Fuzzy online learning in a multi-agent system that controls an intelligent building

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1. Introduction

Modern approaches to the architecture of living and working environments emphasize the dynamic reconfiguration of space to meet the needs, comfort and preferences of it's inhabitants. The configuration can be explicitly specified by a human building manager, but there is now increasing interest in the development of intelligent buildings, which adapt to the needs of it's inhabitants without human intervention. We describe a multi-agent framework for intelligent building control that is deployed in a typical commercial building equipped with standard sensors (e.g. presence, temperature, illumination, humidity, wall-switches) and effectors (e.g. lights, window blinds). Our framework includes a novel online learning algorithm that is capable of learning a maximal structure fuzzy rulebase from very sparse data in an unsupervised environment. Many small agents (learning units) control and learn about sub-parts of the whole environment. Agents communicate with each other by an asynchronous, interested based messaging mechanism. All decision making is fuzzy. The learning algorithm is specifically designed to continually adapt the decision making processes in realtime according to the sparse feedback it receives from the environment. Longterm experimental evidence suggests that the proposed algorithm and framework is capable of substantially improving performance of a building in terms of number of decisions taken in relation to the amount of user feedback received.

Multi-agent system

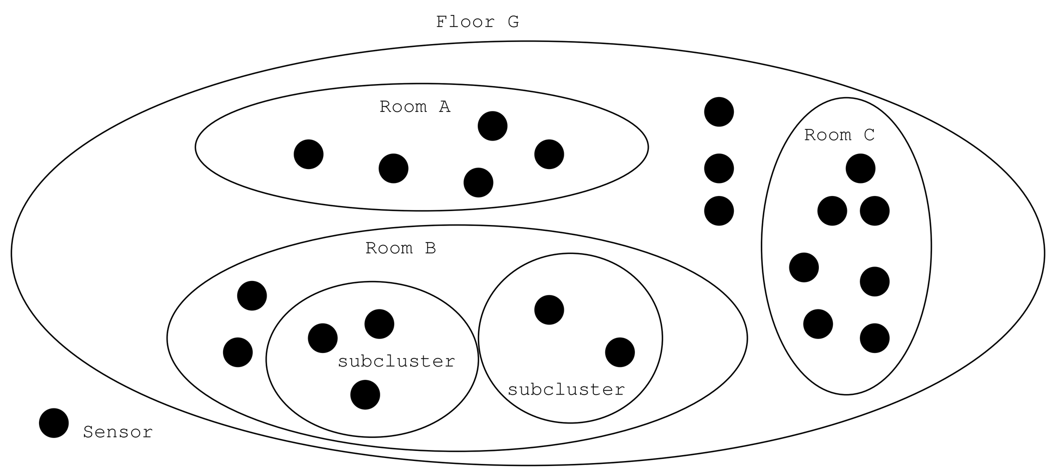

Figure 1: *Clusters*

Sensors and effectors are clustered based on their causal relationship (Figure 1). These hierarchical clusters serve as the basic organizational principle of the system. Both self-organization and learning are based on it.

