuum along which systems could be classified as being more or less AI-oriented if the program characteristics could be quantified. AI the extremes the underlying principles are quite different; examples of these differences were discussed [4].

The human approach to problem-solving uses abstract symbols to refer to certain concepts and to the relationships between them in terms of type, time or space. AI programs manipulate characters representing names or symbols by symbolic reasoning. It is not a simple task to transform such relationships into symbols. Generally, in applications such as remote sensing and image processing, it is not completely known in advance what an image represents or contains. Few computer vision or geographic information system studies have investigated the problem of defining spatial relationships or computing spatial transforms in order to study the information content of an image. A comprehensive study on the development of image analysis of remotely sensed data was made by Zhang et.al [5].

Region-based analysis has developed from statistical classification and has led to using the concept of "object", spatial properties of regions, and multispectral properties. On the other hand, target detection has emphasized the importance of contextual and semantic constructs among objects in their recognition. AI methods have been employed for representing knowledge and for developing control structures for organizing such knowledge in the performance of complex analyses of airborne remotely sensed images [6].

This report reviews current research on the usage of expert systems for remote sensing and the related sub-fields of computer vision and geographic information systems. Some of the difficulties in applying artificial intelligence methods of remote sensing are described.

2. BACKGROUND

In most AI programs, there is a fairly rigid separation of input data concerning the problem, operations which manipulate the data, and the control structure which directs the flow of the program. The knowledge base in an AI program is typically an autonomous component that can be directly modified, augmented or reduced by interactions with the operations portion of the program, or indirectly through the control structure. Knowledge is often stored in the form of rules, especially in so-called "expert systems." In sharp contrast, non-Al programs typically have rules contained within the control structure of the program, making the knowledge somewhat inflexible; such knowledge usually cannot be modified without physically rewriting the program [7].

Encoded knowledge in AI programs tends to be symbolic rather than numeric in nature. Such symbols refer to characters or character strings which may be related to other strings in a list or a data structure. This permits the programming of more cognitive activities such as problem-solving, planning and deduction than do numeric operations. AI programs emphasize "state" specific programming. An action is performed when a specific set of conditions have been fulfilled and not necessarily in any particular order. The control structure dictates what should happen in each "state" but it is not necessary to know in advance when each state should occur. Non-AI programs dictate how the program will move from one state into another, from one moment to the next. These programs are considered to be sequence-oriented. For additional general information concerning AI refer to [8], [9].

Problems being considered by the remote sensing community at present are: taxonomies of terms of LANDSAT MSS image analysis, knowledge bases for contingency analysis, and the identification of rules for specific applications. Among the applications, the following have been developed: (1) land cover analysis (including forest clear-cut monitoring and vegetation change detection); (2) map-assisted photo interpretation; (3) image segmentation; (4) hyperspectral image analysis; (5) cartographic feature extraction; (6) analysis of geological structures; and (7) structural analysis of complex aerial photographs. Considerations are made on the advantages in the new approaches and of the difficulties in the application of artificial intelligence. Of particular interest to remote sensing are intelligent information systems based on workstations that handle both symbolic and spatial data through graphic interaction with raster and vector data structures. The problems currently being investigated with AI techniques by the remote sensing community at the present are: taxonomies of terms of LANDSAT MSS image analysis, knowledge bases for contingency analysis and the identification of rules for specific applications. These applications include land cover analysis, geological structure analysis, map assisted photo interpretation, image segmentation and cartographic feature extraction [10].

