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Hybrid Artificial Intelligence Network in Taxation of Upheaval Damaged Structures

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Abstract

The knowledge base of the new ANN is reconstructed through the use of the Fuzzy Set Theory, which permits to formalization ion the procedures in a non-deterministic way. The uncertainty and the imprecision of the gathered data are managed with techniques topical to Fuzzy Logic. Moreover, the System permits the user to modify the same knowledge base or insert new basheadquartersd use the most appropriate one in specific situations. The gathered data and the evaluations' results are loaded on databases and databases, successively, for further elaborations and new evaluations with different knowledge bases. Implementing and fleshing out several psychological and neuroscience theories of cognition, the AI-ANN conceptual model aims at being a cognitive "theory of everything." With modules or processes for perception, working memory, episodic memories, "consciousness," procedural memory, action selection, perceptual learning, serial learning, deliberation, volition, and non-routine problem solving, the AI-ANN model is ideally suited to provide a functional ontology that would allow for the discussion, design, and comparison of AGI systems. The AI-ANN architecture is based on the cognitive cycle, a "cognitive atom." The more elementary cognitive modules and processes play a role in each mental cycle. Higher-level functions are performed over multiple cycles. In addition to giving a quick overview of the AI-ANN conceptual model and its underlying computational technology, one can argue for the AI-ANN architecture's role as a foundational architecture for an AGI. Finally, lessons For AGI researchers drawn from the model and its architecture are discussed.

Keywords: Artificial Intelligence, Structural Dynamics, AI-ANN dynamic model, Earthquake Simulation, EPEDA.

1. Introduction

After an earthquake strikes a populated area, many buildings suffer damages of various degrees of gravity, possibly leading to the total collapse of the structure. Building officials are then faced with chaotic and confusing circumstances during which they have to make quick and reliable judgments assessing the damage degree, safety, and usability of these buildings. This operation is called Emergency Post Earthquake Damage Assessment (EPEDA). It consists of a quick reconnaissance of the facilities in the area hit by an earthquake to determine whether they can still assume the functions they had been designed for without a substantial change in the safety conditions before the seism [1, 3, 5].

The primary purpose of the emergency damage inspection is to save human lives and prevent injuries by identifying buildings weakened by the earthquake and threatened by subsequent aftershocks [29 – 30]. The other important objective of this operation is to avoid unnecessary waste of resources and additional human suffering by identifying habitable and easily repairable buildings, reducing the number of homeless people, and the disaster's economic cost. Unfortunately, after an earthquake, the demand for building experts often exceeds their availability [2, 4]. In many instances, not experienced engineers and poorly, if at all, trained technicians are assigned to this difficult task without specific criteria about what to do and how to decide. Due to the problem's importance and extent of the problem, official institutions in highly seismic regions, like Italy, have been recently concerned with the issue of EPEDA [6 – 9]. The National Group for Earthquake Loss Reduction has developed a questionnaire with instructions and guidelines on how to proceed with the assessment [31 – 35]. The guidelines suggest several steps to take during the inspection and propose a way to reach the final decision. The methodology presented is the result of the experiences acquired through the various earthquake events that have struck Italy during the past many years and of an effort to structure the process through which the assessment is reached. This effort is tentative and exploratory and is open to improvements as more knowledge becomes available. It attempts to define the criteria behind the condition assessment and present them logically and practically to the building inspector [10 – 15]. However, this questionnaire and the accompanying guidelines give a rigid and unfriendly work platform, especially given the emergency conditions that follow an earthquake and the associated time pressure. The problem then consists of developing a methodology that captures and structures the reasoning of recognized experts in the area and finding a flexible and transparent medium of transfer of the gathered and structured expertise to the inexperienced

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building inspector [16 – 20]. Traditional computer techniques have often provided engineering problems with efficient and fast solutions. However, as pointed out in previous sections, the issue at hand is difficult and complex primarily due to the nature of the knowledge involved, which still is, in part, an art and for which traditional procedural and algorithmic computer techniques have proven to be inadequate. The field of Artificial Intelligence has developed a series of tools for dealing with such problems. The resulting computer systems can very effectively manipulate symbolic data and qualitative measures and can, to a certain extent, mimic human reasoning. Empirical, experience-based, and procedural knowledge can efficiently be encoded in such systems, providing a functional product. These systems are known as Expert Systems or, more generally, Knowledge-Based Systems [21 – 25].

A portable, interactive, knowledge-based system for assisting inexperienced engineers or technicians during the emergency condition assessment would be an excellent answer to the problem of expertise transfer mentioned earlier. Such a system would encode the methodology followed by experts in the field and make it available to profanes. To demonstrate the feasibility and the potentiality of such a system, ANN is a Knowledge-Based System for assisting building inspectors during the emergency post-earthquake damage assessment [26 – 28]. It has become exciting and productive to use the Fuzzy Set Theory that consents to a more prosperous and more conscious definition of uncertainties the operator meet, offering then, in the phase of data processing, the opportunity to combine and "project" the uncertainties about the data to uncertainties about the effects in a sufficiently clear and measurable way; - a critical survey of the procedure as a whole has consented to single out and separate more clearly the different aspects of the same & aspects regarding which parameters to examine and, more in general, how to carry out the surveys preliminary to decisions; - factor concerning collecting information in the Data Base & criteria to set based on the findings, keeping the relevant Code in mind [29 – 32].

2. Methodology

The presented methodology is described in detail in reference [06]. It is characterized by an attempt to define better loads of contact, i.e., the loads for which the building is considered safe, and by an effort to provide a uniform assessment of the safety of the buildings. At first glance, the notion of loads of reference may seem trivial, but it is not surroundings. Some risk concepts are associated with these elements: the structural risk, including the geotechnical risk, and the complementary risk, including the nonstructural and external risk; in addition, a level of induced risk related to the danger caused by the building on its surrounding is defined. These risks, in turn, are evaluated through a consistent procedure. This process mainly involves qualitative data obtained through guided visual inspections or official communications [36 – 40].

