Structural Health Monitoring based on Artificial Intelligence Techniques

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Abstract

Artificial Intelligence (AI) has a long history in computer science and is now being applied to engineering problems in Structural Health Monitoring (SHM) that would be difficult to solve by standard numerical techniques alone. In particular, the methods of Conventional Artificial Intelligence (CAI) and Computational Intelligence (CI), coupled with agent technology, show great promise in delivering monitoring systems that are robust, redundant, environmentally aware, economically sound as well as user friendly and highly adaptive. In this paper, background concepts of AI and an example of a SHM system for monitoring civil engineering structures are presented to clearly demonstrate the potential of intelligent software applications in the field of SHM.

Introduction

Artificial Intelligence is a term that describes the ability of a computational entity to perform activities in a fashion that usually characterizes human thought. By deploying appropriate models, algorithms and systems, the ultimate goal of AI is to completely replicate intelligent human behavior. Thus, many scientists remain doubtful that true AI with inherent, apparently intelligent behavior, can ever be developed because machines are not "mental" and can, as a result, neither incorporate intrinsic meaning nor a true intelligence. However, with the rapidly increasing advancements in modern sciences, the search for AI has taken various directions comprising a multitude of AI-related technologies and methods. Most of them emanate from well-established disciplines such as neurology, psychology, mathematics, logic, communication sciences, philosophy or linguistics. Accordingly, some efforts towards classifying AI-techniques and methods appear at a first glance very diverse whereas other approaches just differ in their nomenclatures: Using different classification criteria, researchers frequently distinguish, for example, between weak and strong AI (Nordlander 2001), others divide AI into Symbolism and Connectionism (Schmidt-

Schauß and Vinciarelli 2006) or into rational and humanoid thinking and acting (Dilger 2006), some categorize engineering-oriented AI and AI that aims at cognitive objectives (Wahlster 2006), etc. It becomes clear that none of these categorizations constitutes a general definition of AI disciplines, nor a holistic list of strategies and methods; rather, various categorizations and definitions have been proposed in the past and novel categorizations will be suggested in the future as soon as problems have been solved and new problems are identified: AI is not a list of areas or a methodology, but consists of work on the enduring and intriguing aims of understanding intelligent beings and constructing intelligent systems (cp. Doyle and Dean 1996). Thereby, two major schools of thought can finally be identified as a common basis underlying these categorizations.

Symbolism and Subsymbolism. First, the *symbolic* school of thought, also known as *Conventional Artificial Intelligence* (CAI), and second, the *subsymbolic* school of thought that includes *Computational Intelligence* (CI), historically represented by Neural Networks.

With respect to CAI, a symbol conveys a certain meaning, i.e. it represents a particular piece of knowledge. Starting at an initial symbol structure describing a particular problem, new symbol structures are created through logical reasoning, usually based on explicit rules. Although AI should not be understood as an irrevocable list of segregated techniques, a snapshot of present methods shows, that in particular

- Expert systems,
- Case-based reasoning and
- Bayesian Networks

are characteristic methods of interest.

CI, by contrast, does not use single symbols for representing explicit knowledge. Instead, interconnected networks of simple units are built up on an implicit, subsymbolic layer. The strengths of different connections between these units represent knowledge, similar to interconnected neurons in a human brain. These connection strengths, or weights, are acquired by a learning process that only requires one precondition: The CI system must have information about what system output should be produced for which input of a problem – explicit information about the rule, which leads to that output, is however not necessary for performing the learning process. Accordingly, using this biologically inspired concept, the overall goal of CI is to model human-like, mental or behavioral phenomena. Popular realizations of this approach are, for example,

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

AI-approaches in Structural Health Monitoring. The above mentioned methods both from CAI and from CI are implemented in a large area of heterogeneous research fields, such as Robotics, Data Mining, Knowledge Representation, Game

Theory or Pattern Recognition. Also, in the rapidly growing field of Structural Health Monitoring (SHM), the need for innovative AI-based approaches to improve damage detection and safety assessment of structures has been recognized. Thereby, also hybrid approaches (to be depicted in an example later on), that combine several CAI and CI methods, gain importance in research of today.

With respect to CAI-associated approaches, for 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. As expert knowledge is inherently required for adequately accomplishing SHM tasks, approaches based on expert or knowledge-based systems are meanwhile well-established and have been successfully evaluated in many fields within SHM: For instance, 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 different 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 location, also Bayesian probabilistic approaches have been proposed, as published by Sohn and Law (2000).

Regarding CI-related approaches, in particular the detection and quantification of structural damages are a main research field of today. Much efforts have been undertaken to improve damage detection: Neural Networks have been used, for example for detecting structural damage inspired by the cortical structures of the human brain (Garrett 1992). Fuzzy Logic is included into SHM systems as damage often has a fuzzy nature (Reda and Lucero 2005). Furthermore, Evolutionary Computation is proposed, allowing for accurately approximating structural damage, inspired by the evolutionary biology (such as selection or mutation) through genetic algorithms (Xia and Hao 2001).

