Intelligent Learning Systems, Adaptive Building Intelligence, ABI Mark II

a novel approach for learning dynamic space behaviors in a non-stationary environment with an adaptive Intelligent Building Framework (IBF)

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I. Introduction

Intelligent learning systems have become increasingly popular as automated robots and self adapting systems have helped to improve user comfort and security.
One such field that gained our research interest here at the Institute of Neuroinformatics(INI) are autonomous building control systems.

Novel building architectures are gradually equipped with an entire communication network that allows devices within a building to be programmed and thereby establishing a whole new world of possibilities. Depending on occupants' needs, such a programmable system could improve user comfort as well as save more energy than a directly controlled system. Already existing ordinary lighting controls systems however suffer from commonly needed tasks such as commissioning, that is necessary to be conducted by building maintenance personnel since sensors as well as effectors age within time. Such re-calibrations and fine tuning tasks of course vary from space to space and are quite often considered as burdensome or costly. This is why it is worth to integrate a self-adapting system that accounts for sensor degradation and enhances visual user comfort.

However such an easy seeming task is above all quite complicated to fulfill since structural changes must be able to be detected and incorporated in any point of time (non-stationary).
One of the major problems when it comes down to learning dynamic space behaviors and configurations is that the sensors perceive and react totally different then the human brain does. For instance we perceive fog with a different intensity of illuminance then the sensors do. Furthermore different skylight levels can therefore be found under the same sunlight conditions. Regardless of whether the sky condition remains the same, the illuminance might increase in consequence of a momentary scattering of particles over the sun. Hence any prediction system needs to be flexible enough to react to such environmental changes. Further in order to control an environment an IB must gradually receive feedback from its occupants to adapt to the new needs which will continuously change like the non-stationary environment. An additional aggravation is that user instructions are very sparse in nature and thus makes learning of any user behavior difficult.

Considering such a variability and non-stationaryness within an environment, we can conclude that certain environments can not optimally be controlled by just providing regular daylight sensors.

In summary we can freeze on to the fact that a building intelligence should:

- **Not disturb occupants:** User wishes are upper priority. For instance: Blind motor noises, flashing or flickering lights, etc. should be minimized. User desires must be manually configurable and should not end up into opposing actions.
- **Be reliable:** An IB application that would suddenly stop controlling an environment because of a network failure would ultimately result in discomfort.
- **Minimize energy consumption:** Decrease the energy consumption, without affecting the user comfort (especially visual comfort). Broadly speaking we can say that the system must provide a reasonable payback period.
- **Incorporate all available sensor information:** In order to enhance the predictions, an IB should consider all possible sensory information that can be received from an environment. Since the bigger the information flow the better adequately a building can be controlled (Multi-sensor environment).

II. Intelligent Building Framework (IBF)

Our approach in making a building act intelligently introduces a novel Intelligent Building Framework (IBF) that is composed of a set of independent Device Agents. Hereby each effector incorporate an individual Device Agent Controller that deals with multiple input dimensions (MISO). Hence each Device Agent controls an effector on a local basis rather then global (i.e. room or even building).
We propose a new algorithm that considers the changing strengths and weaknesses of different prediction algorithms. The algorithm is making a prediction by taking a weighted vote among a pool of prediction algorithms and learns by altering the weight associated with each prediction algorithm. Accordingly all algorithms will start to compete among each other. Thus algorithms which perform better will thereby be rewarded and others rather punished.
The rewards and punishments will hence be steered as a function of the user input.

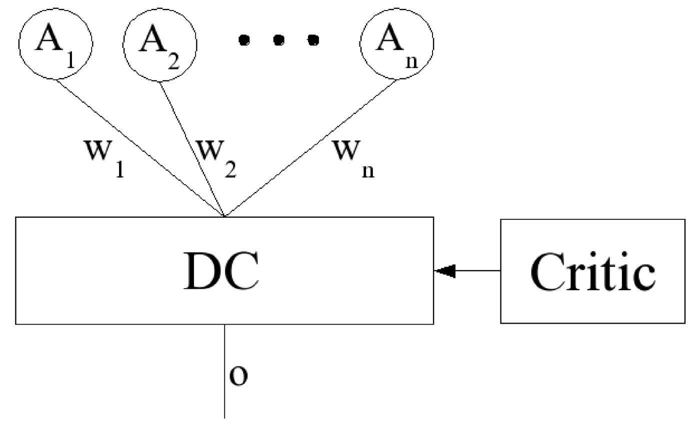

Figure 1: *IB Framework Algorithm*

Herewith we hope to achieve a better hypothesis within any dynamic working and living environment.