The structural risk evaluation is the major operation of this condition assessment procedure. It quantifies the actual or incipient hazards associated with the building's load-carrying components, both vertical and horizontal. The level of structural risk depends on the geotechnical risk, the integrity of the structural system (or damage degree), the story of the seismic test endured by the building, the forecast of subsequent aftershocks, and the structural consistency (or vulnerability) of the building. The geotechnical risk quantifies the hazards associated with the soil conditions, the soil damage, and the type of foundations. A geotechnical risk valued between medium-high and very high will be a decisive negative decision factor in the global risk evaluation. When the damage to the soil under or around the building or to the foundation system exists but is not excessive, the geotechnical risk will be a worsening factor for determining the global threat and, consequently, the usability decision. The structural damage, usually the only criterion considered in the usability decision process, can vary, in this formulation, along six discrete levels of gravity, going from "no observed damage" to "total collapse of the structure." For different kinds of structures, the system assists the user in assessing the level of damage: for masonry and reinforced concrete structures, the system offers a detailed description of crushing and cracking, of their position, and their spread; for steal structures, it describes the particular kind of damages that may be found [41 – 44].

The level of the seismic test endured by the structure depends on the intensity and magnitude of the earthquake, the position of the building concerning the epicentral area, and the maximum historical shock in the area. This concept is an essential factor in determining the structural risk level for cases where the observed structural damage is not high enough to dictate the evacuation of critical direct aftershock forecast is an essential factor for the usability decision. t should be the object of seismological studies and given officially, before the inspections, to the person concerned with these investigations [45, 46]. In the present evaluation procedure, the vulnerability is qualitatively based on typology; in the future, it should be the object of more thorough investigations. The exposure becomes essential when the aftershocks are expected to be comparable to the main shock. The structural risk determination shows an apparent attempt to rationalize the EPEDA and gain insight into the buildings' behavior in the unique environment created by the early post-earthquake conditions. It also is a good illustration of the underlying reasoning process. For example, if the damage level is evaluated to be medium, then there is no need to consider the vulnerability level of the structure. On the contrary, if the damage is light and there is a high probability that the seismic crisis is not over yet (possibility of occurrence of solid aftershocks), then the Vulnerability of the building plays a vital role in the determination of the structural risk level. The complementary risk quantifies the hazards associated with sources other than the pre-cited ones. The complementary risk depends on the level of the non-structural risk and the nature of the external threat. Although the leading cause of trouble for a building subjected to seismic action is the possibility of a structural collapse, the heavy stresses can also cause damage to nonstructural elements creating such a possible danger for the persons. The nonstructural risk depends on the likely fall of more or less consistent fragments of nonstructural features and risks resulting from damages to installations [47 – 49]. As to the evaluation of the external threat, instead, you should consider injuries and consequent risks outside the building in question, induced on the adjacent buildings and the passageways.

Presently, it is a general idea that the damaged state of the building is the only crucial decisional criterion for usability. Therefore, the structures having slight or no damage after the earthquake are declared habitable. This rule implicitly assumes loads of reference to be the just-happening earthquake, thereby neglecting possible stronger aftershocks. Moreover, basing the usability decision on the visible amount of damage exclusively is a poor approach and an incomplete strategy. The insufficiency of this rule of thumb becomes conspicuous in the doubtful cases, where visible injuries of various degrees of gravity have occurred due to the earthquake: a large dispersion of the usability decision has been noted in most historical cases. To overcome these limitations, the present methodology proposed to consider as reference loads - where possible - the seismic loads associated with the expected aftershocks for the area in consideration. The available information about the earthquake's strength, the likely sequence of aftershocks, the position of the building inspected concerning the epicenter, and the earthquake history of the site are used to assess whether the building is potentially exposed to severe loading during possible aftershocks. Another critical issue that is, as of yet, left to the personal judgment of the building inspector is the definition of appropriate levels of safety. In the design of new constructions, these levels are regulated by official texts for the various types of structures, ensuring uniformity and well-considered safety. However, the inspector implicitly chooses some level of protection in the emergency post-earthquake damage assessment. For example, the inspector can declare a building "to be evacuated" after having observed slight structural damages, in which case he is taking too high a level of safety; conversely, he can declare a building to be habitable after having reported a medium-to-high level of damage to the structure, in which case he can be taking excessive risk. This policy puts additional weight on the building inspectors and results in an overall non-uniformity of the assessments. Therefore, there is a need to create a template for decision-making to guide the inspectors in their usability assessment uniformly. Moreover, since these guidelines will be partly based on the experimental conditions of and around the building, an additional set of guidelines is needed to ensure uniformity in quantifying these conditions. The present methodology addresses these two questions and offers a more informative way of proceeding [50].

3. AI - ANN Scheme

3.1 Types of uncertainty

In the new version of ANN, the Fuzzy Set Theory is used to manage uncertainty. The latter can be characterized by three aspects, all present in the domain represented in ANN. The incompleteness of information: to reason within the knowledge of the environment on which the Expert System AI-ANN is based implies the construction of decisional processes when only partial information on the object in question is at disposal. That is why it can happen that the definition of a unique causal process explaining the observations carried out is not possible. In incomplete information, one can formulate a certain number of hypotheses, and each can define all or some information obtained. In the most challenging cases, the System can renounce to make a decision. Uncertainty: the domain on which AI-ANN operates is also characterized by uncertainty about the data and the concepts the same expert has in possession a priori. Often it is impossible to affirm that a given datum, or a given knowledge, is accurate, as, for instance, in the case of the datum expressing the type of soil where a given building is situated and the importance of the

