Artificial intelligence in structural health monitoring

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ABSTRACT: Structural Health Monitoring is a large field that comprises various scientific and practical aspects as well as a number of heterogeneous engineering technologies. The major goal of Structural Health Monitoring is to accurately identify the current state and behavior of a structure. By automatically analyzing measured data obtained from monitoring devices in a structure, anomalies are detected duly and the reliability of structures is assessed almost in real-time. Furthermore, the evolution of structural deteriorations and damages can precisely be observed. As a result, the costs of maintenance of structures are reduced significantly because revitalization can be better scheduled than before.
Artificial Intelligence (AI), which has a long history in computer science, provides a wide variety of methods for coping with monitoring problems that would be difficult to solve by conventional computational techniques alone. Following a survey of AI strategies, this paper examines today's endeavors in applying AI to monitoring problems. Subsequently, the synergetic implementation of advanced AI methods in an autonomous, distributed system for monitoring civil engineering structures is presented. Also known as Hybrid Intelligence, this approach is evaluated in a further step within a prototype example.

1 INTRODUCTORY REMARKS

Entitled "man vs. machine", Artificial Intelligence (AI) gained great publicity in the last decades when the question was raised whether a machine is capable of defeating a man in playing chess – a game that epitomizes a high degree of intelligence. Indeed, since the beginning of this millennium, powerful chess programs, called "Rebel", "Deep Blue" or "Deep Fritz" (cp. Schroeder 2004, IBM 1997, ChessBase 2006), permanently defeat world champions and international grandmasters. As a result, computer chess was regarded as a prominent AI success story although the above programs are largely based on fairly simple analysis routines. That is to say that chess programs "simply" examine possible moves, then, all counter-moves to those moves, etc. Such a process is internally represented in terms of a directed graph, called search tree, whose nodes are "positions" and whose edges are "moves" in the game. Well-established search algorithms – in the past, mostly brute force search algorithms, nowadays alpha-beta pruning and null-move heuristics (see Heinz 1999) – are adopted to select the most promising moves as fast as possible. But is a program worth to be called "intelligent" when it is winning a chess game based on calculating $2 \cdot 10^8$ chess positions per second e.g. with a 32-node cluster (Pal 2007)? And would, consequently, a grandmaster be called un-intelligent when he is calculating approximately 3 positions per second?

The question, whether a program acts intelligently without any human-level cognitive ability or self-awareness is a crucial issue in AI research. Answers to this question strongly depend on the particular view point taken. As a consequence, neither a positive nor a negative answer should be given before it is not clear,

(i) if AI aims at *incorporating* human-like intelligence, covering thought, consciousness and self-awareness, by replicating biological models leading to a philosophically grounded definition of intelligence,
(ii) if AI specifically enhances special, computational problem solving mechanisms, that *simulate* intelligent human behavior without including any relation to human cognitive abilities.

These two diametric views on AI lead to a large spectrum of various approaches among leading AI researchers towards defining and classifying AI, its objectives and its methods: Based on different criteria, frequently a distinction is made between weak and strong AI (Nordlander 2001). In other cases AI is divided into Symbolism and Connectionism (Schmidt-Schauß and Vinciarelli 2006), or into rational and humanoid thinking and acting (Dilger 2006). Again, others categorize engineering-oriented AI and AI that aims at cognitive objectives (Wahlster 2006), etc. Even more categorizations will probably emerge in the future as more and more problems are solved and new problems identified. It is evident that none of these categorizations constitutes a general definition of AI disciplines.

2 CONVENTIONAL ARTIFICIAL INTELLIGENCE AND COMPUTATIONAL INTELLIGENCE

With respect to incorporation or simulation of human intelligence, a dualism can be identified as a common basis for all the aforementioned AI categorizations leading to two major schools of thought: First, the *symbolic* school of thought, also known as *Conventional AI*, and second the *subsymbolic* school of thought that includes *Computational Intelligence*, historically represented by Neural Networks.

