THEORETICAL ASPECTS OF EVIDENCE – INFERENCE RELATIONSHIPS IN REMOTE SENSING EXPERT SYSTEMS

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Commission VII

KEY WORDS: Remote sensing, Expert Systems, Inference, Recognition Theory

ABSTRACT:

Understanding inference–evidence relationships in recognition tasks is fundamental for developing methods utilizing Artificial Intelligence. Recognition of geographical phenomena in wide areas from remote sensing images is a most complex due to its high dimensionality (spectral, temporal, spatial). The objectivity, consistency and accessibility of remote sensing data make it a good case study for assessing different recognition concepts within the framework of Artificial Intelligence. In this article there are discussed issues of types of evidence, methods of inference and their relationships.

1. INTRODUCTION

Scientific remote sensing involves reasoning the recognition path between factual evidence (consisting to large extent of data from remote sensors) and the observed environmental phenomena. Understanding the epistemological aspects of the interpretation process is crucial when considering that the environment is very complex spatio-temporally, whereas the remote sensing evidence can be regarded as a snapshot. Spatial, spectral and contextual evidence can be implicitly or explicitly linked to surface phenomenon. Inference is a crucial methodological element of the transformation from these facts/evidences to knowledge (Miller and Han, 2001; Gahegan, 2001; Brodaric and Gahegan, 2002). Interestingly, inference methods in general and inference – evidence relationships in particular had received relatively limited attention during this phase of massive growth of environmental remote sensing. The objective of this article is to discuss the theoretical aspects of inference – evidence relationships and their functioning in Knowledge Based Expert Systems utilizing Domain Independent Inference (DII) and Domain Dependent Inference (DDI).

2. SCIENTIFIC REASONING IN KNOWLEDGE - LEAN TASKS

Scientific reasoning is perceived as that element of thinking and intelligence, which is coherent with scientific explanation (Winston, 1992; Voss et al., 1995). It is a concept that lies at the heart of a philosophical debate regarding the rational or empirical basis for causality. Practical reasoning (Raz, 1978) has been one of the ways to overcome the debate (rather than resolve it) and address scientific procedures and methods of reasoning. Zimmerman (2000), following Koslowski (1996), refers to a dichotomy of reasoning in a problem-solving task: that which is related to methods or principles of scientific inquiry (experimental design) as differentiated from knowledge–lean tasks based on evidence evaluation leading to knowledge. Recognition is closely related to the latter type and deals -with the transformation of data and evidence into meaningful information. Reasoning the recognition requires an assessment of the relationships between three elements:

- <u>Propositions</u>: observable evidences denoting relationships between remote sensing indicators/signatures and a class of recognised phenomena.
- <u>Hypothesis</u>: a new scientific knowledge or concept formed by the confirmation of a set of mutually related propositions containing or declared within a stated context. Popper (1972) stresses two important issues: the hypothesis is preferably integrated within the framework of multiple competing hypotheses and it must be refutable.
- <u>Inference</u>: a deductive, inductive or abductive process by which a hypothesis is confirmed or refuted based on a judgement made from relevant rational and/or empirical evidence.

3. REASONING IN EXPERT SYSTEMS

Expert systems are tools for performing knowledge- lean tasks, and defined as : '…computer systems that advise on or help solve real world problems requiring an expert's interpretation and solve real-world problems using a computer model of expert human reasoning reaching the same conclusion the human expert would reach if faced with a comparable problem.' (Weiss and Kulikowski, 1984). Thus, expert systems are means of implementing artificial intelligence as a computerized representation of human reasoning rather than strictly scientific reasoning. Human intervention in the process is exhibited in two fundamental aspects: in the semantic definition of categories of surface phenomenon; and in judging the accuracy and reliability of the computerized system performance. In other words, the aim of expert systems is to reach the same conclusion that an expert would reach given a parametric description of the recognition situation. Such parametric description does not represent the human expert knowledge implemented during the human recognition, but those available information sources which can be represented in a computerized format. Thus, there is primary importance to the adjustment between type of evidence (information sources) and type of inference utilized by the expert system.

4. EVIDENCE VERSUS INFERENCE IN EXPERT SYSTEMS

There are two main types of propositions representing evidence at hand in the recognition problem: explicit and implicit. The first refers to the notion of plain distinct expression that leaves no need to infer (Merriam-Webster, 2002**).** The second type of proposition represents a conclusion "capable of being understood from something else though unexpressed: capable of being inferred" (Merriam-Webster, 2002). Explicit or implicit propositions would be established on explicit or implicit evidence respectively. In this context, inference facilitates proof where there is no explicit evidence.