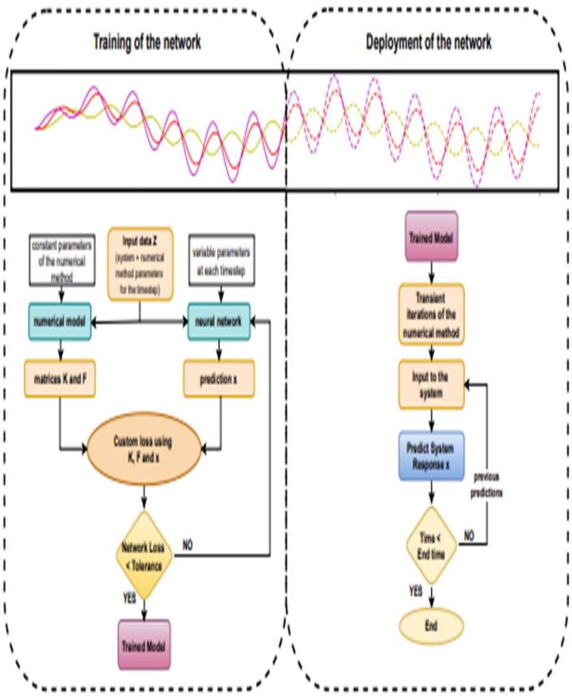

Fig. 1: Physics-informed machine learning workflow for transient physical systems

same in determining the geotechnical risk. Imprecision: finally, you should consider imprecision, which also can characterize both the data and the knowledge of the domain. For instance, you can define vague the datum reporting the macroseismic intensity of expected aftershocks or the evaluation of the power of the shock, which could be described as "very high."

3.2 The Fuzzy Set Theory

The use of the Fuzzy Set Theory has permitted the utilization:
- of natural language, in the realization of the user interface;
- of linguistic variables for the definition of notions, concepts, and truth values;
- fuzzy relations;
- fuzzy numbers;
- fuzzy modifiers.

Moreover, in some parts of the System, heuristic production rules based on Plausible Reasoning have been used. Plausible Reasoning is based on the symbolic elaboration of information. It consists simply in deducing conclusions from facts that appear to be correct, that is to say, connecting the identity of symbols in implication and conclusion.

3.3 Approximate Reasoning

ANN is based mainly on the semantic elaboration of information, made possible using Fuzzy Set Theory, and is realized using Approximate Reasoning.

Approximate Reasoning is based on the concept that a fact is considered an evaluation, and a rule is regarded as an elaboration of evaluations. Approximate Reasoning has the means to represent the propositions of natural language in a form intelligible to a machine and the methodology to carry out inferences from the above information.

According to the theory of Approximate Reasoning, the application of inference rules to information in natural language, translated in fuzzy sets, produces other fuzzy sets

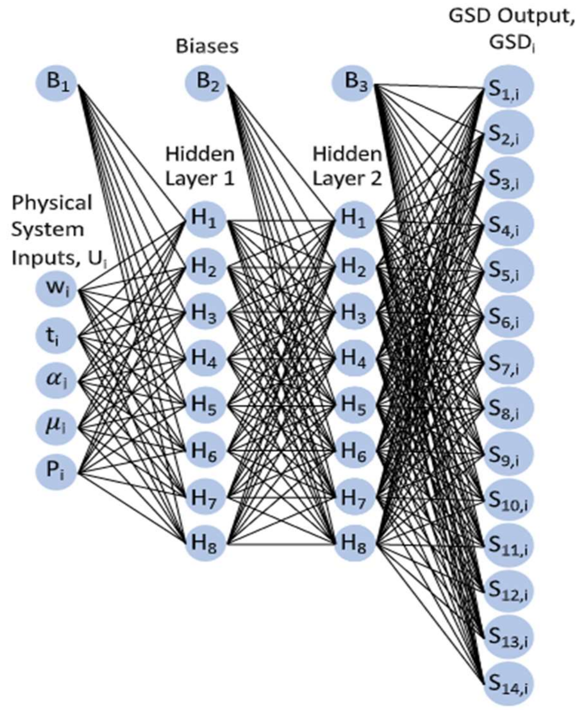

Fig. 2: Topology of the final artificial neural networks

that, retranslated in linguistic values, take back to approximate consequences of the original premises.
In decisional processes, the following methods of Approximate Reasoning have been used:
- fuzzy logic;
- compositional rule of inference;
- vertex method;
- linguistic approximation.

3.4 Updating of the System

3.4.1 Updating of the knowledge base

The Expert System AI-ANN has an updating module that allows intervention within the same knowledge base, making possible modifications necessary in different situations or contexts.
The module permits the following operations:
- addition of new rules,
- removal of existing rules,
- modification of existing rules,
- the creation of new knowledge bases.

If different knowledge bases are at their disposal, the user can choose the one he intends to apply in the current session while activating the Expert System.
When a knowledge base is modified, or a new one is created, the System activates a control module that checks the internal consistency of the whole knowledge base: If the surface were not respected, the modifications, or the new knowledge base, wouldn't be accepted. Episodic memories come in several varieties. *Transient episodic memory* has a decay rate measured in hours or perhaps a day (Conway 2001, Franklin et al. 2005). Long-term episodic memories have the potential to store information indefinitely. Long-term *declarative memory* includes *autobiographical memory*, the memory of events as described above, and *semantic memory*, the memory for facts.