Conventional AI (CAI) attempts to represent human knowledge explicitly, in a declarative form. Thereby, implicit or procedural knowledge and expertise acquired by humans is translated into an explicit form, where particular symbols and symbol structures convey certain meanings. Theses structures are manipulated and new symbol structures are created through well-defined, explicit rules. Thus, human-like intelligence is mimicked without any human cognitive abilities. Popular methods in CAI include, for example,

- Expert systems,
- Case-based reasoning and/or
- Bayesian Networks.

Computational Intelligence (CI), is focused on the incorporation of human-like intelligence and thought on a subsymbolic level. By modeling mental phenomena as emergent processes of interconnected networks of elementary units, knowledge can be implicitly represented. Examples for this are the strengths of particular connections between these units – similar to neurons (seen as units) and synapses (being connections) in the human brain (see figure 1). Characteristic realizations of this approach are

- Neural Networks,
- Fuzzy systems and
- Evolutionary Computation,

representing biologically inspired methods within CI.

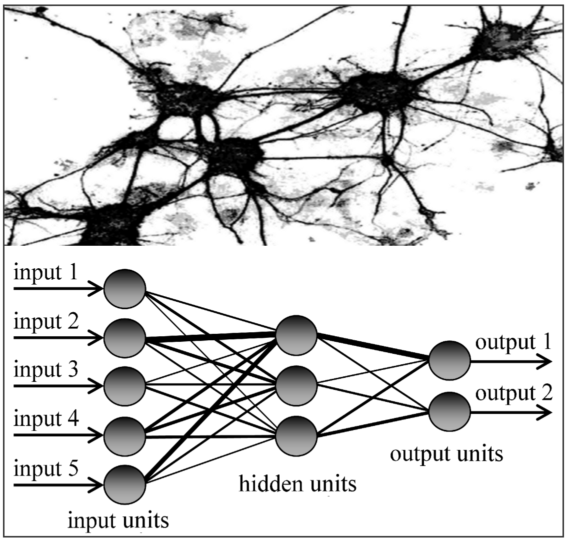

Figure 1. Interconnected neurons in a human cerebral cortex and artificial Neural Network.

3 ARTIFICIAL INTELLIGENCE IN STRUCTURAL HEALTH MONITORING

Numerous AI methods deriving from CAI and CI, as well as hybrid approaches, have already been successfully implemented in various disciplines, such as Robotics, Data Mining and Pattern Recognition, Knowledge Representation and Agent Systems. Also, Structural Health Monitoring (SHM), a rapidly growing and innovative academic field, benefits increasingly from the advances in AI. The prime goal of SHM research today is in general, to accurately identify the state and actual behavior of a structure. In addition, it is intended to develop appropriate tools for assisting and supporting the involved human experts in performing their specific monitoring tasks.

For that purpose, *CAI*-associated methods, and in particular those approaches, that are based on expert or knowledge-based systems have been successfully evaluated in many fields within SHM. Of course, sufficient expert knowledge is required for an adequate solution of SHM tasks. By way of example, Hartmann and Smarsly (2005) incorporate expert knowledge into a SHM system for the automated computer-based assessment of acquired structural data by using Expert Systems; Madani (2006) has used Expert Systems for assisting bridge engineers in adopting maintenance strategies, Lücken (2004) for damage diagnoses of bridges and Sriram (1997) pursues the application of Expert Systems in various SHM-related fields and engineering problems, such as diagnosis, control, etc. Also, Case-Based Reasoning is frequently proposed to develop deterioration models for analyzing and predicting deterioration rates of structural members like concrete bridge decks (Lounis et al. 2002), pipes (Mujica 2003) or full-scale civil engineering structures (Smith 1998). For detecting damage locations, also Bayesian probabilistic approaches have been introduced, as published by Sohn and Law (2000).

With respect to *CI*-related approaches, in particular the detection and quantification of structural damages are a main research field of today. A plentitude of efforts has been undertaken to improve damage detection by utilizing biologically inspired approaches: Neural Networks have been used for a long time to detect, e.g., structural damage in various engineering structures (Garrett 1992, Ni et al. 2001). Another strategy aims at applying Evolutionary Computation that allows for a precise approximation of structural damage by means of evolutionary biology based on mutation, inheritance and natural selection mechanisms (Xia and Hao 2001). Furthermore, Fuzzy Logic is included into SHM systems (Reda and Lucero 2004) as damage has often a fuzzy nature.

