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A hybrid approach for Structural Monitoring with self-organizing multi-agent systems and inverse numerical methods in material-embedded sensor networks

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ABSTRACT

One of the major challenges in Structural Monitoring of mechanical structures is the derivation of meaningful information from sensor data. This work investigates a hybrid data processing approach for material-integrated structural health and load monitoring systems by using self-organizing mobile multi-agent systems (MAS), and inverse numerical methods providing the spatial resolved load information from a set of sensors embedded in the technical structure with low-resource agent processing platforms scalable to microchip level, enabling material-integrated real-time sensor systems. The MAS is deployed in a heterogeneous environment and offers event-based sensor preprocessing, distribution, and pre-computation. Inverse numerical approaches usually require a large amount of computational power and storage resources, not suitable for resource constrained sensor node implementations. Instead, the computation is partitioned into spatial off-line (outside the network) and on-line parts, with on-line sensor processing performed by the agent system. A unified multi-domain simulation framework is used to profile and validate the proposed approach.

1. Introduction

Structural Monitoring of mechanical structures allows to derive not just loads by using Load Monitoring (LM), but also their effects to the structure, its safety, and its functioning from sensor data, offering some kind of Structural Health Monitoring (SHM). A load monitoring system is a basic component of a SHM system, which provides spatial resolved information about loads (forces, moments, etc.) applied to a technical structure, with applications ranging from robotics to building monitoring.

One of the major challenges in SHM and LM is the derivation of meaningful information from sensor input. The sensor output of a SHM or LM system reflects the lowest level of information. Beside technical aspects of sensor integration the main issue in those applications is the derivation of a information mapping function $Map(\boldsymbol{s}, \boldsymbol{E})$: $\boldsymbol{s} \times \boldsymbol{E} \rightarrow \boldsymbol{i}$ that basically maps the raw sensor data input $\boldsymbol{s}$, a n-dimensional vector consisting of n sensor values, on the desired information $\boldsymbol{i}$, a m-dimensional result vector. The result of the computed information commonly depends on some abstract environmental setting $\boldsymbol{E}$ (see Fig. 1) arising in all technical systems, i.e., the disturbance of data caused by communication, data processing, energy supply, or temporal and spatial data distribution. The goal of the mapping function it to reduce the data dimension significantly, i.e., $m \ll n$.

This work investigates a hybrid data processing approach for material-integrated LM systems by using self-organizing and event-driven mobile multi-agent system (MAS), with agent processing platforms scaled to microchip level which offer material-integrated real-time sensor systems, and inverse numerical methods providing the spatially resolved load information from a set of sensors embedded in the technical structure. Such inverse approaches usually require a considerable amount of computational power and storage resources, not very well matching resource constrained sensor node implementations. Instead, off-line computation is performed, with on-line sensor processing by the agent system. Commonly off-line computation operates on a continuous data stream requested by the off-line processing system delivering sensor data continuously in fixed acquisition intervals, resulting in high communication and computational costs. In this work, the sensor preprocessing MAS delivers sensor data event-based if a change of the load was detected (feature extraction), reducing network activity and energy consumption significantly. Inverse numerical algorithms use matrix computations extensively, so it is in principle possible to distribute and perform

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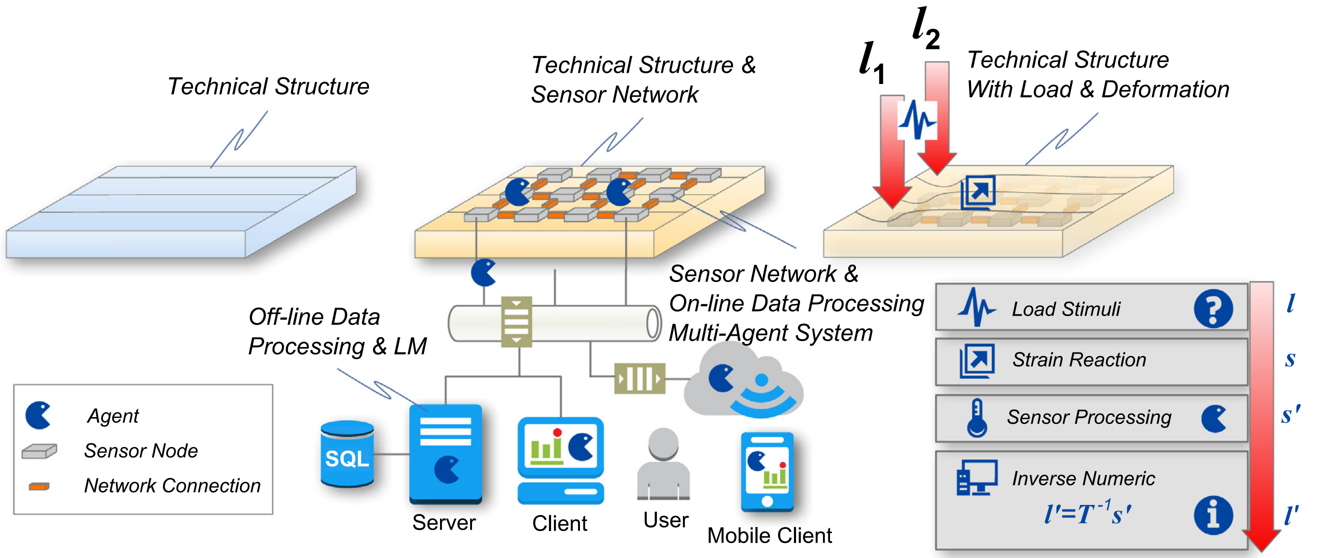

