Robot Manipulator with emergent Behaviour supported by a Smart Sensorial Material and Agent Systems

Stefan Bosse(1,3), Stefan Edelkamp(1,2,3), Florian Pantke(1,2)

(1) University of Bremen, Department of Computer Science, Workgroup Robotics

(2) ISIS Sensorial Materials Scientific Centre, University of Bremen

(3) Institute for Artificial Intelligence, TZI, University of Bremen

1. Introduction

Intelligent behaviour of robot manipulators become important in unknown and changing environments. Emergent behaviour of a machine arises intelligence from the interactions of robots with its environment. Sensorial materials equipped with networks of embedded miniaturized smart sensors can support this behaviour.

In this work an integrated autonomous decentralized sensor networks is shown providing perception in a robot arm manipulator. Each sensor network is connected to strain gauge sensors mounted on a flexible polymer surface, delivering spatial resolved information of external forces applied to the robot arm, required for example for obstacle avoidance or for manipulation of objects.

Each autonomous sensor node provides communication, data processing, and energy management implemented on microchip level.

Commonly a high number of strain gauge sensors are used to satisfy a high spatial resolution. Our approach uses advanced Artificial Intelligence and Machine Learning methods for the mapping of only a few non-calibrated and non-long-term stable noisy strain sensor signals to spatially resolved load information and a decentralized data processing approach to improve robustness. Robustness in the sensor network is provided by 1. autonomy of sensor nodes, 2. by smart adaptive communication to overcome link failures and to reflect changes in network topology, and 3. by using intelligent adaptive algorithms. Robust cooperation and distributed data processing is achieved by using Mobile Agent systems **[1]**. Agent behaviour and cooperation is implemented on microchip level **[3]**.

The central aim is to derive useful information constrained by limited computational power and noisy sensor signals not able to be captured by a complete system model. Machine Learning methods are capable to map an initially unknown n-dimensional set of input signals to a m-dimensional output set of information like the position and strength of applied forces **[4]**.

Without any interaction and material model Machine Learning requires a training phase. Additional material models and FEM simulation can reduce or avoid the training phase **[2]**.

The training set contains recorded load positions, masses and classification results for different load cases determined via sensor measurement.

The hyper-elastic behaviour of polymers reduces the long-term prediction accuracy of learned models as well as the consistency with FEM output, requiring Machine Learning models that automatically adjust their output to the structure's ageing process.

2. Machine Based Learning and Multi-Agent Systems

Perception of a robot requires some kind of sensitive skin. The proposed skin consists of a smart strain-gauge sensor network. Machine learning methods with prior training are used to map (classify) a set of (pre-processed and filtered) noisy sensor signals to spatially resolved load information applied to the skin. This approach allows usage of lower sensor density and non-calibrated sensors with unknown electromechanical signal model without loss of spatial resolution. Fig. **1** shows different machine learning approaches (classification and regression) used for mapping of sensor signals to load information with k-nearest-neighbourhood, descision tree, and neuronal network algorithms enabling agent-based structure monitoring based on trained (condensed) data **[4]**. K-nearest-neighbourhood algorithms are used for numerical regression of load position, load strength, and displacement vectors, C4.5 decision trees can be used for strength classification, and neuronal networks are suitable for numerical regression of load position and strength.

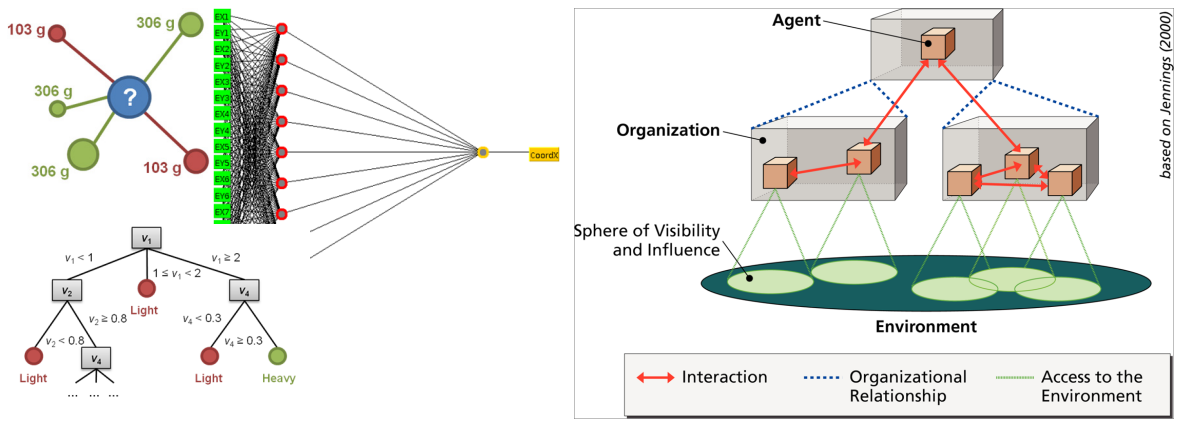

Fig. 1. Different machine learning methods (k-nn, c4.5 desc. trees, neuronal networks) used to retrieve load information (position and strength) and agent-based structure monitoring based on trained data.