4 DEVELOPMENT OF AN AI-BASED STRUCTURAL HEALTH MONITORING SYSTEM

At the Institute for Computational Engineering, a hybrid, AI-based SHM system for monitoring safety-relevant engineering structures has been developed. For a reliable and efficient monitoring, several appropriate AI methods have been encapsulated and wrapped into the SHM system using so called software agents. Software agents represent, in general, proactive software entities that interact with other agents, and, if necessary, with humans, they are perceptive to their environment and can respond to changes in their environment. Then, the total group of interacting software agents forms an agent system (the SHM system). There is no need to implement the agent system on a single computer. By contrast, equivalent to the distributed nature of the monitoring problem, individual software agents can be located on different computers, which can communicate with each other via the HTTP.

To provide an efficient real-time monitoring for civil engineering structures, each monitoring task is mapped onto an individual software agent. Accordingly, software agents are in charge of specific tasks, such as the automated acquisition of structural data, or data analyses by utilizing suitable AI methods considered subsequently in more detail. Agents which execute specific monitoring tasks are called T or *task agents* (see figure 2). In addition, T agents cooperate with three other agent categories in the same agent system. The multi-level approach leads to the introduction of C or *cooperation agents* that act as "personal assistants". Thus, each of the C agents is assigned to a respective human actor (for example the head of department, a chief engineer or technicians) to support that actor proactively in solving his specific tasks. Consequently, a C agent provides an interface between a user and the agent system. P or *project agents* are responsible for providing needed structural information associated with the observed structure. Finally, W or *wrapper agents* encapsulate external software (e.g. database systems, finite element programs, etc.) as well as hardware, such as sensory devices to make them available to the agent system.

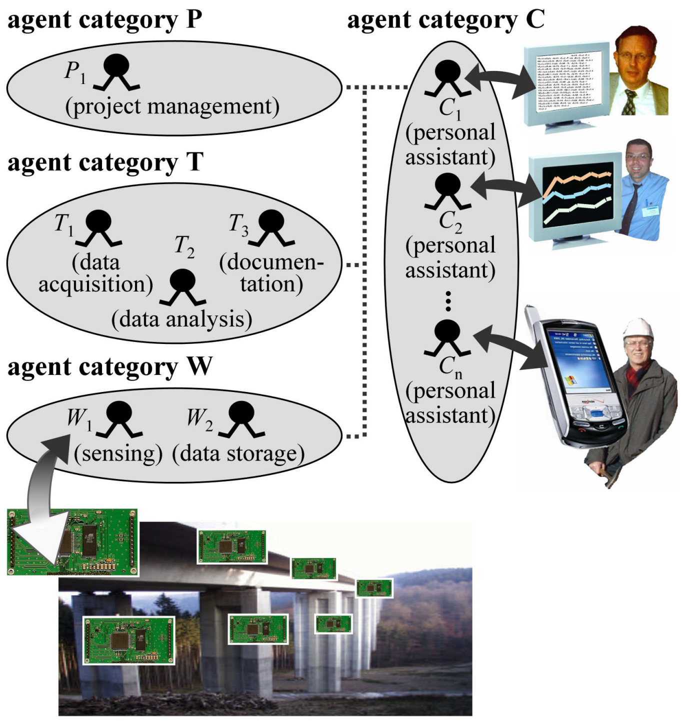

Figure 2. Schematic illustration of the SHM system.

In brief, an agent may be a member of the set

$$A = \{T, C, P, W\}, \quad (1)$$

where each A interacts in an environment E = {A, O} containing a set of objects O (with $A \subseteq O$). E can be created, destroyed and modified by the agents using several operations Op. Objects, agents as well as inter-agent coherences are described in terms of an assembly of relations R.

In total, the agent system can be defined as

$$AS = \{E, R, Op, U\}, \quad (2)$$

where U is a set of operators representing system modifications as well as the environment's reactions to this modifications.