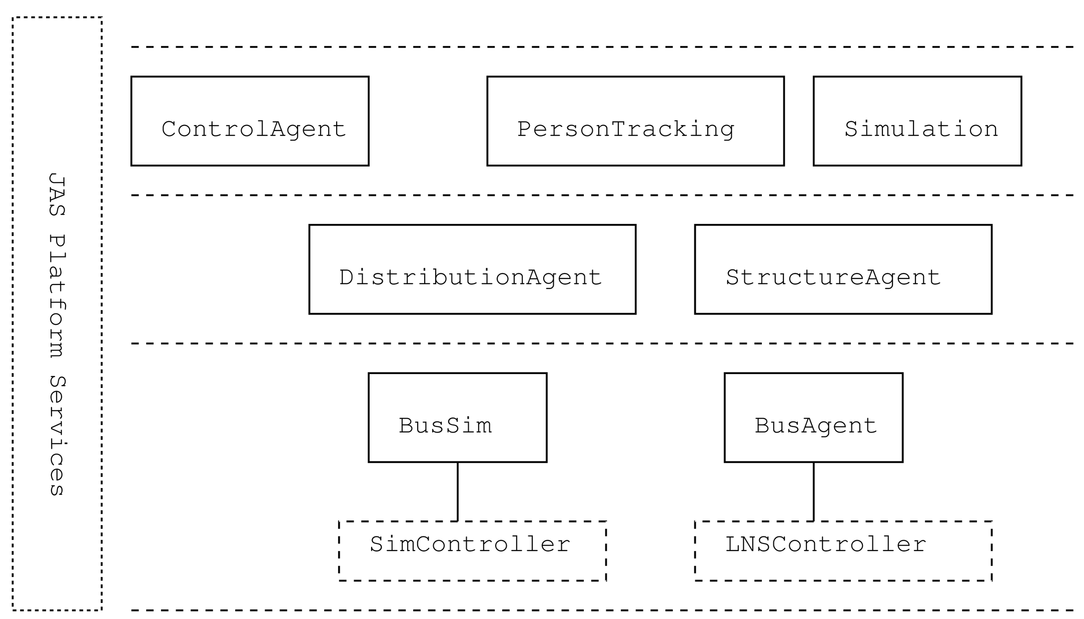

Figure 2: *Sensors/Effectors of a building*

A layered multi-agent system (Figure 2) is used to control the building. Agents are based on the JAS-compatible toolkit ABLE. Decisions are taken by many different agents. Every agent is responsible for a small subset of the whole state space. This emphasizes localized decision making which makes the system much faster. The same principle is applied to learning. There are different learning units. Each of these learning units learn about a small subset of the whole state space. This guarantees much faster convergence of the learning.
The system is composed of the following agents:

1. Simulation: Simulates a building in case no real (physical) fieldbus is present.
2. BusSim: Simulates a physical fieldbus system. Has the same external interface as the real BusAgent.
3. BusAgent: Generic interface to the physical bus system (for example a LON network).
4. DistributionAgent: Collects interests and distributes messages asynchronously according to this interests.
5. StructureAgent: Defines the structure of the sensor/effector relationships. Reads this structure information from XML files.
6. ControlAgent: Controls a single room consisting of multiple clusters. Learns and adapts rules. Takes decisions.
7. PersonTracking: Interface to Bluetooth. Tracks and identifies persons. Notifies other agents when someone enters or leaves a room.
8. VirtualPerson: Simulates an artificial person in a simulated environment

