A Science Fiction Tale? A robot called Archaeologist

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ABSTRACT

In this paper I imagine an automatic archaeologist as a machine able to act as any of us, archaeologists, learning through experience to associate archaeological observations to explanations, and using those associations to solve archaeological problems. Such a machine is here described as a device which perceives its environment through some mechanisms called sensors and acts upon that environment through other mechanisms called actuators or effectors.

Such an automaton should be capable of solving archaeological problems through a sequence of epistemic actions or cognitive behaviors. Artificial Intelligence techniques and technology is used to address the question How a robot can solve "automatically" archaeological problems.

1. AUTOMATA: THE AWFUL TRUTH ABOUT HUMANS AND MACHINES

Is it possible to build a machine to do archaeology? Will this machine *be capable of acting like a scientist? Will this machine be capable of understanding how humans act, or how humans think they acted in the Past?*

May be some of you will say that "not yet" and others will claim: "fortunately, never!" "Computers will never *emulate* humans", they may think, and even worst, "*why we need such an awful machine?*" This paper is a possible answer to this last question. We should imagine an *automatic archaeologist* as a machine able to act as any of us, archaeologists, learning through experience to associate archaeological observations to explanations, and using those associations to solve archaeological problems. Our automated archaeologist is a computer program that *acts*. In our case, we are speaking of *epistemic actions*: namely, actions whose purpose is to make available information required as part of a problem solving routine. In that sense *explanations* are for our automatic archaeology machine a form of *behaviour*. The automatic archaeologist should correlate evidence and explanation adequately in order to *generate* an adequate action. Expressed in its most basic terms, the task to be performed may be understood in terms of *predicting* which explanations should be generated in face of determined evidence. This task is performed by a *function* that maps any given percept sequence to an action. Consequently, we should characterize our automatic archaeologist as an *automaton that* is a device with defined inputs, outputs and structure of inner states, which perceives its *environment* through some mechanisms called sensors and acts upon that environment through other mechanisms called *actuators* or *effectors* (Aleksander and Morton, 1993, p. 97). Automata have a bad reputation, because automatic processing has been characterized as a simple, direct association of a stimulus with a response. Nevertheless, what gives its truly "intelligent" character to our automatic archaeologist is not a passive storing of individual rules, but an enhanced ability to *react* in a certain way to a certain stimulus (Franklin, 1995). Don't panic! When using the word *automaton*, I am not speaking of an android, but to any "intelligent connection of perception to action" (Brady, 1985). It is important to realize that the formal definition of automaton includes human beings within the class of *automata*. A human has input senses, a muscular output and an ability to use this to great effect (excavating old sites, teaching archaeology, etc.). A human has a state structure of wondrous complexity, which is the seat of consciousness and intelligence. This complexity distinguishes archaeologists from computers, but mathematically even the best of us can be described as an automaton. Therefore, the activity of machine and human automata can be described and analyzed in the same terms. In its most basic level, the performance of both human and automatic archaeologist is a 3 stage process: Feature Extraction, Recognition, and Explanation by which a visual input (archaeological record) is transformed into an explanatory model of a human society (Fig. 1). For instance, in order the system be able to make a decision as to whether the object is a knife or a scrapper, input information should be recognized, that is "categorized", in such a way that once "activated" the selected categories will guide the selection of a response.

I am trying to show how archaeological problems can be "automatically" solved by a machine. Such a machine should not be considered a mere science fiction tale. It is a technological reality. In other scientific domains the performance of humans at a particular task has been used to design a robot that can do the same task in the same manner (and as well). In many different domains it has been shown how 'robot scientists' can interpret experiments without any human help (Arkin, 1998; Moravec, 1999; Murphy, 2002; Santore and Shapiro, 2004; Kovacs and Ueno, 2005; King *et al.*, 2004). Such robots generate a set of hypotheses from what it is known about a scientific domain, and then design experiments to test them. That is, a robot scientist can formulate theories, carry out experiments and interpret results.

The question of whether it is possible to automate the scientific process is of both great theoretical interest and increasing practical importance because, in many scientific areas, data are being generated much faster than they can be effectively analyzed. Making a computational model forces us to be explicit about our assumptions and about exactly how the relevant process actually works. Such explicitness carries with it many potential advantages. As such, it should provide novel sources of insight into archaeologist's behavior. It should allow dealing with complexity in ways that usual verbal arguments cannot, producing satisfactory explanations of what would otherwise just be vague hand-wavy arguments. Explicitness can contribute to a greater appreciation of the complexities of otherwise seemingly simple process.