4.1 *Process distribution*

The team of distributed software agents solves a given monitoring problem cooperatively and collaboratively. An often disadvantage of distributed systems is the latency occurring when information from remote sources is to be transferred. Also, agents that are operating in a networked environment suffer from increased latency. As an example, obtaining the latest measured data item from a structure, in technical terms, means for an agent that, instead of just calling a method, it has to set up a request message, fill this message with its concern and send it through the network. After receiving and opening this message, the addressed agent has to extract the content, interpret it, execute the action corresponding to this content, prepare a response message containing the requested measured value, etc.

To overcome latency problems, in the AI-based SHM system considered here, large parts of the monitoring problem have been separated from the overall software system and put to individual microcontroller-based, intelligent sensing units located on-site in a structure. The main purpose of the sensing units is to automatically control the acquisition of structural data via connected sensors. According to figure 2, the sensing units are wrapped into the agent system by wrapper agent W_1. By transferring the execution of plausibility-checks of acquired data from the agent system to distributed sensing units, the network load within the SHM system can be reduced to a large extend. Furthermore, emerging implausibilities can be detected in a more context-aware fashion and by embedded algorithms. In total, this leads to an increased safety and reliability.

4.2 *Application of Hybrid Intelligence for data interrogation*

Various sophisticated AI methods, stemming from *CAI* as well as *CI*, have been investigated and evaluated during the development of the SHM system. As a result, a hybrid approach incorporating new methods from both CAI and CI, called *Hybrid Intelligence*, has been established.

This hybrid approach is exemplarily elucidated for data interrogation, which plays a substantial role in monitoring. To achieve a comprehensive safety assessment of structures, the interrogation of measured data acquired is divided into two different tasks, (i) the *check of plausibility* and (ii) the *data analysis*. The check of plausibility is carried out at the microcontroller-based sensing units, directly after structural data are being entered. Data analysis is conducted by one of the task agents, the so called "analysis agent T_2". In figure 3 it is demonstrated where both tasks are placed within the automated monitoring workflow using a Petri Net notation: The net shows a typical monitoring sequence, that is automatically managed by the SHM system and executed in a cyclic manner. A monitoring sequence starts with the acquisition of actual structural data items, which are then checked with respect to its plausibility. Concurrently, reference data are collected from data bases, condensed and, after assembling, used for a detailed analysis of the new data, the result of which is then stored in a central data base. Subsequently, an internal report of the analysis results is updated and permanently made available to the software agents and human users as well. If no anomaly has been detected, the sequence starts again with the acquisition of recent data.

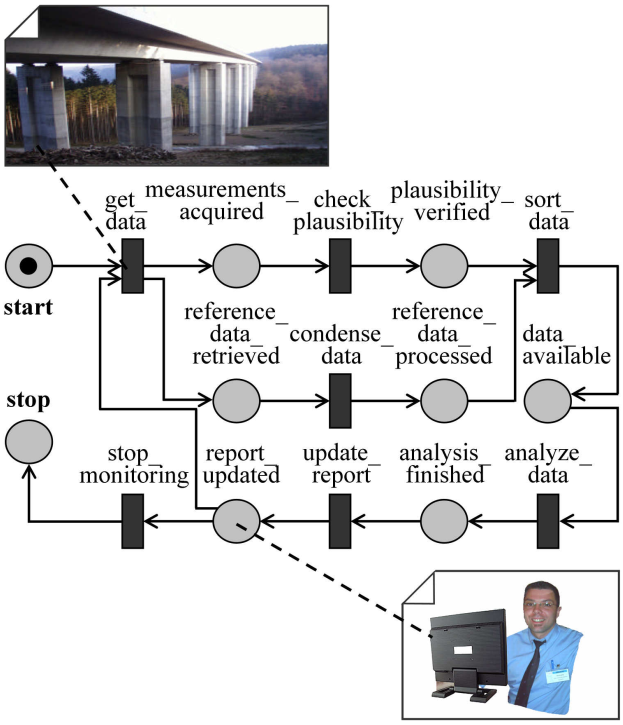

Figure 3. Typical monitoring sequence.