Fig. 1. Initially unknown external forces acting on a mechanical structure lead to an deformation of the material based on the internal forces. A material-integrated active sensor network [22] composed of sensors, electronics, data processing, and communication, together with mobile agents can be used to monitor relevant sensor changes with an advanced event-based information delivery behaviour. Inverse numerical methods can compute finally the material response. The unknown system response for externally applied load $\boldsymbol{l}$ is measured by the strain sensor stimuli response $\boldsymbol{s}'$ (a function of $\boldsymbol{s}$), and finally inverse numerical methods compute an approximation $\boldsymbol{l}'$ to the applied load.

some of the matrix computations in the sensor network offering an on-line pre-computation by the MAS. This is a main advantage over Machine Learning methods used in LM and SHM systems [1–3], which are more difficult to distribute efficiently due to long distance data dependencies.

Basically there are two different information extraction approaches for material-integrated LM systems and a possible optimization of sensor positions: (I) Those methods based on a mechanical and numerical model of the technical structure, the Device under Test (DUT), and the sensor; (II) Those without any or with a partial physical model. The latter class can profit from artificial intelligence, which is usually based on classification algorithms derived from supervised machine learning or pattern recognition using, for example, self-organizing systems like multi-agent systems with less or no a priori knowledge of the environment.

One common approach in SHM is the correlation of measured data resulting from an induced stimuli at run-time (system response) with data sets retrieved from an initial (first-hand) observation, which makes it difficult to select damage relevant features from the measurement results. Other variants are based on statistical methods, data analysis using Fourier- or wavelet-techniques, or neural network approaches. We refer to [4–8] (Chapter 12) posing examples illustrating the variety of possible approaches.

Inverse methods generally belong to the first class of approaches since they are based on a mechanical model $\boldsymbol{T}$ of the technical structure mapping loads to sensor signals. In this study, we consider measurements of surface strains and aim to compute the associated spatially varying (discretized) loads $\boldsymbol{l}$ on the structure. The mechanical model $\boldsymbol{T}$ is gained from linear elasticity and can, in a discretized setting, be represented by a matrix. Given a sensor signal vector $\boldsymbol{s}$ (serialization of a two-dimensional sensor matrix $\boldsymbol{S}$, which is a approximately linear depending on the measured strain), inverse methods try to stably "invert"; the mapping $\boldsymbol{T}$, that is, to find a stable solution $\boldsymbol{l}$ to the problem $\boldsymbol{Tl} = \boldsymbol{s}$. Since measured signals and the underlying physical model always contain numerical and modelling errors, inverse methods do not attempt to find an exact solution to the latter equation. Indeed, inversion problems, in particular those with incomplete data, are usually extremely ill-conditioned, meaning that small errors in the signals or the model lead to huge errors in any "solution"; gained by such a naive approach. Instead, inverse methods try to stabilize the inversion process, using, e.g., one of the following techniques:

- A classical and well-known inversion method is Tikhonov regularization. Pick amongst all approximated solutions to $\boldsymbol{Tl} = \boldsymbol{s}$ the one that minimizes a certain functional – the simplest functional to minimize would be the Tikhonov functional

$$\boldsymbol{l} \mapsto \|\boldsymbol{Tl} - \boldsymbol{s}\|_2^2 + \alpha\|\boldsymbol{l}\|_2^2, \tag{1}$$

where $\alpha > 0$ and $\|\cdot\|_2$ is the 2-norm of a vector defined by Eq. (2), but different and more complicated variants exist and might also be convenient choices. The latter vector norm is defined for any dimension $n \in N$ and any vector $\boldsymbol{v} = (v_1, \ldots, v_n)^\top \in \mathbb{R}^n$ by

$$\|\boldsymbol{v}\|_2 = \left(\sum_{j=1}^{n} |\boldsymbol{v}_j|^2\right)^{1/2}. \tag{2}$$

- Alternatively, consider any iterative method that minimizes the residual $\boldsymbol{Tl} - \boldsymbol{s}$ and stabilize the inversion by stopping the iteration when the norm of the residual is about the magnitude of the expected signal and modelling error. Examples for such iterative techniques include the Landweber iteration, the conjugate gradient iteration, but also recent soft shrinkage techniques, see [9,10].

If the mechanical model $\boldsymbol{T}$ is linear, then the best known inversion method in the first class is the Tikhonov regularization minimizing the quadratic functional (Eq. (1)) by solving the equivalent linear system $(\boldsymbol{T}^*\boldsymbol{T} + \alpha)\boldsymbol{l} = \boldsymbol{T}^*\boldsymbol{s}$, where $\boldsymbol{T}^*$ denotes the transpose matrix of $\boldsymbol{T}$. The most powerful algorithm in the second class is, arguably, the conjugate gradient iteration. The disadvantage of inverse methods with regard to applications based on sensor networks usually is their cost in terms of computing time and memory requirements which definitely is a drawback for material-integrated SHM and LM systems. The possibly high computing