Rather than use intuition as the sole guide for formulating explanations of past human behavior, we need a theory of why a specific computation or a group of related computations should be performed by a system that has certain abilities (be it a human or a robot). Note that computational theory does not mean the "theory of computer science" but the practice of expression models of information processing in *precise mathematical and algorithmic notation*. The present approach owes much to the work of David Marr on computational psychology (see Marr, 1982). According to his suggestion, theories of computation – and an automatic archaeology is just a theory of computation – are at the top of a three-level hierarchy. A theory of computation specifies *what* is computed. The next level down is a theory of the algorithm, which specifies *how* a computation should be performed, and specifies the conditions where the procedure can generate valid results. The theory of the algorithm specifies an explicit set o steps that will guarantee a given output when provided with a given input. Consequently, while a theory of computation can be seen as a description of the problem, a theory of the algorithm is a description of a particular solution. The theory of the computation may be treated as paramount because it characterizes the problem that must be solved by a system – and until one understands what a system does in specific circumstances, one cannot specify the details of how the system works. We can place the algorithm at a lower level of the hierarchy because it does not characterize a problem, but rather specifies a possible solution to a problem that is characterized at the more abstract level. Typically, many different algorithms can carry out a computation. The third level specifies how the algorithm is actually implemented: in the human brain or in the human-made cognitive core of a computer. I am not arguing that an artificial archaeologist will substitute human archaeologists, because it works better and cheaper than us. I do not think that "natural" archaeology can be fully described in terms of an "automatic" archaeology. What I am exploring is just an analogy with the idea of "intelligent" machine. I am trying to understand the way we, archaeologists, think. My methodological suggestion is to adopt the approach of synthetic psychology and build computer simulations that instantiate detailed theories of archaeological reasoning. My argument is that, logically speaking; computers can perform processes representative of human thought (i.e., decision making and learning). Therefore, the purpose of an *Android epistemology* (see Ford *et al.*, 1995 for the meaning of the term) is not to study machines in themselves, but *human cognition*. This "automatization" approach is based on the study of particular human capabilities and how humans solve certain tasks, and then build computational cognitive models of this ability.

2. AUTOMATIC COGNITION

An "automatic" archaeologist "reasons" because it is able to infer values of features that cannot be sensed directly. In this sense, "inference" is only a mechanical way of creating a well-formed formula from others. Essentially the idea is to set up appropriate, well conditioned, tight feedback loops between perception and action, with the external world as the medium for the loop (Fig. 2).

The actions are gated on perceptual inputs and so are only active under circumstances where they may be appropriate. The automatic archaeologist should store and retrieve abstract mathematical or logical descriptions implemented in a computer program which takes the current observation as input from the sensors and returns some explanation. Therefore, the automatic archaeologist objective is to rigorously apply the scientific method to iterative archaeological object recognition and explanation. This action of machine behaviour implies to *predict* the cause or formation process of some archaeological entity given some observed evidences of the effect of this causal process. Prediction problems can be represented under the form of a contingent association between an input stimulus (*archaeological description*) and an output response (*explanation*). The main assumption is that the input is related causally to the action it produces. We solve the problem when we define how the input is associated to the output, that is to say, when we understand the nature of the *causal relationship,* which resides in the specific mapping between stimulus and response. There are two contenders for modelling the structure of the mapping between perception and epistemic action, each of which tends to emphasize different aspects of cognition. PRODUCTION SYSTEMS places emphasis on the fact that much of our behaviour, particularly problem-solving behaviour, is rule governed, or can be construed as being rule-governed, and is often sequential in nature-we think one thing after another. Each rule is a process that consists of two parts – a set of symbols acting as tests or *conditions* and a set symbols acting as *actions*. Here, conditions are only a specific set of key features (empirical or not), and actions are explanatory concepts associated to those features, and used to reach the goal. In general, the condition part of a production rule can be any binary-valued (0, 1) function of the features resulting from perception of the problem givens (initial state). The action part can be either a primitive action, a call to another production system, or a set of actions to be executed simultaneously. The conditional part enumerates those situations in which the rule is applicable. When those conditions are "true", we say that the knowledge represented in the rule consequent has been activated. The underlying logical mechanism is:

IF **FEATURE1 = true**
(object O has Feature1)