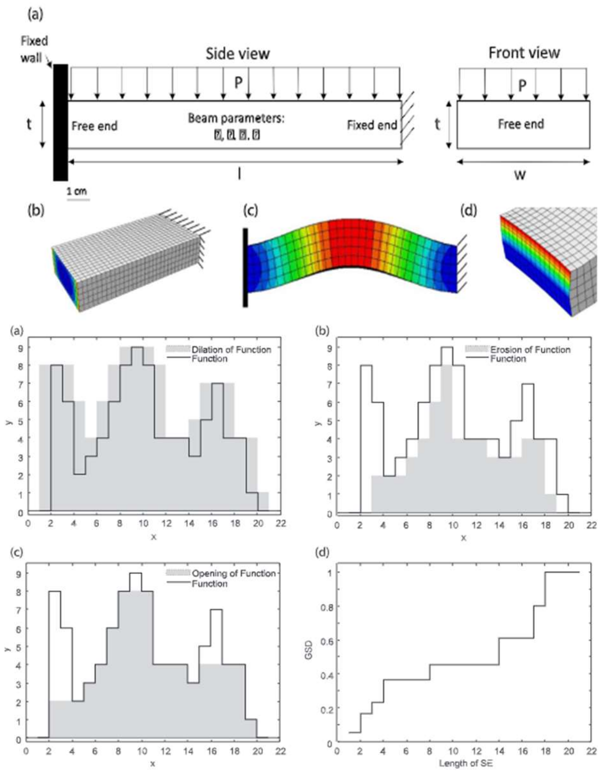

Fig. 3: The (a) dilation, (b) erosion, and (c) opening size distribution (d). PVR

Attention & Action Selection

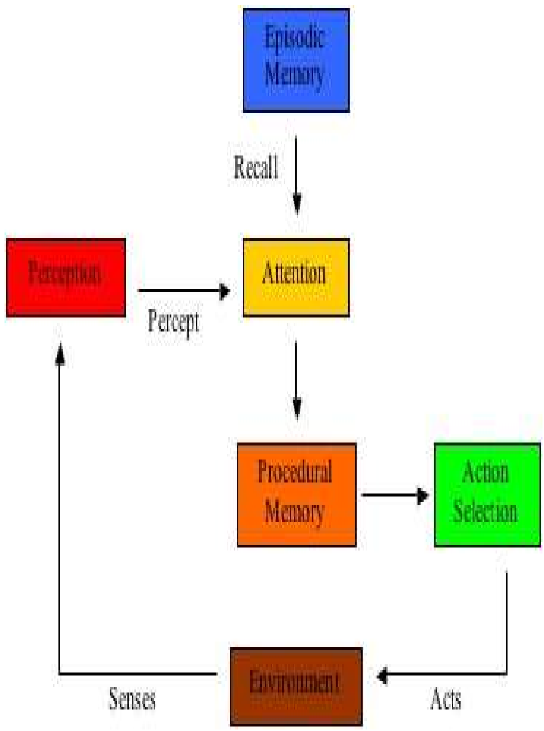

Fig. 4: Attention and Action Selection

In this section, the gray "rest of cognition box" has disappeared to be replaced by attention and action selection. *Attention* is the process that brings information built from perception and episodic memory to consciousness. The global workspace theory of consciousness (Baars 1988, 1997, 2002) postulates a competition for consciousness (see Cognition as Filtering below). The competition aims at selecting the most relevant, the most important, the most urgent, or the most insistent information to become conscious. This is a functional view of consciousness and takes no stand on the possibility of subjective machine consciousness in an AGI (Franklin 2003). The winning conscious information recruits internal resources from which the action selection mechanism selects the next task. For an AGI, such action selection must be pretty sophisticated. In particular, it must be able to choose well between jobs serving different concurrent goals. It also must be able to bounce between seeking two such contemporary plans to take advantage of opportunities offered by the environment.

Cognition as Filtering

Following the *cognitive cycle* in Figure 4 above, one can think of each step as a filtering process. An agent's sensory receptors filter all of the possible sensory data available in the environment, letting through only that to which the agent's sensors respond. Perception, as described above, is also a filtering process. Some sensory data coming in are ignored, while others are processed into possibly valuable and helpful and become part of the percept that moves forward. The recall associations returned from a possibly substantial episodic memory, accumulated over sometimes long periods, are also the result of a filtering process; what's wanted is information relevant to, and essential for, the agent's current situation, including its goals. Hopefully, that's what comes out of this filtering process so far. Attention is yet another filtering process that decides what part of the recent percepts and episodic recall to bring to consciousness. The criteria for this filtering include relevance, importance, urgency, and insistence. Procedural memory then uses the contents of consciousness, what comes to attention, to recruit only those actions that might be possible and useful in the current situation, yet another filtering process. Our final filtering process is action selection, choosing the following step. The more complex the environment and the agent, the more filtering is needed. One can think of the whole cognitive cycle and cognition as a strict filtering process.

Learning

Since an AGI must learn by its very nature, we next add several sorts of learning to the cognitive cycle (see Figure 5 below). One can assume that the agent knows to which it attends (Baars 1988 section 5.5). Thus the learning arrows, in red, immerge from the Attention box. Though there are others, you'll see three different kinds of learning denoted here. There's *perceptual learning*, learning new meanings of objects, categories, relations, etc., or reinforcing existing definitions. The *episodic understanding* of events, the what, the where, and the when, is denoted by its encoding. Finally, *procedural learning* improves skills and helps learn new skills.

A Foundational Architecture for AGI

So, if one can aim for an AGI, where do you look for it? How should one go about trying to build an AGI agent? In my view, if you want innovative software, copy it after a human. That is, model the early AGI agents on what one can know about human cognition. In the previous sections, one can've discussed modules and processes derived from human understanding that must be included in any AGI architecture. Where can one go from there? One possibility is to dive right in and attempt to build a full-blown AGI directly. This