Initially, a sensor network is a collection of independent computing nodes. Interaction between nodes is required to manage and distribute data and computed information. One common interaction model is the mobile agent providing autonomy. Mobile agents are used to implement data processing, data distribution, data organization in the sensor network and interaction between the robot and the sensor network. The agent behaviour can reflect information collected and retrieved from machine learning and training, e.g. condensed database values. In our approach, the structure is partitioned into connected substructures, which can be further partitioned into regions. To each region an individual monitor agent is assigned, requiring an appropriate description of how loads and their effects are transmitted across the boundaries between the agent's region and each of the adjacent regions.

3. Robot Manipulator and Distributed Data Processing Architecture

The proposed robot manipulator consists of actors (joint drives) and intersection el-

ements with integrated smart sensor networks. Distributed data processing is provided by mobile agents. The agent behaviour is implemented on hardware-level and SoC designs, shown in Fig. **2**. The intersection element connects two joint actors with a rigid double-pipe construction with surrounded two opposite placed load sensitive skins (bended rubber plate), equipped each with four strain-gauge sensor pairs (biaxial aligned). Each sensor pair is connected to a sensor node providing parallel data processing, agent behaviour implementation, and communication/networking. All sensor nodes are arranged in a mesh-like network connected with serial point-to-point links. Communication is established by a smart and robust routing protocol.

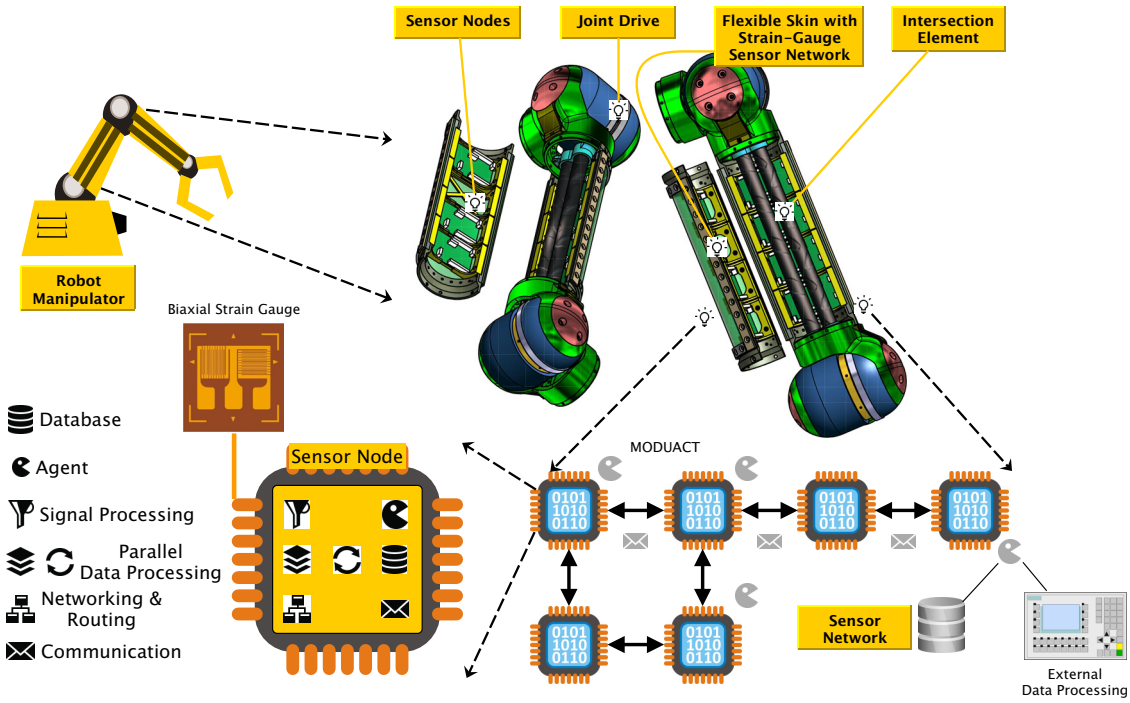

Fig. 2. Robot arm manipulator intersection element equipped with smart sensor networks providing perception information of external applied load forces.