And **(If Feature1 then Concept X) = true**

THEN **CONCEPT X = true**
(The presence of object O allows the use of Concept X in the circumstances defined by Object O)

Opposite to the use of this kind of logical rules, there is the CONNECTIONIST approach. The emphasis of this architecture is on learning and categorising, and on how we can spontaneously generalise from examples. This approach is based on the idea that functions like perception, problem solving or memory emerge from complex interactions in highly distributed neuronal networks which, unlike conventional information processing systems, are shaped by learning and experience-dependent plasticity. In such networks, information processing does not follow explicit rules, but is based on the self-organization of patterns of activity. In this sense, information processing is not carried out as a sequence of discrete computational steps. Just as we apply knowledge gained from previous experiences to solving new problems, an artificial Neural Network "looks" at a set of answers to previously solved examples to build a system of "connections" that makes decisions, classifications, forecasts, and finds solutions to problems in a non-linear manner. The more historical data is used in the learning phase, the better the resulting network at finding correlations and solving new problems.

This way to carry out its task suggests that the performance of the automatic archaeologist may be understood in terms of *mapping* one class of patterns (input or empirical data) onto another class of patterns (epistemic actions). Pattern mapping is actually a very broad concept, and it is useful to distinguish among types of mappings. *Pattern recognition* has been defined as the mapping of a specific pattern onto a more general pattern (that is, the identification of an individual as an exemplar of a class). *Pattern completion* is the mapping of an incomplete pattern onto a completed version of the same pattern. *Pattern transformation* is the mapping of one pattern onto a different, related pattern. Finally, *pattern association* is the arbitrary mapping of one pattern onto another, unrelated pattern. We should consider that pattern matching is not a mere reading by a feature extractor, but an active intentional interpretation of empirical data or sensory clues. It is generally understood as an action-oriented cognitive task by some perceptual system, whose deliverances of are often cast in action-relative, and even, action *inviting* terms. That means that, what is recognized, is always known in terms directly related to an agent's current possibilities for future action.

Paul Churchland (1989) argues that explaining a phenomenon is very similar to the process of recognizing it. He proposes that explanation involves activating an input-output function (*explanans*) that enables the automaton to deal with a situation (*explanandum*) for which understanding is needed. It consists in the apprehension of the problematic case as an instance of a general type, a type for which the machine should have a detailed and well-informed representation. Such a representation allows the system to anticipate aspects of the case so far unperceived, and to deploy practical techniques appropriate to the case at hand.

The suggestion that cognition might simply consist in a sequence of pattern recognitions has been developed, among others, by Howard Margolies (1987). In his theory, the recognition of one pattern constitutes an internal cue which, together with the external cues available from outside the brain, facilitates recognition. The outcomes of preliminary classifications should be combined to obtain more global patterns, which in turn serve as input patterns to higher-level recognition devices. Eventually, levels of abstraction should be reached at which the classes have conceptual labels. Traditionally these semantically interpretable categories have been regarded as cognitive, but the same overall process of pattern recognition is involved in sensation and perception, as well. In fact, the term *categorization* is generally used to refer to pattern recognition at any level. Thus we solve problems by recognizing something, and with the help of that result, recognizing further. Learning involves modification of the template to accommodate a new scene better. In Margolies's account we are capable not only of recognizing something is the case, but also of reasoning why we have made that judgment. Reasoning why does not involve any introspection into the process of recognition, but rather is itself a process of pattern recognition – one that proceeds through smaller steps to justify the judgment.

This proposal offers a variety of benefits. It accounts for the observation that explanation often seems to have much in common with pattern recognition and is sometimes arrived at instantaneously: one simply sees that a puzzling phenomenon fits a well-established pattern. It also seems to accommodate the fact that archaeologists sometimes arrive at an explanation before they are fully able to verbalize it. Finally, it provides a new perspective on the relationship between discovery and justification. In Churchland's or Margolies's proposal, these two processes are closely linked; both involve determining which input-output function best fits the situation. The problem is how to transform any incoming sensory vector into its appropriate outgoing conceptual vector, into a conceptual vector that will provide the correct solution to the problem at hand.