III. Real-Time Simulation Platform

In order to investigate each developed prediction algorithm within the IB Framework, we implemented a real-time simulation platform that allows to mimic or replicate any real environment that an IB should deal with. Consequently any working AI should have been analyzed and tested with different varying conditions before put in practice.

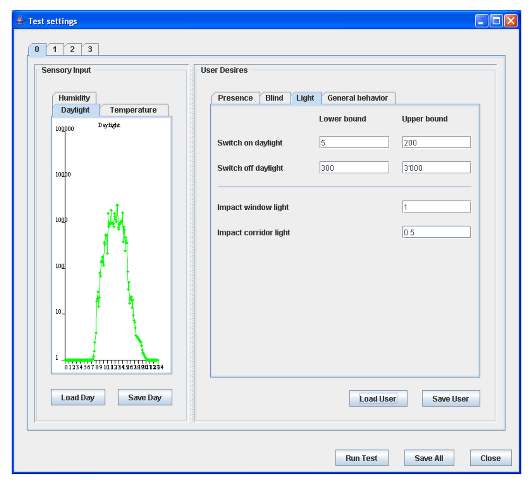

Figure 2: *Configuring a test-row*

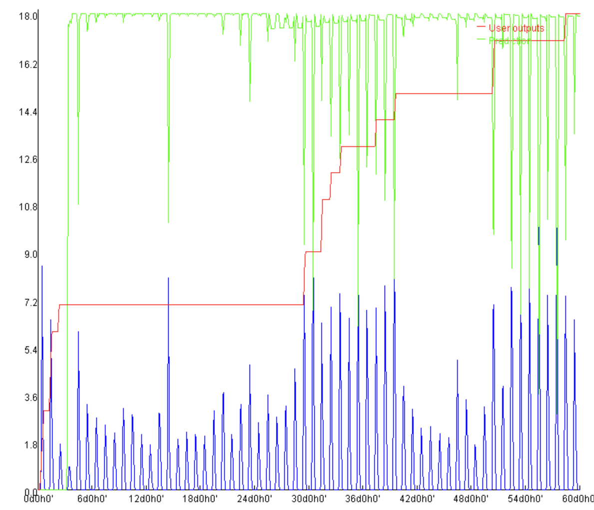

Figure 3: *Sample simulation over 60 days using statistical learning*

IV. Prediction Algorithms

In regard to building intelligence, we examined a row of different AI algorithms. We are chiefly interested in their strengths and weaknesses as well as under which conditions or circumstances they have been proven to be successful in learning dynamic space behaviors. Herewith we try to compose a set of algorithms that we finally intend to embed into the IBF algorithm.

Clustering Algorithms

One of our core learning approach that we're still investigating involves the examination and the development of algorithms that are capable of keeping environmental knowledge in form of clusters. Each of which hereby represents a variety of configurations that were encountered within different situations. The flip side upon applying such an unsupervised approach is that we cannot presume a premature quantity of clusters in the first place.
Hence we realized a recently proposed algorithm called g-means that that discovers an appropriate number of clusters using a statistical test for deciding whether or not creating new clusters. We then applied a simple regular regression technique (Artificial Neural Network for example) across the gained clusters.

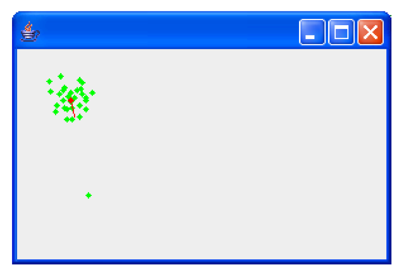

Figure 4: *Stage 1: First centroid created, error grows...*

Figure 5: *Stage 2: 2nd centroid created error small*

Recent tests and the entire theory have shown that clustering could bring some major improvements to a prediction system in general. Hence we continued to follow up on this matter a little longer and explored another variant or form of dynamic clustering. - *Growing Neural Gas (GNG).*