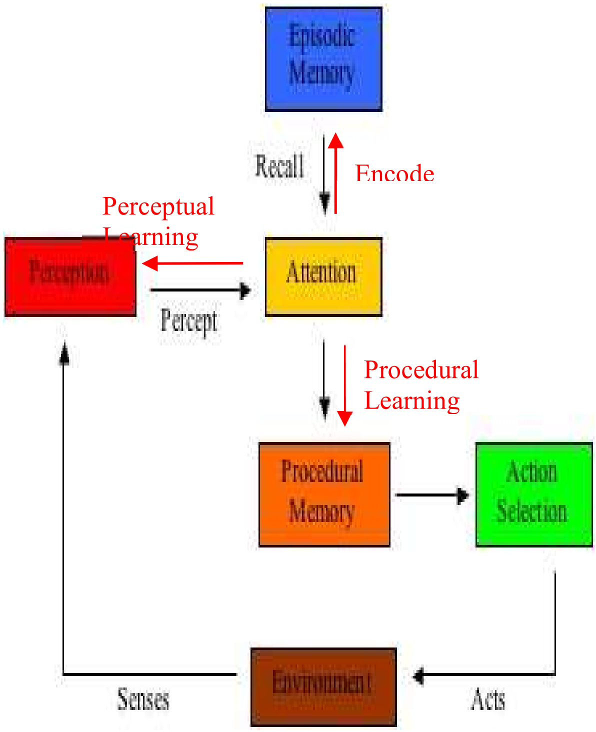

Fig. 5: Learning

strategy, while indeed ambitious, may well succeed. A second possible strategy might be constructing a sequence of increasingly complex, intelligent, and general artificial agents, culminating in a true AGI. This second strategy may prove to be even more likely to succeed. They suggest enabling this second strategy through a typical foundational architecture for each agent in the sequence. Such a foundational architecture would allow each successive agent to be built by adding higher-level cognitive processes to its predecessor. Let's assume, as one can must (Posner 1982, Franklin 2000a, Weng 2004, Franklin 2005b, D'Mello et al. 2006), that learning via a developmental period must be an integral part of the life cycle of any AGI. The strategy suggested might allow what's known by one robot to be initially incorporated into its immediate successor.

Any autonomous agent, and hence any AGI, must operate using a continuing iteration of cognitive cycles, the sense-cognize-act cycles described above. Each such mental cycle acts as a cognitive moment, an atom of cognition, in that each higher-level cognitive process is performed via the execution of a sequence of cognitive cycles. Higher-level cognitive processes are built on these mental cycles as cognitive atoms. Thus, a foundational architecture for AGI must implement a cognitive revolution to be continually iterated and must provide mechanisms for building higher-level cognitive processes composed of sequences of these mental cycles. The AI-ANN architecture, to be described next, accomplishes both.

The AI-ANN Architecture

IDA denotes a conceptual and computational model of human cognition. AI-ANN, short for Learning IDA, indicates another model with learning added. Let's start with a brief description of IDA. The US Navy has about 350,000 sailors. As each sailor comes to the end of a particular tour of duty, they need a new billet and job. The Navy employs some 300 detailers, as they call them, personnel officers who assign these new billets. A detailer dialogs with sailors, usually over the telephone but sometimes by email. These detailers read personnel data from a sailor's record in a Navy personnel database for items bearing on qualifications. They check job requisition lists in another Navy database to see what jobs will come available and when. They enforce the Navy's policies, adhere to the sailors' wishes, and look to the needs of the particular job. Eventually, the detailer offers the sail or one, two, or, rarely, three positions. Some back-and-forth negotiations ensue, involving several communications. Hopefully, the sailor agrees to take a job offered by the detailer. If not, the detailer assigns one. IDA, an acronym for Intelligent Distribution[1] Agent, is an autonomous software agent which automates the tasks of the detailers as described in the previous paragraph (Franklin, Kelemen, and McCauley 1998, McCauley and Franklin 2002). Built with Navy funding, IDA does just what a human detailer does. In particular, she communicates with sailors in her natural language, English, through email rather than telephone. The sailor writes any way they want to write. There's no prescribed protocol or format, no form to fill out. IDA understands what the sailor writes in knowing how to pick out relevant and essential information from the email message and what to do with it. IDA is implemented, up and running, and tested to the Navy's satisfaction. To accomplish the tasks of a human detailer, IDA employs several higher-level cognitive processes. These include constraint satisfaction (Kelemen Franklin and Liang 2005), deliberation (Sloman 1999, Franklin 2000b), sophisticated action selection (Negatu and Franklin. 2002), and volition (Franklin 2000b). Both in its cognitive cycle and its implementation of higher-level cognitive processes, IDA, and its learning extension AI-ANN, implement primarily several psychological theories of cognition. We'll briefly describe each and its role in the AI-ANN architecture.

The AI-ANN Cognitive Cycle

AI-ANN operates as any autonomous must, with a continuously iterating cognitive cycle. Higher-level cognitive processes are sequences of several or many of these mental cycles. Higher-level cognitive processes might include deliberation, volition, problem-solving, and metacognition. Let's take a quick, guided tour through AI-ANN's cognitive cycle based on Figure 5 above. Figure 6 below will provide a helpful map for our time. Note that this mental cycle is highly complex, yet all of this must be accomplished in every cognitive moment. Computational resources may well prove an issue. Beginning at the upper left of Figure 6, one can see stimuli coming in from both the internal and the external environment. Recall that, by definition, every autonomous agent is a *part* of its environment. AI-ANN is modeled after humans; one must deal with external and internal stimuli. Any AGI will likely have also to do so. In *Sensory Memory* (SM), one would find the sensors and primitive, built-in feature detectors. It would also include early learned, and therefore not primitive, feature detectors that provide the beginnings of an understanding of the stimuli. Note that information from SM goes both to Perceptual Associative Memory, which we'll discuss next, and to the Effectors via the SMA (sensory-motor automatisms). In the latter role, SM is crucially involved in quickly providing precise spatial, temporal, and egocentric information that permits such actions as successfully hitting

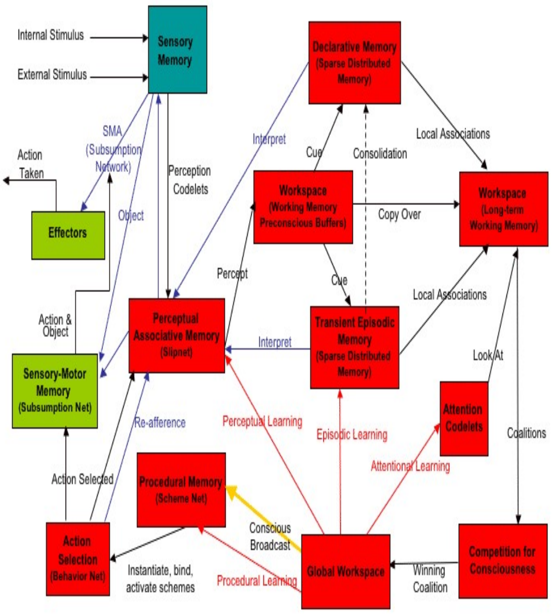

Fig. 6: The AI-ANN Cognitive Cycle

an oncoming fastball fastballrasping a cup. Such SMA's in humans operate on their direct sensory-motor cycles at about five times the rate of the more extensive AI-ANN cognitive process.