3. THIS MAY BE STILL A SCIENCE FICTION TALE, BUT...

Seen from outside, an automatic archaeologist may be imagined as a *robotic*-ROV (Remotely Operated vehicle), able to move in the field, take samples, and build a model of the environment based on its interaction with it (movement, navigation), and the information is able to gather (visual models, sample analysis). Like most robots, it has 5 main parts. These are the end effector, controller, sensor, and drive. The end effector is best likened to a "hand". It is the part of the robot that directly performs the task. It is at the end of the arm. The arm is the part of the robot that positions the end effector, in order for it to complete its programmed tasks. The controller is the "brain" of the robot. It is the part of the robot connected to a computer that keeps the pieces of the arm working in harmony. Controllers are run by programs. The sensor is the part of the robot that provides feedback to the controller. This part acts in the same way our five senses do. The drive is like an engine. It is the part of the robot that drives the sections between joints into their desired position. Such a robot has already been imagined in the case of underwater archaeology (Coleman *et al.*, 2000).
Seen from inside, the automatic archaeologist should be built around four main components (Fig. 3):

- Mobility component that establishes the possibilities of interacting between the robot and its environment (the archaeological space).
- Performance component that decides what actions to take so as to achieve the best outcome or, when there is uncertainty, the best expected outcome.
- Perception component that establishes a direct mapping between salient perceptual features and knowledge structures.
- Understanding component. The automatic archaeologist should be capable not only of performing some task but it should show that it *understands* what it has done, and why.

Mobile robots able to fulfil those specifications proliferate in our modern world. Commercial companies like ZagrosRobotics, Irobot, Activerobots, and others, offer different units for a range of prices between 7000 and 75000 euros (as seen on May 2005).
The best known example of robotic use in archaeology has been the Pyramid Rover. It is a robot probe created by the company *iRobot*, equipped with motors, mountings for camera and threads to grip the top and bottom of a shaft. On 17 September 2002 it was used to explore a shaft that opens into the queen's chamber of the Great Pyramid of Khufu[1]. Better examples for our purpose are the family of space exploration robots, like the path finder rover used on Mars as well as other specific rovers for missions like volcano explorations (Wettergreen *et al.*, 1999; Anttila and Ylikorpi, 2003; Bertrand and Van Winnendael, 2003; Landzettel *et al.*, 2004; Schwehr *et al.*, 2005).
Such robots are the most convenient mechanism for perceiving space and acting on it based on their input perceptions. They have onboard navigation sensors and computing which enable them to reason around obstacles and navigate in reduced communication areas without operator assistance. The idea is to develop an exploration system that allows a robot equipped with CCD cameras, sonars, infrared sensors and georadar to explore and build a representation of some archaeological environment. To achieve that objective the robot has to be able to extract relevant features from the World around it, and express them in some specific way. In other words, to adequately understand the perceived archaeological spatiotemporal continuum, the robot builds a model made up of discrete, irregular, discontinuous geometrical primitives (surfaces, volumes).
Computer visualization is a rapidly evolving field into archaeology (see Barceló, 2000), but this research has not been integrated into the idea of a robotic archaeology. Only in the case of underwater archaeology, we can find some relevant examples (Ballard, 1993; Coleman *et al.*, 2000; Ballard *et al.*, 2000; Chapman *et al.*, 1999; Derbes and Ota, 1999; Schwehr *et al.*, 2005). Especially interesting for our purpose are the new modular "hybrid" user interfaces that support interaction metaphors. In such systems, multiple users can interact with the real environment using tracked hand-held displays, through a virtual model built by a computer (Van Gool *et al.*, 2002; Pollefeys and Van Gool, 2002; Pollefeys *et al.*, 2003; Benko *et al.*, 2004; Acevedo *et al.*, 2001; Vote, 2001; Allen *et al.*, 2004; Chapman *et al.*, 2004).
In the imagination exercise here suggested, the archaeological robot sends visual (CCD cameras) and non visual (georadar) information to the perception component to build the geometrical model of the environment. The specific combination of the visual and non-visual allows the understanding component to make decisions about how to find archaeological evidences. This capacity implies that the "thinking core" of the robot is able to understand remote sensing information – georadar or geomagnetic signals, for example – in terms of buried evidence. It is easy to see that the real interest of robotic perception goes beyond building a 3D model. In any case, robotic automated "perception" should not be limited to the "observational". Visual models by themselves lack important context information to be of relevant use in archaeological

1 http://www.ngcasia.com/explore/egypt/home.asp. Another example is provided by the Adrian I robot for underground explorations. http://www.underome.com/eng/tecniche/robot.php.

research. Archaeological robots should do then much more than just explore and visualize what is *observable.* They should take samples from the ground, and they should even dig and unearth material evidences.