A hybrid, AI-based Structural Health Monitoring system

At the Institute for Computational Engineering (ICE), a SHM system based on software agents has been developed. A software agent is a software entity that exhibits some form of Artificial Intelligence. According to figure 1, it acts in an environment by i) using its sensors for perceiving its environment, i.e. acquiring data from its environment, ii) processing the acquired data internally[1] and iii) manipulating its environment by acting with its effectors. Consequently, an agent system is a group of agents, cooperating and coordinating their activities by using specified agent communication languages to produce an effective overall system behavior. With respect to the SHM system, the key priority of the system behavior is a reliable

[1] The way of processing differs significantly depending on the agent type: A simple *reflex agent*, for example, may simply use a table defining all possible rules necessary to interact in an environment without having an internal symbolic model of the environment. A *deliberative agent* may contrarily possess knowledge about how its actions will change its environment: It predicts possible consequences by having a central reasoning system that constitutes its "intelligence".

observation and analysis of structural conditions. For that purpose, various AI-methods have been wrapped into the monitoring system for appropriately and efficiently analyzing structural data and, by that, for assisting the involved human experts.

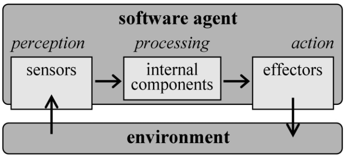

Figure 1. Basic structure of a software agent.

General agent-oriented design considerations. SHM is considered as a distributed engineering task. Consequently, each process within the monitoring problem has been mapped to a single software agent. Every agent is specialized in solving specific tasks and offers specialized services that can be used by other agents or human users. For example, some agents build user-interfaces, other agents encapsulate external software or hardware and make it available in the agent system. In detail, four collaborating agent categories have been designed in order to provide a sophisticated monitoring of engineering structures with an increasing degree of pro-activity and autonomy from category i up to category iv:

Category i: *Wrapper agents* encapsulate external software (e.g. database systems) as well as hardware, in particular sensing units, and make them available to the agent system by offering special services.

Category ii: *Project agents* administrate and provide information about the respective monitoring project.

Category iii: *Process agents* are responsible for solving specific processes within the agent system, such as data acquisition and data analyses.

Category iv: *Cooperation agents* are "personal assistants" to the involved, cooperating human experts. They are arranged in an artificial organization, representing (mapping) the real, specific human organization. Thus, each of the cooperation agents is assigned to one human expert to support that actor proactively in solving his specific tasks; it provides an interface between a user and the agent system.

Process distribution. In addition, large parts of the monitoring problem have been separated from the overall software system and put to individual microcontroller-based, intelligent sensing units located in a structure. The main purpose of the sensing units is to automatically control the acquisition of structural data via connected sensors. The sensing units are wrapped into the agent system by an agent of category i (the sensors agent, see figure 2). By distributing the execution of plausibility-checks of acquired data from the software system to the sensing units, it becomes possible to reduce the network load within the SHM system to a large extend. Furthermore, emerging implausibilities can be detected by embedded algorithms in a more context-aware fashion and in real-time which leads to an increased safety and reliability.

Application example. During the development of the SHM system, the application of various symbolic as well as subsymbolic AI methods, i.e. those stemming from

CAI as well as CI, have been investigated and evaluated. As a result, a hybrid approach, incorporating new methods from both CAI and CI, that is called *Hybrid Intelligence*, has been developed for automatically accomplishing the process of "data analysis and knowledge acquisition" – a key monitoring process.

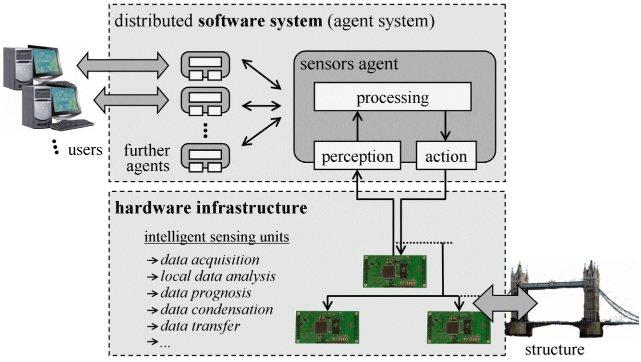

Figure 2. General concept of the SHM system.

The process of data analysis and knowledge acquisition is a central part in the whole monitoring task. With respect to figure 3, it is carried out after automatically acquiring data relevant to reliably assess a structures' condition. After having analyzed and evaluated the data, it is stored persistently in a central database for further processing or archiving and the results are documented. If neither a system failure (e.g. temporarily interrupted remote connection) nor a structural anomaly has been detected, which is the normal case, the sequence starts again with the acquisition of actual data.

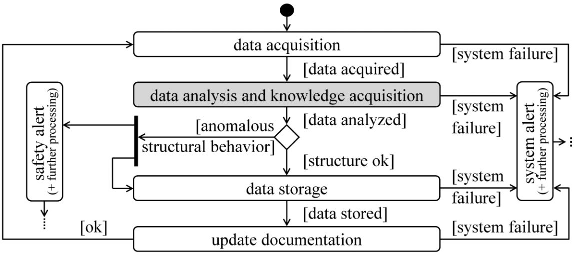

Figure 3. Possible arrangement of data analysis and knowledge acquisition within a monitoring sequence.