3. EXPERT SYSTEMS

An area of AI which appears to have significant near-term potential for application to remote sensing is that of expert systems. Human experts are often distinguished by their possession of extensive knowledge concerning a specific domain of problems. It is this very specification of knowledge that has made it feasible to develop "expert system" computer programs [11]. Classification programs tend to be the simplest and the most successful expert systems and they have the most potential for immediate application to remote sensing tasks. Human experts do much more than just solve problems. Their activities are characterized by a wide range of behaviors with problem-solving being the most evident. Experts also explain results, learn and restructure their knowledge, and determine the relative importance of different elements within a given situation. This was done only in extremely well-defined and narrow applications by programming expert systems. Organized information about a problem domain is called a knowledge base. "Experience" is stored separately in knowledge-based systems, or expert systems, from the knowledge about organized problem-solving, which is called an inference engine. It is mainly due to the programming of expert systems that the practical usefulness of AI was successfully demonstrated. Many expert systems have been developed for scientific and industrial applications, including medicine, military science, engineering, geology, space technology, pattern recogn1t1on, mathematics, and physics. Numerous examples are described in a recent guide to expert systems [12].

Flexibility of intelligence in an expert system is largely derived from the range and levels of rules it contains. A large number of rules is typically necessary because the program can be faced with a wide range of situations. Performance of these systems is highly dependent on the depth and structure of the knowledge base. Much of the power of these computer programs is contained in the knowledge they possess rather than their control structure or data storage [13].

Important operational characteristics found in many expert systems include the ability to predict outcomes for events in their limited domain, utilize various types of data in reaching conclusions, modify their knowledge base when confronted with conflicting assertions, and “explain” a line of reasoning by providing the user with the pieces of knowledge used in reaching a conclusion. These characteristics have been important in user acceptance of these systems. Another key characteristic is the "user interface." It is noteworthy that expert systems are almost always programmed with user interactions in mind (geologists speak as geologists, chemists as chemists, etc.). Indeed, "natural language" processing is an important area of AI research and this greatly enhances the likelihood of improved user interfaces in future systems [14].

4. APPLICATIONS OF AI TO REMOTE SENSING

A number of broad and somewhat overlapping areas of remote sensing applications appear well suited for the use of AI techniques. These include intelligent "onboard" processing, advanced database interrogation, and automated analysis of multispectral imagery. Emerging artificial intelligence technology allows for novel software-based tutorials that accommodate highly-visual domains, like that of remote sensing, and offer enhanced multimedia, interactivity and adaptive capabilities. An Intelligent Tutoring System (ITS) is a software program that aims to offer the benefits of one on- one instruction automatically and cost effectively. However, ITS goes beyond training simulations by tailoring instruction and providing individualized guidance. Unlike other computer-based training technologies, ITS systems closely monitor students as they work in interactive environments and develop a model, called the student model, of each student's knowledge, skills, and expertise. Based on this model, ITSes determine instructional strategies, in terms of both the content and style, and provide explanations, hints, examples, demonstrations, and practice scenarios as needed [15].

Current remote sensing platforms must often accomplish a great deal of onboard processing (e.g., recording and transmission of imagery to ground stations). When the platforms are unmanned, this processing is usually accomplished in a semi-autonomous manner. This is especially true for platforms containing sensor systems which are traveling in deep space, but even in earth orbit, significant benefits may be obtained from more intelligent onboard processing. Examples of advanced onboard processing include: automated navigation and locating of scenes to be imaged, screening of conditions that might influence data collection, and automated change detection [16].

When remote sensing and other types of spatial data (e.g. maps) are integrated for analysis, it is common for this to be done within the framework of a geographic information system (CIS). Such systems typically offer some level of database management capabilities and few have database management facilities comparable to those of well-established commercial database systems. Commercial database management systems (DBMS) have been extremely successful in banking and accounting applications, but these commercially-oriented systems are not easily modified to handle spatial data manipulation. As a result, the development of advanced spatial database management systems has suffered and many CIS packages do not exploit the current level of DBMS sophistication. Management of imagery and other types of spatial data can be critical to remote sensing projects. As spatial data sets become larger, the tasks involved in access, processing, and analysis become more difficult and often more important. Among the key tasks of remote sensing database management are: identifying existing remotely sensed and collateral data germane to the task, selecting what new data are required, and providing user-friendly interaction between the user and the database [17].