It is of paramount importance that the automatic archaeologist be capable of explaining the *causal* mechanism of perceived input. To perform this cognitive task, the automatic archaeologist should take into account the physical and mechanical attributes that control the visual features of perceived input (shape, size, texture, composition and location) (Fig. 4). After all, such archaeological properties should be explained as the qualitative nature of observable changes in the physical space generated by social action, and their properties also explain how they influence the spatiotemporal location of other actions (Barceló, 2002, 2005).

To actuate in the world, our automatic archaeologist would need three specialized arms. One for excavate (drill arm), one for remove the excavated sediment (suction tube), without moving the unearthed materials, and finally a manipulator arm (specialized hand). It needs a smooth and "intelligent" drill able to remove the sedimentary matrix covering archaeological materials and structures. Technically speaking, this the most complex effector. To excavate carefully without damaging archaeological materials, the drilling head should have a sensitive flat and soft point incorporating inertial sensors for purposes of feedback control and estimating the intensity, speed and depth of drilling. A camera linked to this specialized arm would allow a human to interact with the robot in order to move the arm according to the special needs of the excavated area.

The action of the robotic excavation unit generates a lot of sediment, which should be removed, before continuing with the excavation. I imagine a technology like the suction tubes used in underwater archaeology. Each suction tube transports sediment to other units in charge of looking for micro-evidences, and also mineralogical analysis.

Once the sediment has been drilled and removed, archaeological materials should be extracted and transported to the laboratory. We need a special unit for this task. These kinds of manipulators have already been used for underwater archaeology. There should be no problem for using them in any other archaeological excavation.

As we see, an automated archaeologist may be a too complex machine, with many arms and effectuators. Instead, you can imagine a group of specialized robots working together as a team. When manipulating or carrying large objects, a given load can be distributed over several robots so that each robot can be built much smaller, lighter, and less expensive. As for sensing, a team of robots can perceive its environment from multiple disparate viewpoints. Team members may exchange sensor information, help each other to scale obstacles, or collaborate to manipulate heavy objects (Mondada *et al.*, 2002; Grabowski *et al.*, 2003).

To sum up, the job of the automatic archaeologist sensors and manipulators is to provide the system with the information it needs to interact with the world. The understanding component and the perception component of the robot should work together in order to receive different kinds of input, update the current representation of the environment, and decide new tasks to be performed according to the information available and the current perceptual model of the environment. The idea is then to combine visual data with a variety of newly acquired information. In this way, when using such a robot for studying archaeological data we get the ability of not merely seeing what already exists (objects, handles, surfaces, gaps, holes, etc.) but also to see the *possibilities* for action and the constraints on possible actions.

4. CONCLUSIONS

In this paper I have described a virtual robotic system that applies techniques from artificial intelligence to carry out cycles of archaeological research. I have tried to imagine an "automatic archaeologist" as an integrated ensemble of components or individual devices with specific tasks. The first component would simulate Explorer *behavior, and* is concerned with mechanisms able to learn how to find an archaeological site, and build a visual (geometric) model to understand the spatial properties of the observed archaeological evidence. Remote sensing equipment can be integrated in order to consider also the non-visual archaeological evidences. The second component would emulate *what most archaeologist think is the definition of their job: the* Excavation of an archaeological site. *After* distinguishing buried structures and materials from the covering sediment, this componen*t* is concerned with another mechanism in charge of physically discover archaeological evidences, the unearthing and removing of sediment, and the manipulation and physical analysis of evidences. The robot also needs an understanding component. *This component is concerned with a specific mechanism able to identify archaeological evidences, and solve specific goals linked to this distinction. Finally, our intelligent machine should have* the ability to explain what is done and why, to answer questions about why it did not do something and about what would have happened if it had done something different, or about what someone else has done wrong. This last component should be built on top of the others: each of them will provide a test-bed for the mechanisms and representations proposed for acquiring and using reflective-understanding of both actions and thought processes. May be some of you will say that we do "not yet" have automatic archaeologists, but we should hurry up to the engineering department and build them for having someone able to substitute us in the tedious task of studying ourselves. Nevertheless, other readers will claim: "fortunately, such a machine will never exist!" "We do not need a machine that "seems" intelligent but it is just a mechanical processor unable to *emulate* what we, archaeologists, do. The so called "intelligent" machines may incite instinctive fear and anger by resembling ancestral threats – a rival for our social position as more or less respected specialists. The reader is asked to evaluate this claim on the basis of my defense of this position