From SM, information travels to *Perceptual Associative Memory* (PAM), which one can implement as a slip net (Hofstadter and Mitchell 1995). Here, the next stage of constructing meanings occurs in recognizing other features, objects, and categories. Passing activation brings some nodes and links over the threshold and thus into the *percept*.

The AI-ANN cognitive cycle includes two episodic memory modules, the short-term *Transient Episodic Memory* (TEM) and the potentially long-term *Declarative Memory* (DM) (Conway 2001, Franklin et al. 2005). Recording such information as where I parked my car in the garage this morning, TEM encodings decay in humans within hours or a day. DM encodings only occur through offline concoctions from TEM. Though they can wear away when sufficiently reinforced DM encodings can last a lifetime. Both episodic memories are computationally implemented using a modified sparse distributed memory (Kanerva 1988, Ramamurthy D'Mello and Franklin 2004, D'Mello, Ramamurthy and Franklin 2005). The percept produced by PAM (described in two paragraphs above) is moved into the *Workspace*, an amalgam of the preconscious working memory buffers and long-term working memory (in Figure 6, the Workspace is split into two boxes). Here additional, more relative, less precise scene understanding structures are built. As well as the current percept, the Workspace contains previous percepts and recent local associations recalled from both TEM and DM, all in various stages of decaying away. These contents of the Workspace serve to cue TEM and DM for current local associations. An understanding of the currecontemporarye is produced in the Workspace using additional, quick, two-way communication, including downstream communication, with TEM, DM, PAM, and SM. Next, the *Attention Codelets*[2], whose job is to bring relevant and essential information to consciousness, comes into play. An attention code has unique interests that it wishes to draw attention to. Each attention code searches the workspace for items (objects, relations, situations) of interest and creates coalitions[3] of these items if it finds them. These coalitions move into the Global Workspace, where consciousness is competition. This competition constitutes the final filtering of input. The idea is to attend to filter the most relevant, the most important, the most urgent, and the most insistent aspects of the current situation. Once the competition for consciousness is resolved, GWT call for a global broadcast of the contents of consciousness. Aside from learning, which we'll discuss later, the primary recipient of the worldwide broadcast is *Procedural Memory* (PM), which one can implement as a scheme net modeled after the schema mechanism (Drescher 1991). PM uses the contents of the global broadcast to pick out those possible actions that might be relevant to the current situation. Each scheme in PM is a template for the activity, with its context and result. The systems that might be relevant are those whose context and consequences respect the contents of the global broadcast, including goals, instantiate themselves, and bind their variables with information from the broadcast.

These instantiated schemes then go to Action Selection (AS), which is implemented as a behavior net (Maes 1989, Negatu and Franklin. 2002), a very sophisticated action selection mechanism. In AS, instantiated schemes compete to be the single action selected, possibly a compound of sub-actions in parallel. Over multiple cognitive cycles, AS may choose a sequence of steps to accomplish a given goal. It might also bounce opportunistically between lines of actions serving different purposes. The single action chosen during a given cognitive cycle is sent, along with the object(s) upon which it is to act, to Sensory-Motor Memory (S-MM), which contains procedures for performing the selected action, the so-called sensory-motor automatisms. Our representation of these sensory-motor automatisms is undecided, but we're leaning toward a net built from subsumption networks (Brooks 1991).

In our tour through the AI-ANN cognitive cycle, one can postpone a discussion learning, which we'll take up now. Our basic premise is that one can learn to which one can attend (Baars 1988 pp 213-214). Thus learning occurs as a consequence of, or at least in conjunction with, the conscious broadcast from the Global Workspace. The effect modulates learning following an inverted U curve. Knowledge is strengthened as the effect increases up to a point. After that, the product begins to interfere, and the learning rate diminishes with further increases in development (Belavkin 2001, Cochran, Lee, and Chown 2006). The AI-ANN cognitive cycle includes four types of learning, three of which were discussed earlier in the chapter (D'Mello, Franklin, Ramamurthy, and Baars, 2006). The perceptual learning of objects, categories, relations, etc., occurs in PAM (Franklin 2005b). Episodic understanding of what, where, and when are encoded in TEM, while procedural learning of tasks occurs in PM (D'Mello, Ramamurthy, Negatu, and Franklin 2006). The hitherto unmentioned form of education is attentional learning, the learning of what to attend, which takes place in the Attention Codelets. One can know little about attentional learning, which is an object of current research. Each type of learning has its selections and instructional form (Edelman 1987). SelSelectionsarning reinforces existing memory traces positively or negatively. Instructional learning adds new entities to the various memories, often by altering or combining existing entities. Following our strategy of producing innovative software by copying humans, the AI-ANN cognitive cycle was modeled after what one can hypothesize happens in humans (Baars and Franklin 2003, Franklin et al. 2005). Though asynchronous, each mental cycprocessns in about 200 milliseconds. But they can cascade, so a new cycle can begin while earlier processes are completed. As a consequence of this cascading, the rate of this cognitive cycle processing is five to ten cycles per second. Though asynchronous, the seriality of consciousness must be preserved. Though none is conclusive, there is considerable evidence from neuroscience suggestive or supportive of these cognitive cycles in nervous systems (Lehmann, Ozaki, and Pal 1987, Lehmann et al. 1998, Halgren et al. 2002, Freeman, Burke, and Holmes. 2003).