In most image interpretation problems of interest to geographers, computer-assisted techniques lag far behind human techniques in terms of both speed and accuracy. Continual improvement in computing hardware, especially lower-cost array processors well-suited for image processing, is rapidly improving the speed of computer-assisted image processing techniques. But substantial improvements in the accuracy of thematic products may not be possible without fundamental changes in the structure of automated procedures. The tasks of both a human image interpreter and automated image interpretation are basically similar, namely detection, identification (classification), measurement, and problem solving. For additional background comparing and contrasting the current status of human and computer-assisted approaches to image interpretation, the reader is directed to [18]. One of the most significant contributions to date of the computed-assisted approach to image interpretations has been the focus upon the basic elements and techniques involved in image interpretation. Early automated classification work emphasized pattern recognition approaches [19]. A substantial subfield has developed within computer science aimed at improving the ability of computers to "recognize" patterns of data. When these techniques were first developed, the mathematical elegance of the basic ideas was so attractive that many early researchers were very optimistic about their general utility. It is now recognized that pattern recognition methods alone are inadequate in situations which require an awareness of context or a priori knowledge, characteristics common to most image analysis problems. AI researchers are actively addressing these types of problems, and techniques already developed promise to improve automated image classification [20]. In many cases these changes will result in techniques similar to those employed by human image analysts. This similarity may speed acceptance of these new techniques once they are more fully developed.

5. OPTIMIZED ALGORITHMS IN CLASSIFICATION OF REMOTE SENSING DATA

One of the most important digital image processing steps in the remote sensing is undoubtedly classification. As a branch of classification, unsupervised classification is a general concept which defines natural structures and groups in data without training. The K-means (KM) and Fuzzy C-means (FCM) are the most common unsupervised classification methods. For over the last two decades, Artificial Intelligence (AI) optimization algorithms (heuristic algorithms) such as Genetic Algorithm (GA), Particle Swarm Optimization (PSO), Differential Evolution (DE) have been using for different nonlinear problems in many disciplines successfully. As an AI optimization algorithm, Artificial Bee Colony (ABC) was recently proposed. PSO is inspired from the social behaviours of bird and fish shoals, GA is similar to the evolutionary process in the nature, DE is a GA-based intuitional algorithm and ABC which is inspired from honey bees. These AI optimization algorithms are especially preferred when the classical deterministic methods are inadequate because of too many parameters and data sets are not homogenous. These AI tools are effectively used in remote sensing, as well [21]. Figure 1 shows the artificial intelligent architecture used for remote sensing data classification.

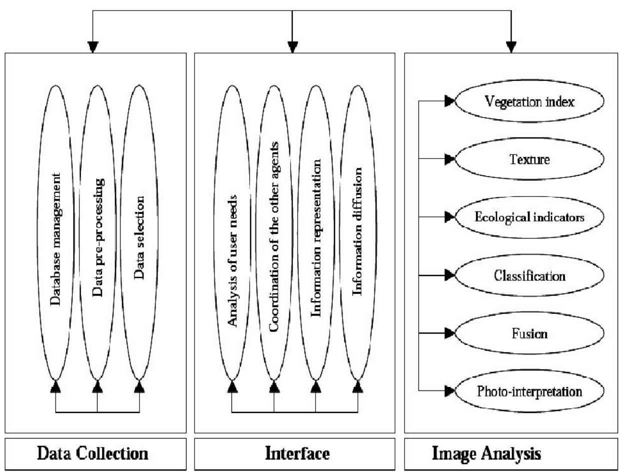

Figure 1: AI architecture of data classification

Land cover mapping is one of the most important application areas of remote sensing discipline. Classification is preferential step for producing thematic spatial information from satellite image data. Classification can be defined as grouping of similar pixels by aid of mathematical equations which describes neighbourhood relations of pixels. There are basically two approaches for image classification. In supervised classification, training areas are selected by user and these data are used for training of classification procedure. In unsupervised classification, there is no training process. So, instead of training process, clustering is done according to spectral brightness value. Most frequently used methods in unsupervised classification of satellite imagery are FCM, K-Means. Besides heuristic optimization methods such as GA, DEA and PSO are also being used for solution of problems.