(and other arguments in the literature), rather than on the basis of slippery metadisputes about whether or not my position and arguments for it are prima facie plausible.
The purpose here has been to understand how archaeological problem solving is possible inside a computer. The methodology is to design, build and experiment with computational systems that perform tasks commonly viewed as intelligent. The goal is not to simulate intelligence. The goal is to understand real (natural or synthetic) archaeological problem solving by synthesizing it. Bringsjord (1992) argues that Artificial Intelligence will eventually produce robots (or androids) whose behavior is dazzling, but it will not produce robotic persons. Robots will DO a lot, but they won't BE a lot.

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FIGURES

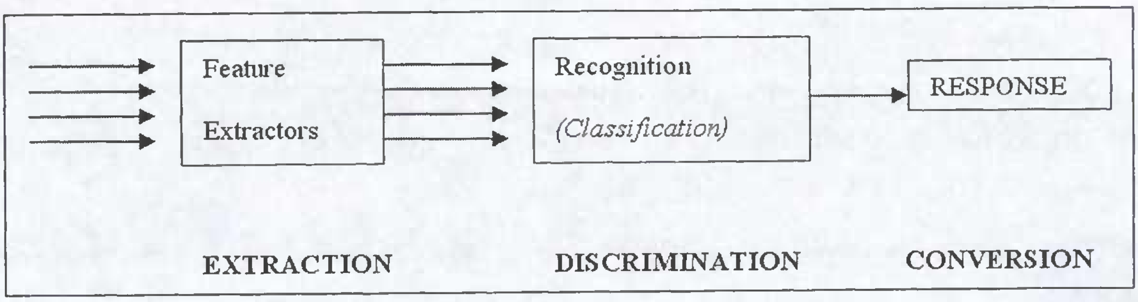

Fig. 1 – The basic functioning of an automaton (human or machine).

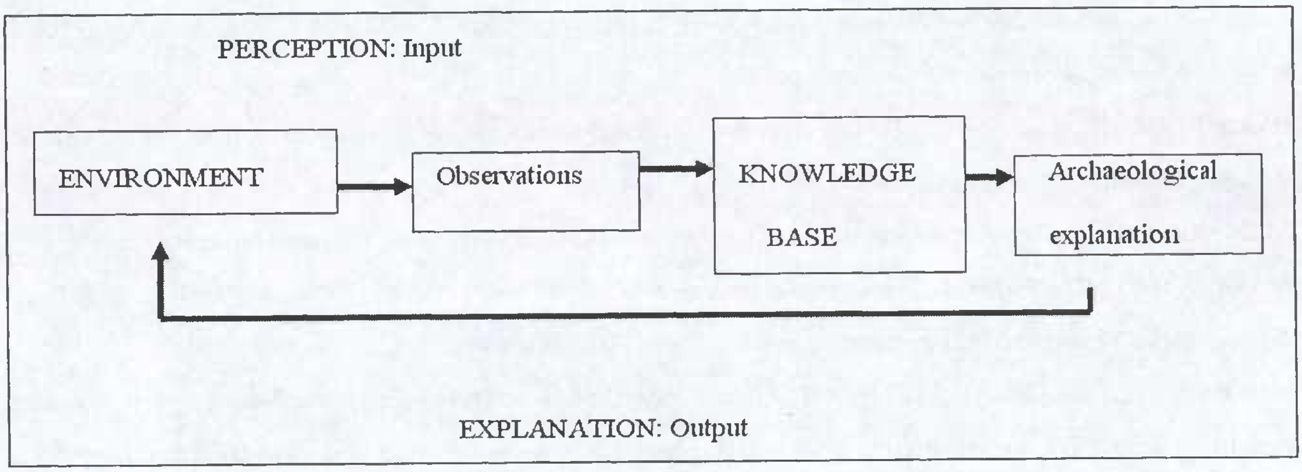

Fig. 2 – Inside the robot's mind: from perception to action (explanation).