Multi-cyclic Cognitive Processes

In the AI-ANN model, cognitive cycles are the atoms from which higher-level cognitive processes are built. Here we'll briefly describe several higher-level functions: deliberation, volition, atomization, non-routine problem-solving, metacognition, and self-awareness. Each is a multi-cyclic process that can be implemented over multiple cognitive cycles using the AI-ANN architecture as a foundation. Let's take them up one at a time, beginning with deliberation. *Deliberation* refers to such activities as planning, deciding, scheduling, etc., that require one to think about an issue consciously. Suppose I want to drive to the airport from a new location in a city I know. It will be a route I've never taken, so I may imagine landmarks along the way, which turns to take, and so, and deliberate about how best to get there. When IDA thinks about whether she can get a sailor from a current job to a specific new job with leave time, training time, travel time, and so forth all fitted in between, that's deliberation. This higher-level deliberative process takes place in IDA (and AI-ANN) over multiple cognitive cycles using behavior streams instantiated from PM into the behavior net (AS) (Franklin 2000b). As GWT specifies, conscious, volitional decision-making, a kind of deliberation, is implemented via William James' ideomotor theory (James 1890, Baars 1988, Franklin 2000b). Once again, *volition* uses an instantiated behavior stream over several cognitive cycles. For example, suppose that being thirsty one morning, I consciously considered the possibilities of coffee, tea, and orange juice, weighing the advantages and disadvantages of each, perhaps by arguing with myself. Mine eventually deciding to drink tea is a volitional decision, as opposed to my typing of this phrase, which was not consciously decided on ahead of time. IDA decides volitionally on which jobs to offer sailors. How can one get from intentionally going through all the steps of learning to drive an automobile to the effortless, frequently unconscious, automatic actions of an experienced driver? One can call this higher-level cognitive process *automation* and implement it in the AI-ANN model via pandemonium theory (Jackson 1987, Negatu, McCauley, and Franklin in review). Once again, automization is accomplished over multiple cognitive cycles using the AI-ANN architecture framework.

In the AI-ANN architecture, Procedural Memory (PM) consists of templates for actions, including their contexts and expected results. Activities are selected from action templates instantiated in response to a conscious broadcast. What if PM doesn't contain any action templates to be recruited to deal with the current situation? In this case, *non-routine problem-*

solving would be required. The AI-ANN architecture is a foundation for an unpublished, non-routine problem-solving algorithm based on an extension of partial order planning (McAllester and Rosenblatt. 1991). Defined by psychologists as thinking about thinking, *metacognition* [4] has, in recent years, become of interest to AI researchers (Minsky1985, Sloman1999, Cox, 2005). There's even a website for Metacognition in Computation (www.cs.umd.edu/~anderson/MIC). Metacognition is often used to update a strategy. Suppose I think I was too hard on my daughter in our interaction last night, and decide that I want to be more empathetic with her next time. That's an example of metacognition. After early, misguided attempts (see, for example, Zhang, Dasgupta, and Franklin 1998), one can now know how to build metacognition as a collection of higher-level cognitive processes on a foundation of the AI-ANN architecture and its mental cycle. This work is currently in an early stage and has not y published. Philosophers, psychologists, and neuroscientists have defined and studied several varieties of selves (Damasio 1999, Strawson 1999, Gallagher 2000, Baars, Ramsoy and Laureys 2003, Goldberg, Harel, and Malach 2006) as shown in Figure 7. Finally, it's possible to implement several varieties of *self* as higher-level cognitive processes on the foundation of the AI-ANN architecture. Again, this work has currently just begun and is as yet unpublished.

All these and many more multi-cyclic processes can be built using the AI-ANN architecture's cognitive cycles as cognitive atoms. This possibility supports producing an AGI as a sequence of ever more intelligent, adaptable, and versatile autonomous agents, each containing the previous and each based on the AI-ANN architecture.