2. Online learning

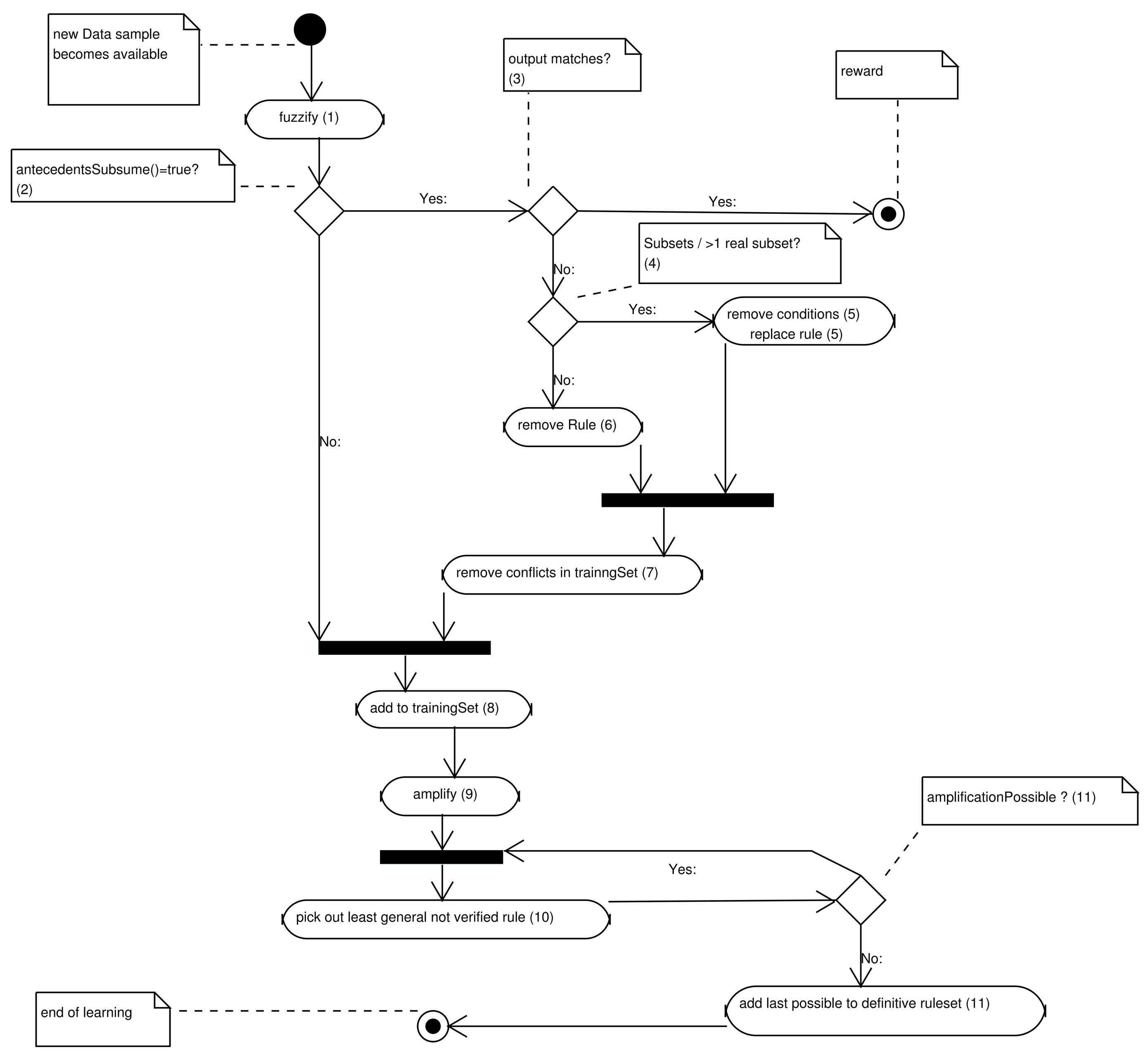

Figure 3: *Anytime learning algorithm for learning maximal structure fuzzy rules*

Figure 3 shows the learning algorithm used for making a building intelligent. It is an online learning algorithm which continuously updates the rulebase of fuzzy logic controllers. It continually adapts itself to the changing conditions of the environment through a implicit punish/reward feedback mechanism. The inputs to the learning process are real valued variables acquired from sensors, the output of the learning algorithm is a model consisting of a number of fuzzy rules. These fuzzy rules are used by a fuzzy logic controller to take decisions. Feedback acquired from the environment is continuously used by the learning process to adapt the fuzzy logic rules. These algorithm is specifically designed to learn from very sparse data.