4.2.1 *Check for plausibility*

In this monitoring task, the acquired measured data are analyzed with respect to potential inconsistencies and given thresholds. To this end, the microcontroller-based sensing units check for unaltered values: If equal values are acquired from a particular sensor repeatedly, e. g. for n times (where n depends on the structure and the type of measured value), inconsistencies are indicated. Also, the sensing units accomplish a regression analysis of the acquired data. For that, a simple time series analysis is carried out for detecting implausible values. Such a time series approach can efficiently be executed on a microcontroller with its limited computational power (s. STMicroelectronics 2003). If the response measurement y_{rp} of a structure at a particular sensor location may be regarded, prediction values y_{pp} are estimated. A comparison of y_{pp} to y_{rp} indicates implausibilities, if $|y_{rp} - y_{pp}|$ is greater than δ_{yp}. The permissible range $\delta_{yp} = \delta_{yp}(y_{rp}, y_{pp})$ depends on the particular monitoring project while the prediction value y_{pp} is then computed as

$$y_{pp} = \beta_0 + t\beta_1 + \varepsilon. \qquad (3)$$

Here, t is the time index, β_i are the regression coefficients and the term ε represents the unpredicted or unexplained variation in the variable y_{pp}. In addition, depending on their settings the sensing units may automatically condense the oncoming data to a certain extent by aggregating several values e.g. to a mean value. Afterwards, relevant data are communicated to the software system for accomplishing the data analysis as described in the following.

4.2.2 *Data analysis*

To achieve a comprehensive analysis and a reliable acquisition of knowledge about the structural behavior, the data analysis is subdivided into

- a short-term data analysis and
- a long-term data analysis.

This subdivision is mandatory because each subprocess gets different objectives. Thus, each subprocess demands for an implementation of specific algorithms: In principle, the implemented short-term data analysis consists of two main steps, a prognosis and an evaluation. First, a prognosis value y_{ps} is computed using a simple Multiple Regression model. Similar to the embedded time series analysis, the prognosis value is calculated as

$$y_{ps} = \beta_0 + x_1\beta_1 + x_2\beta_2 + \ldots + x_K\beta_K + \varepsilon, \qquad (4)$$

where the parameters x_i are the corresponding variables independently measured from different sensor locations.

Second, based on the prognosis value y_{ps}, the measured variable y_{rs} is evaluated by using a Fuzzy Expert System (s. Smarsly 2003). Hereby, according to the nature of human knowledge, linguistic terms are introduced for grading the measured value. Typical linguistic terms are “value normal”, “value slightly increased”, etc. (see figure 4).

In a concluding step, which is carried out simultaneously to the short-term data analysis, the long-term data analysis is accomplished based on Data Mining and Machine Learning. An analysis with respect to the long-term behavior of a structure is necessary for an appropriate safety assessment because specified safety-relevant long-term trends can not be recognized through short-term analysis.

For pattern recognition of long-term structural behavior, detailed jump and trend analyses are accomplished: Jump analyses are based on an iterative segmentation of data sets into sub-sets which are then compared to each other. Taking into account a sequence of statistical tests (Mann-Whitney-U-, χ^2-, F- and t-test, s. Lohninger 2005), it is examined whether the expected values of the sub-sets differ and where a jump between the considered sub-series is identified. For determining trends within data series, a Mann-Kendall test generally indicates if a trend is possible. As a result, correlations between the respective parameters can be computed and found.