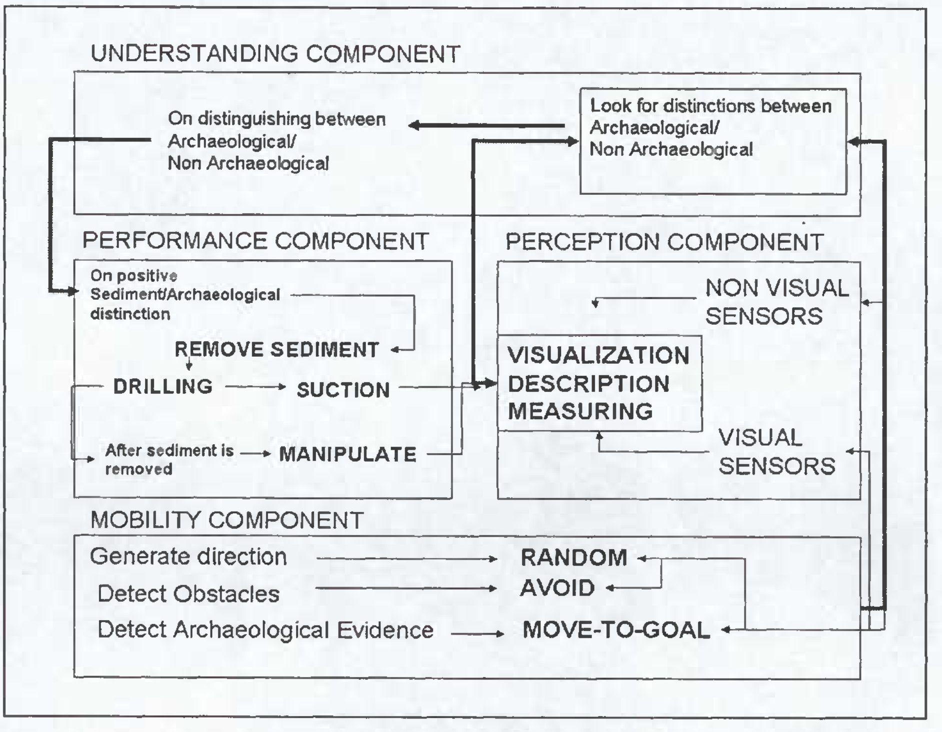

Fig. 3 – A possible design for an automatic archaeology system.

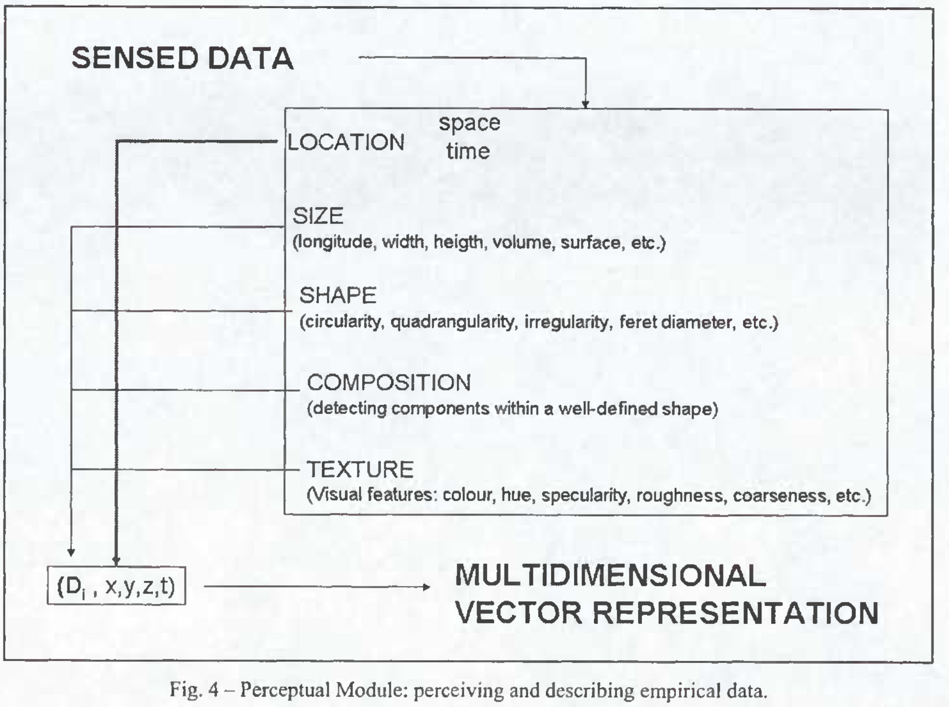

Fig. 4 – Perceptual Module: perceiving and describing empirical data.