In the remote-sensing discipline narrow band signatures of specific materials and very unique combinations of spectral reflectance thresholds are examples of explicit evidence. The production of such evidence would typically require exhaustive search (see method proposed by Peddle and Ferguson, 2002).

Implicit evidence would consist of generalizations, associations and contextual information representing some level of non-uniqueness and conflicts with reference to the object subject to recognition (e.g., Cohen and Shoshany, 2005). While the production of such evidence might be relatively easy, its use would require inference capable of overcoming such non-uniqueness and conflicts.

Significant number of categories exhibit some level of spatial/ spectral/ temporal uniqueness. Such uniqueness can be easily detected using unsupervised clustering or data mining techniques. Furthermore, detection of erroneous attribution of objects of one class into another is also valuable since it specifies a conflict or confusion. From these reasons, the maximum recognition level (separability) achieved by utilizing unsupervised clustering techniques provide the starting point for designing and implementing expert systems. This ensures that sophistication embedded in the clustering or data mining techniques is not confused with the inferential functioning of the expert systems. It also reduces the efforts required for establishing the knowledge base, since it transforms some of the information content in the continuous spectral data into thematic data.

The dichotomy between inference and evidence is further embedded in Knowledge Based Expert Systems' strategies developed, representing two extreme types:

- Domain Dependent Inference (DDI): is suitable for relatively explicit body of evidence in which the conclusion is entailed and no or low level of inference is required. DDI inference mainly controls the combination order of the different evidences and is represented in the procedural knowledge. The intelligence in DDI is embedded within it during its construction rather during its implementation. The construction of procedural knowledge and evidential basis requires heavy information analysis, learning procedures and feature assessment. Rule based expert systems implementing binary decision trees are extreme examples of DDI and are widely used in remote sensing. GeoAIDA (Growe, 2004) is a good example of such strategy, where expert system based on semantic networks was developed implementing specific (explicit) evidence, including contextual information. The inference mechanism applied was then a procedural sequential decision tree type. Other extremely different example of this strategy concerns the use of Classification Tree Analysis (CTA) techniques and their recent improvements in with Boosting and Bagging methods (e.g., Lawrence et. Al., 2004). Again in this method there is maximal exploitation of the information content in the data and the (computerized) construction of a decision tree specifically (explicitly) applicable to the data at hand.
- Domain Independent Inference (DII): is suitable for relatively implicit body of evidence. The DII inference relate to their associated characteristics: the relative belief, support, certainty and weight, rather the information sources themselves and thus is independent of any specific recognition or decision making problem. The combination of evidence would then be based on general deductive, inductive or abductive procedures (Durkin, 1994). A significant element of the intelligence represented by DII is embedded within it during the development of the generalized inference algorithm which is independent of any specific recognition or decision making problem, and usually adopted without investing in such development. The sophistication of the system which is embedded in the inference methodology is then dependent on the inference capabilities to overcome non-uniqueness and conflicts. Examples are expert systems based on Fuzzy sets, those utilizing Dempster Shafer or Support Vector Machines.

In reality there is rather a mixture of strategies tailored according to information sources and expert systems tools available. However, there is relatively little comparison made between DDI and DII based strategies in terms of their performance and the types of evidences used. Performance assessment of these strategies in areas which differ from the training areas is of special interest: would it be better in terms of cost and performance to deepen the search for domain explicit evidence or to broaden the implicit evidential basis?

5. CONCLUSION

The science of geographical complexity, which studies "how simple, fundamental processes derived from reductionism can combine to produce complex holistic systems" (Malanson, 2000) is highly relevant to the remote sensing recognition issue. From the remote sensing perspective this is equivalent to recognition approaches enabling the identification of a phenomenon with high spatio-temporal variations using sensory patterns consisting of simple, fundamental, implicit indicators. The highest level of intelligence would be represented by a remote sensing expert system in resolving most complex problems from a most redundant data/information of the implicit type. In this article we have suggested that such intelligence could be embedded in the evidence discovery (rules determination) or in the inference mechanism. The sophistication of the recognition system would be proved by recognizing different variants of surface types which were not 'learnt' during the formation of the expert system' rule base.

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