As a bottom-up approach, Swarm Intelligence (SI) is actually a complex multi-agents system, consisting of numerous simple individuals (e.g., ants, birds, etc.), which exhibit their swarm intelligence through cooperation and competition among the individuals. Although there is typically no centralized control dictating the behaviour of the individuals, the accumulation of local interactions in time often gives rise to a global pattern, SI has currently become a hot topic in artificial intelligence research, and it has succeeded in solving problems such as travelling salesman problems, data clustering, combination optimization, network routing, rule induction, and pattern recognition. However, using SI in remote sensing classification is a fairly new research area and needs much more work to do [22].

SI mainly involves two algorithms, i.e., particle swarm optimization (PSO) and ant colony optimization (ACO). In this paper we try to introduce PSO into remote sensing image classification. Particle swarm optimization PSO is an efficient and effective global optimization algorithm, which has been widely applied to nonlinear function optimization. Complex society behaviour can be well simulated and explained by PSO, which is effective to solve complex optimization problems. Compared with evolution algorithms, PSO reserves the global searching strategy based on community; avoiding complex genetic operators with a simple speed-offset model; tracing current searching situation and tuning the strategy when necessary for strong memory, which makes PSO have powerful global convergence and stronger robustness [23].

6. APPROACHES TO COMPUTER ASSISTED CLASSIFICATION

The most common computer-assisted classification procedure is also among the most primitive. Statistical pattern recognition makes use of training data to characterize patterns of interest in some statistical manner. This decision-making method has been found to be most effective in the following two types of problems [24] which are classification of complex signals when the proper features are measured and the number and recognition of simple shapes. Examples of statistical pattern-recognition algorithms include minimum distance, maximum likelihood, and bayesian classifiers.

To support this approach, major efforts towards optimal representation and feature extraction have been undertaken. Examples include remote-sensing band selection and various transformations, such as principal components, directed towards reducing the dimensionality of the data. As noted earlier, pattern classification methods alone are virtually useless in situations which require awareness of context and/or the use of pertinent a priori knowledge. From the study of languages comes another slightly higher-order procedure termed syntactic pattern recognition. Language may be defined as a set of strings over an alphabet, where the alphabet consists of the set of all symbols which can appear in the language strings. A string is a definite ordered sequence of symbols. Grammar is a set of rules which define how the strings of the language are formed. Grammar can be used to recognize the language's strings by using the rules in reverse order. This concept can be generalized in a number of ways to define grammars for classes of images. This approach has been most widely used in image analysis to recognize shapes based upon the order of component image parts. Syntactic methods have been used for locating highways and rivers in Landsat images and for texture modelling [25].

Symbolic reasoning procedures have grown out of deductive logic and provide an effective way of expressing relationships between objects and linking information to objects. These procedures employ formal logic to make inferences from a given set of conditions. The application of symbolic reasoning procedures to image analysis is being vigorously pursued by computer scientists interested in computational approaches to "image understanding". In image understanding, knowledge is applied to the image interpretation process. A feature in the image is matched with knowledge; the object is labelled, and associated with the knowledge. Understanding is considered to have occurred when the interpretation generated by the program can be used to derive higher-order information about the scene which is not expressly contained in the image, for example, identifying sailboats on a lake and inferring that the lake is a recreational facility [26].

7. CONCLUSIONS

Many techniques under development in the artificial intelligence community appear suited to the needs of remote sensing. From improved classification performance to better user interfaces, the potentials offered by AI-based techniques appear promising and could significantly aid in facilitating more widespread acceptance of computer-generated remote sensing products. The development of better computer-assisted procedures for image analysis will require substantial efforts even if we achieve an improved understanding of current procedures. Recently, Artificial Intelligence (AI) techniques have been increasingly incorporated in the classification of remote sensing images. AI-based techniques seem to be appropriate for improving image analysis but special attention will need to be directed towards those conditions somewhat unique to geography in particular and earth resources applications in general. We feel research towards combining image analysis and information systems assisted by AI techniques is a major key to the future of large-scale remote sensing applications.

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