4. Experimental Results using Machine Based Learning and a Rubber Plate

Preliminary experiments were performed with a flat rubber plate (equipped with nine biaxial strain-gauge sensors and the sensor network previously introduced, 70 mm sensor distance) and an experimental set-up shown in Fig. **3** with circular weights. Figures **3** and **4** show the analysis of the difference between measured and predicted load positions (position accuracy) retrieved by machine learning with two different sensor array configurations. The plots show the spatial vector difference between predicted and observed position with a mean value below 25 mm and 50 mm, respectively. The training set consisted of two different masses (103 g and 306 g) and 150 positions. During learning mode the position (of the weight) was monitored with a camera mounted above the rubber plate together with sensor data. A system with reduced number of sensors (Fig. **4**, 150 mm sensor distance) results in a decrease of prediction position accuracy in the boundary region, but is still usable for structure load monitoring especially in the middle area spawned by the edges of sensors.

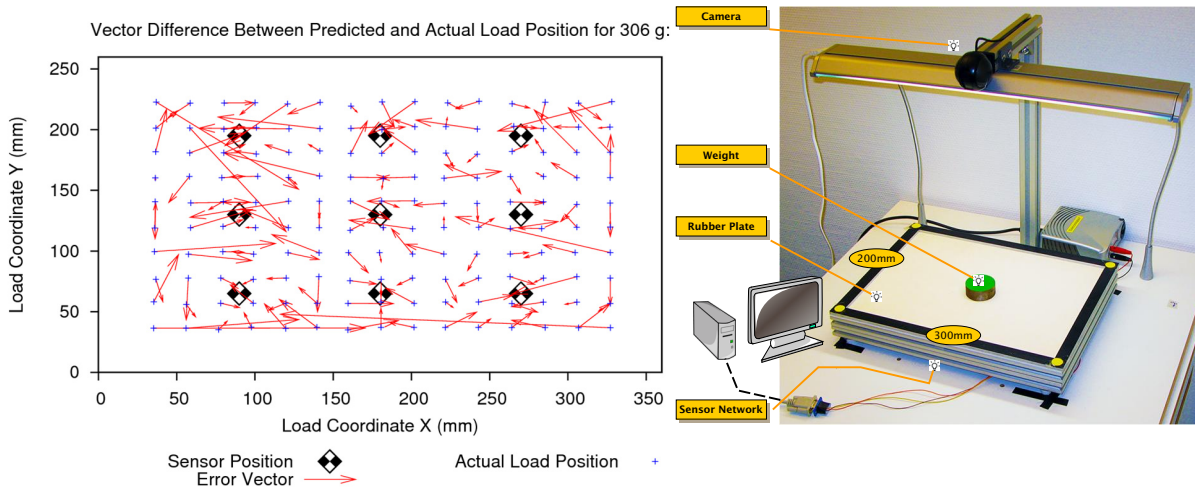

Fig. 3. Experimental results of predicted load positions (306 g weight) with nine strain-gauge sensor pairs mounted on backside of a rubber plate (experimental test set-up shown on right side).

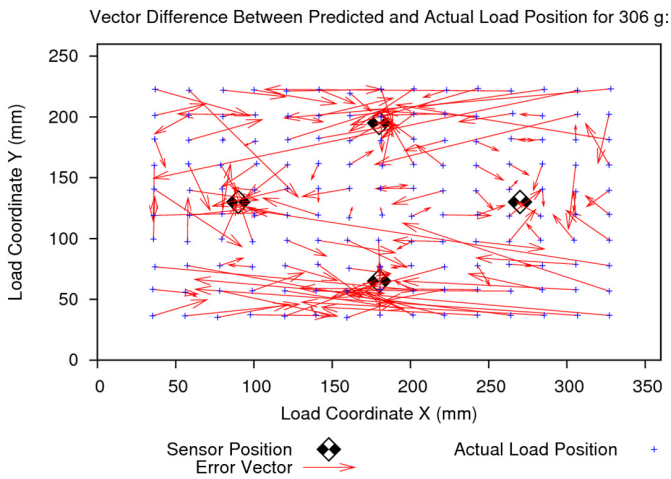

Fig. 4. Experimental results of predicted load positions (306 g weight) with only four strain-gauge sensor pairs.

5. References

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