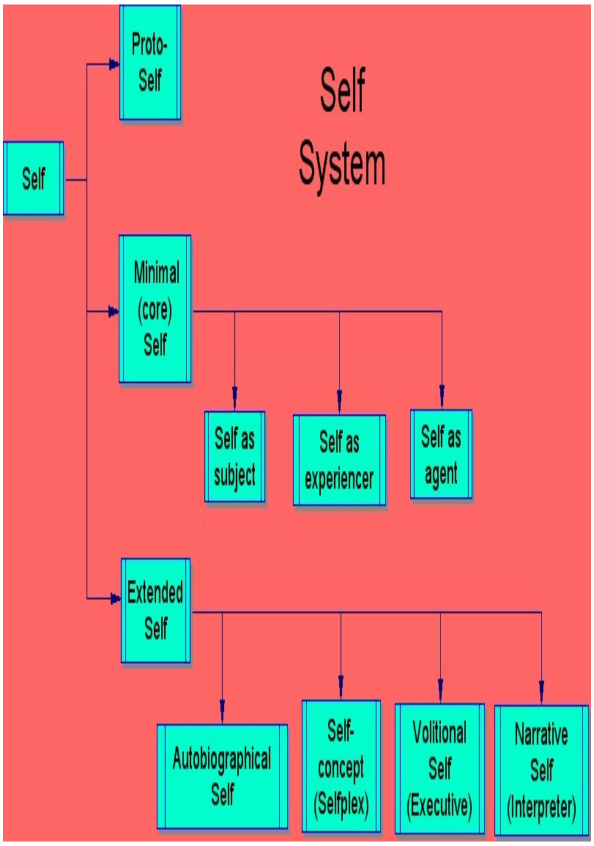

Fig. 7: Various Selves

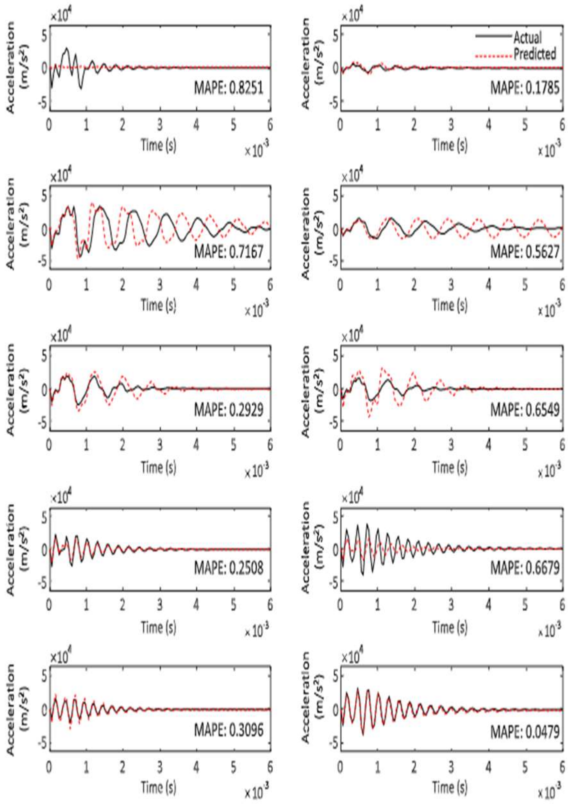

Fig. 8: Characteristic acceleration curves from the ANN compared to the actual acceleration curves

Suppose one can accept the strategy of building an AGI as the culmination of an increasing sequence of ever more intelligent and adaptable AGI agents, each built on the foundation of the AI-ANN architecture with its cognitive cycles as atoms. What general lessons can one learn as a result? Here are a few. One can choose a suitable domain for our agent. A domain? An environment for an AGI agent? I thought an AGI was supposed to generalize. It certainly must be generalized, but it's still an autonomous agent. Every such agent must come with built-in sensors, motivators, and effectors.

Lessons for Building an AGI

That means the agent must have an environment on which to sense and act, that is, a domain. What is needed is a well-chosen domain from which it can be generalized. This would entail a broad enough territory with several sub-domains from which it can generalize. The successor of each agent in the sequence may be situated in a more inclusive domain and may be provided with additional sensors, motivators, and effectors. In my view, an AGI agent is much too much to handcraft. By definition, it's supposed to generalize, that is, to add to its store of knowledge and skill. Therefore it must learn. And how shall it learn? At least at the start, I suggest that it learns like a human, that one can build inhuman-like learning capabilities. Later on, one can or may find better ways of learning. Let's note that some principles of human knowledge can be adapted to human-like understanding in an AGI agent and its predecessors. There's no learning from scratch, from a blank slate. For example, human infants come equipped to recognize faces. The practice of the more sophisticated machine learning research community is to build in whatever you can build in. This same principle should be followed when attempting to make an AGI. Learning, yes. Learning from scratch, no.

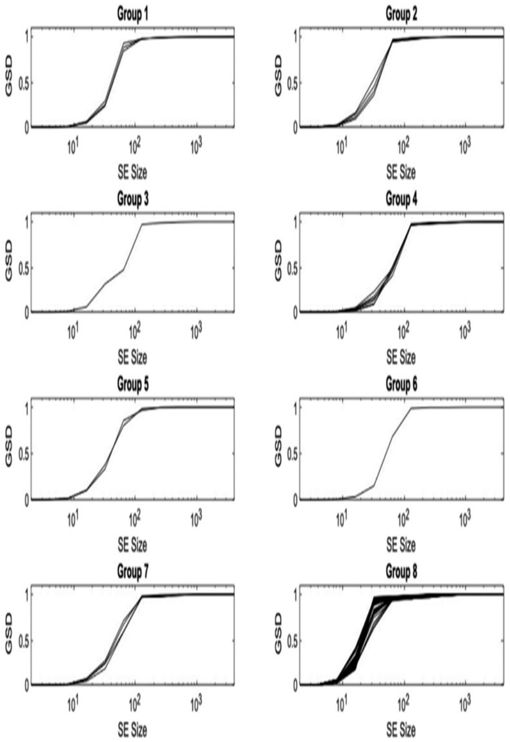

Fig. 9: Clustering of the GSD curves created from the mid-span beam acceleration data

With trivial exceptions, one can learn to which one can attend and only that. The implication is that an AGI must come equipped with an attention mechanism, with some means of listening to relevant information. This implies the need for some functional consciousness, but not necessarily subjective (Franklin 2003). Human learning is incremental and continual. It occurs at every moment, that is, during every cognitive cycle. And it's unsupervised. Supervised machine learning typically involves a training period during which the agent is taught, after which it no longer learns. In contrast, an AGI agent will need to know incrementally and continually as humans do. Though such an agent may go through a developmental period of particularly intense learning, it must also be a "lifelong" learner. Humans learn by trial and error, that is, by what one can in AI call a generate-and-test process. The AI-ANN model hypothesizes that one can learn potential new objects in PAM quickly and on the flimsiest excuses (Franklin, S. 2005b). This is the process of generation. New things are reinforced by being attended to survive, while others decay. This is the testing process. All this is done incrementally and continually, that is, in every cognitive cycle. And this perceptual learning by generate-and-test is not restricted to new objects but applies to categories, relations, etc. Similar processes are in place for episodic and procedural knowledge as well. I suggest that such generate-and-test education will also be needed in AGI agents.

4. Conclusion

The philosophy at the base of AI-ANN is that of considering as far as possible the qualitative and not deterministic, sometimes even ambiguous, nature of reality that it must comprehend and evaluate without abandoning scientific and methodological rigor with which the usability assessment of a building hit by an earthquake must be carried out. The necessity to keep together these two exigencies and integrate them arises from the usability assessment's primary aim: saving human lives. It is important to stress that the system assists the inspector in focusing attention on the relevant issues during the inspection and suggests some conclusion about the building's usability; its objective is not to replace the inspector's decision-making for which they remain fully responsible.

Disclosures

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