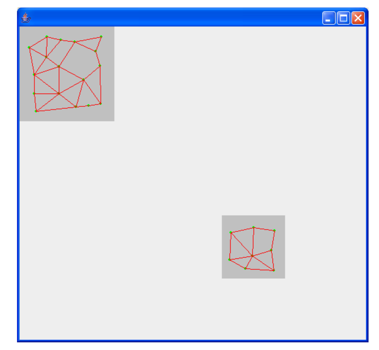

Figure 6: *A growing neural gas in a stationary environment*

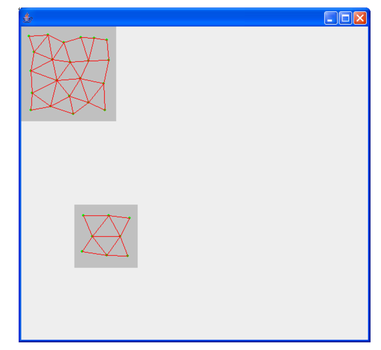

Figure 7: *The gas succeeds to track a non-stationary signal*

We found that the GNG algorithm is one of the most powerful and successful cluster algorithms that is capable of keeping long as well as short term data. Generally we found that neurons are created where it is required and rather tends to evict neurons which are left alone due to connection aging. However in order to achieve a suitable behavior which can be brought into our context, some crucial modifications needed to be made that among other things involved the successful tracking of a non-stationary signal (environment).

Statistical Learning

Next to clustering we've been investigating other techniques such as Statistical Learning that has proven to succeed in so called *Simple Environments*. Such an environment signifies that learning can be performed by only using the interior daylight and the daytime as the major measure.

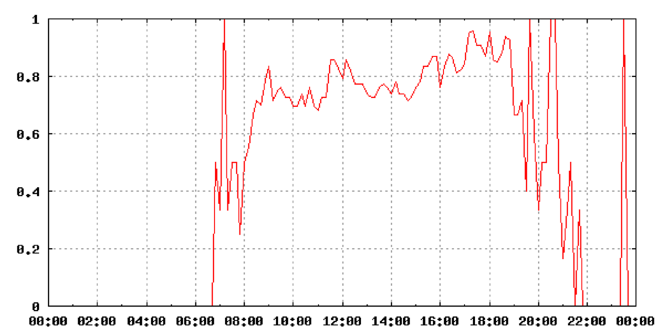

Figure 8: *Simple Environment*

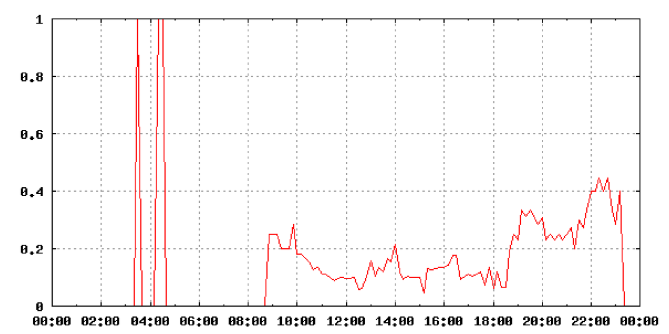

Figure 9: *Complex Environment*

Artificial Neural Network (ANN)

In order to apply conventional multi-layered ANNs we had to make the algorithm to work online rather then offline.
Next to conventional artificial neural networks we've been trying another interesting form of dual artificial neural networks. The intention was based on the fact that LTM in human brains have a strong influence on the perception through top-down processing. Our prior knowledge affects how we perceive sensory information. Our expectations regarding a particular sensory experience influence how we interpret it. This is how we develop bias.

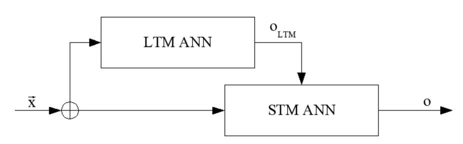

Figure 10: *LTM-STM Network decomposition with no user input control*

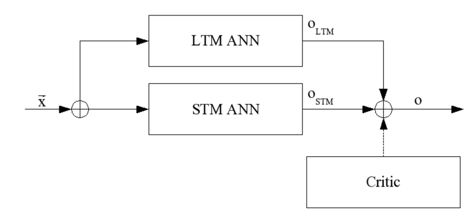

Figure 11: *LTM-STM Network decomposition with a user controlled LTM consideration.*

By taking user inputs also into account we hope for a more accurate environment function to be approximated. LTM hereby corresponds to a much larger set of data whereas the STM contains $\frac{1}{10}^{th}$ of the LTM size. Hence upon receiving many user inputs the STM should govern the prediction. Vice versa if user inputs are sparse the LTM will dominate.