In detail, data analysis and knowledge acquisition is carried out in real-time by one single software agent (the so called analysis agent, one of the process agents of category iii). For achieving a comprehensive analysis and a reliable acquisition of knowledge about the structural behavior, the process is subdivided into

- a check for plausibility,
- 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 different, specific algorithms:

Check for plausibility. In a first step, the acquired measured data are analyzed with respect to inconsistencies and thresholds. In the first case, the microcontroller-based sensing units check for constant values: If an identical value is acquired from a particular sensor repeatedly for n times (where n depends on the structure and the type of measured value), inconsistencies are indicated. In the latter case, the sensing units accomplish a regression analysis for the acquired data. Thereby, a simple time series analysis is suitable for detecting implausible values because it can efficiently be executed, in particular on a microcontroller with its limited computational infrastructure (JControl 2007): Regarding a response measurement y_{rp} of a structure at a particular sensor location, prediction values y_{pp} are estimated and compared to y_{rp} as

$$|y_{rp} - y_{pp}| > \delta_{yp.} \tag{1}$$

The permissible range $\delta_{yp} = \delta_{yp}(y_{rp}, y_{pp})$ depends on the particular monitoring project; the prediction value y_{pp} is then computed as $y_{pp} = \beta_0 + t\beta_1 + \varepsilon$, where t is the time index, β_i are regression coefficients and term ε represents the unpredicted or unexplained variation in the variable y_{pp}. Depending on the setting, the sensing units may automatically condense the oncoming data to a certain extent e.g. by aggregating several values to a mean value. Subsequently, relevant data are communicated to the software system for accomplishing the short-term analysis.

Short-term data analysis. The implemented short-term data analysis consists of two main steps, a prognosis and an evaluation. At first, a prognosis value y_{ps} is computed using a Multiple Regression model. Similar to the embedded time series analysis, a prognosis value y_{ps} is calculated as

$$y_{ps} = \beta_0 + x_1\beta_1 + x_2\beta_2 + ...+ x_K\beta_K + \varepsilon, \tag{2}$$

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

Secondly, based on the prognosis value y_{ps} the measured variable y_{rs} is evaluated by incorporating expert knowledge 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., exemplarily shown in figure 4.

Long-term data analysis. In a concluding step, which is carried out simultaneously to the short-term data analysis, the long-term data analysis is accomplished. An analysis with respect to the long-term behavior of a structure is necessary for a comprehensive safety assessment because some 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 executed by an iterative segmentation of the 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-set differ, and where a jump between the considered sub-series is identified. For determining trends within data series, a Mann-Kendall test indicates if a trend is possible. As a result, correlations between the respective parameters can be computed and found.

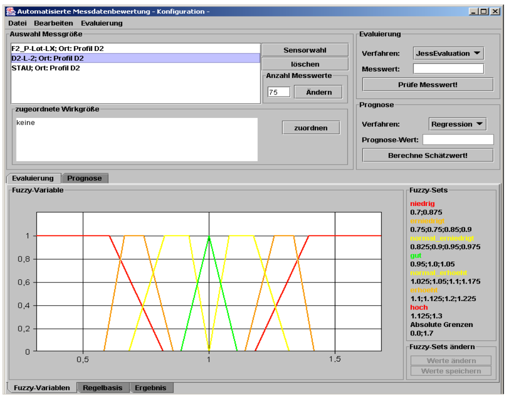

Figure 4. Visualization of the Fuzzy-based evaluation of measured data.

As an example showing the importance of trend analyses, the Triebisch-seitental valley bridge, a box girder bridge near Dresden, Germany, is considered. A trend analysis with respect to horizontal superstructure displacements at its bearings and the corresponding air temperature, observed during one year (2000), created a remarkable result and discovered structural behavior interpretable as an "anomaly": In detail, the trend within the acquired data changed during the year of monitoring. 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). This is documented in figure 5, where the different correlations between displacement d and temperature ΔT, partitioned into first and second half of the year, are depicted (for further details s. Kaschner 2000).

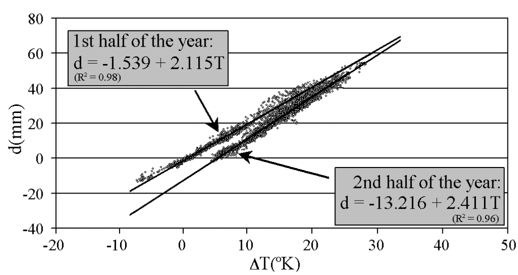

Figure 5. Seasonal displacement and temperature.

Conclusions

It has been shown, how theoretical concepts of AI can help to create distributed, agent-based software systems for providing high quality monitoring services. Using computational powerful and economical viable active monitoring components governed by AI techniques and communicating over low-bandwidth channels, engineers have a tool at their disposal which can supply: Both detailed information, presented in a clear graphical manner as well as an "intelligent" analysis tool which can alert well in advance of a critical solution, as demonstrated in the given example.

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