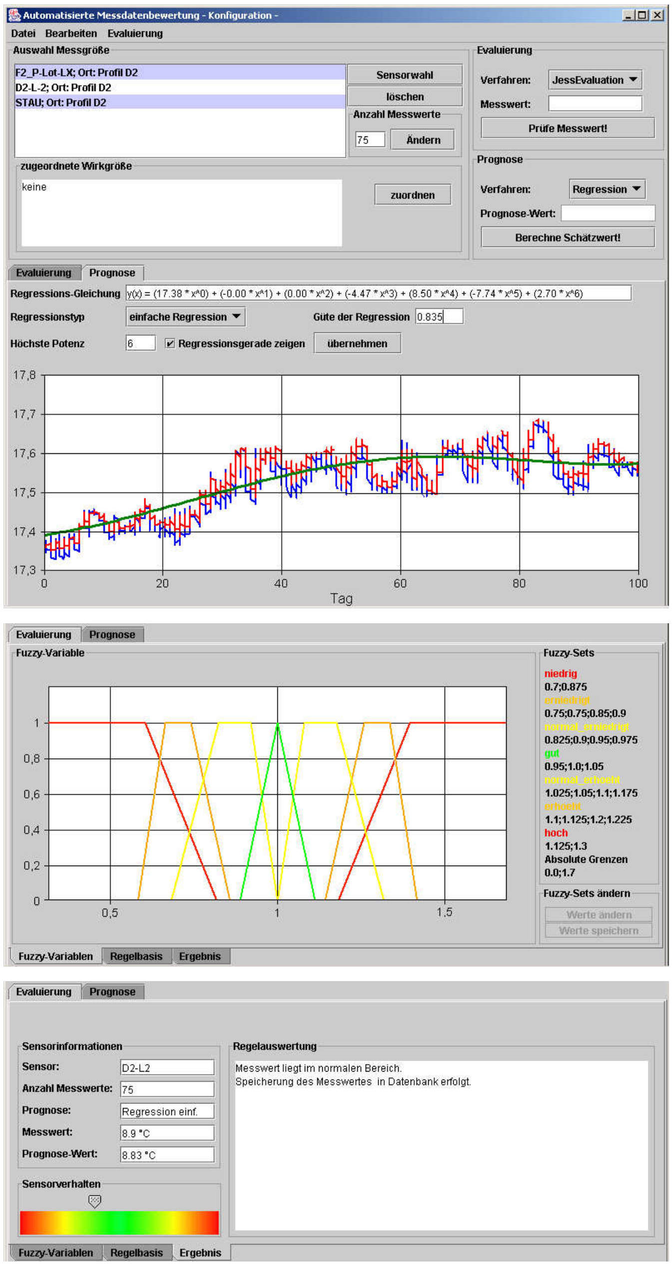

Figure 4. Visual representation of (i) regression analysis, (ii) Fuzzy sets and (iii) evaluation.

As an example showing the importance of trend analyses, the Triebischseitental valley bridge, being erected as a box girder bridge and located near Dresden in Germany, is considered (figure 5). A trend analysis with respect to horizontal superstructure displacements at its bearings along with the surrounding air temperature observed over one year (2000), created a remarkable result interpretable as an “anomalous” structural behavior. In detail, a structural trend within the analyzed data changed during the observed period. Reasons for that were different degrees of creep and shrinkage, represented in the acquired data (due to aging and seasonal differences in air temperature and humidity). The anomaly is documented in figure 6, where the different correlations between displacement and temperature, subdivided into first and second half of the year, are depicted (for further details s. Kaschner 2000).

Figure 5. Triebischseitental valley bridge at its construction.

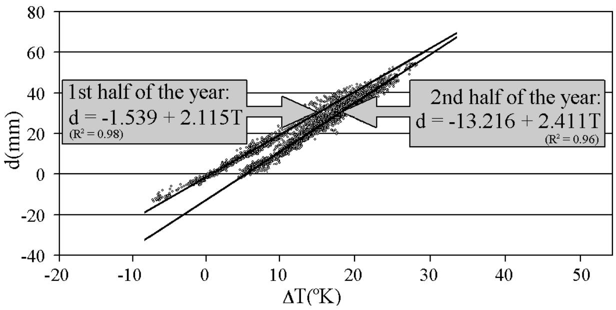

Figure 6. Seasonal displacement and temperature.

5 CONCLUSIONS

In this paper, the application of AI methods, emanating from Conventional AI as well as Computational Intelligence, to engineering problems in Structural Health Monitoring has been presented. For a specific task within monitoring, for the automated data interrogation, it has been demonstrated, how a Hybrid Intelligence approach can help to implemented a distributed agent-based Structural Health Monitoring system. The application of advanced AI concepts and strategies to monitoring problems provides innovative means and ways for improving the efficiency and accuracy of Structural Health Monitoring. By that, structural safety can be drastically improved. Also maintenance costs can be significantly decreased.

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