3. Decision making

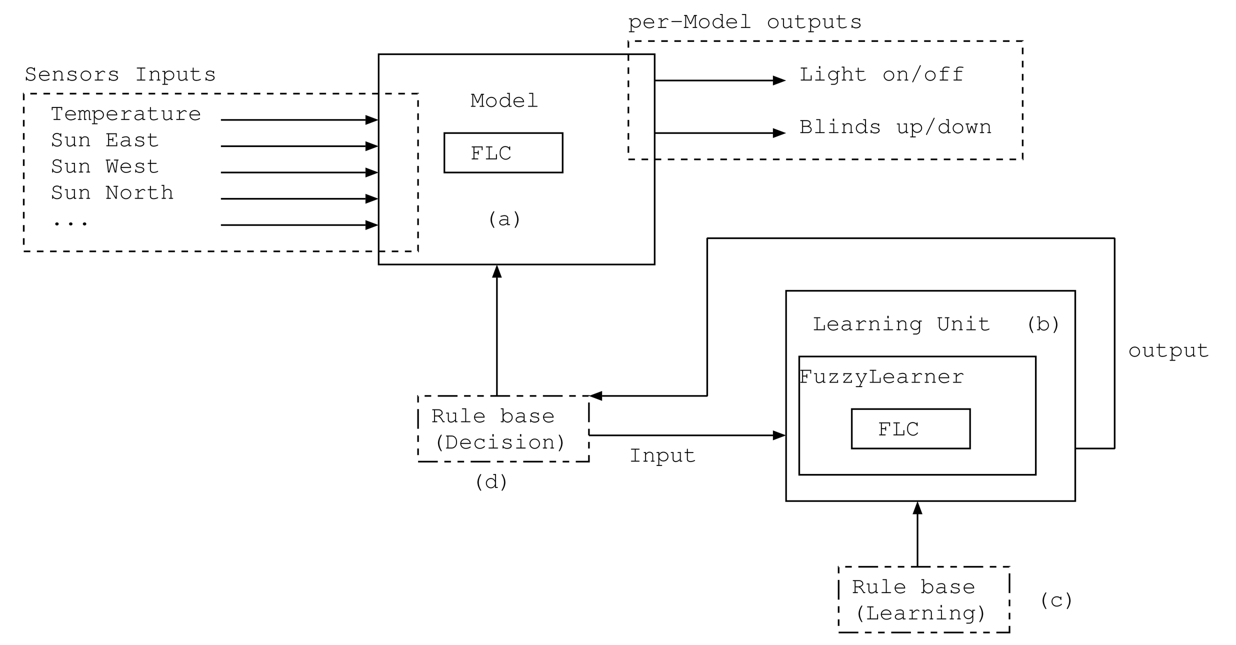

Figure 4: *Clusters*

Figure 4 shows the relationship between a model that takes decisions about a room and a learning unit. The learning unit (b) takes decisions about the rulebase of the model (a). For the learning the learning unit (b) uses the learning algorithm as well as a rulebase (c). The rulebase used for the learning process (c) is fixed and is only required for the fuzzification of the data samples that the learning unit gets as reinforcement signal. The learning unit fuzzifies this data samples and generates punishments/rewards from it. The model that takes decisions about the environment uses the rulebase (d) as a basis which gets constantly updated by the learning unit (b).

4. Self-Organization and structural learning

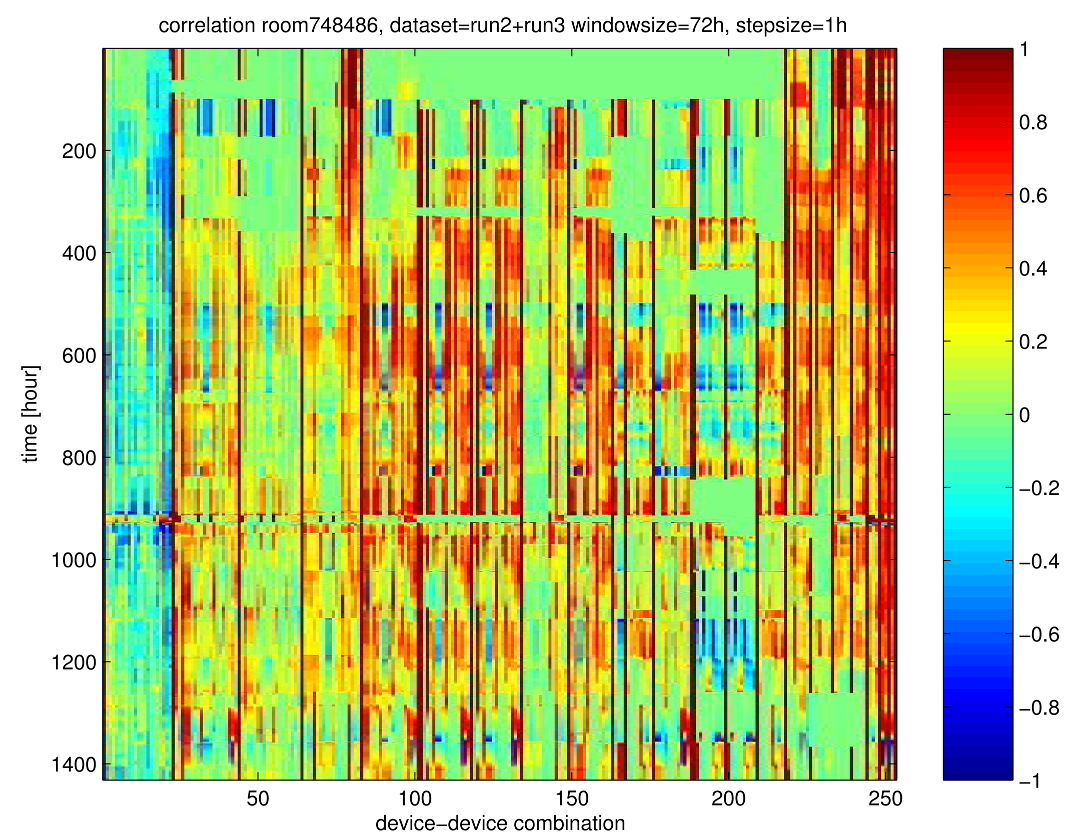

Figure 5: *Co-Correlation analysis*

To dynamically cluster sensors and effectors into a hierarchical tree structure an online self-organizing principle is used. Based on the co-correlation matrix (Figure 5) of devices this mechanism is capable of dynamically detecting the sensor/effector relationships. This makes the building completely autonomous and adaptive also to structural changes on which basis learning takes place (structural learning).

5. Future work

Further research will be conducted for:

- Policy transfer between agents/learning units
- Extending the learning algorithm to make it more efficient
- Use self-organizing algorithms to obtain structure information
- Personalize learning