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A Bionic Approach to Dynamic, Multimodal Scene Perception and Interpretation in Buildings

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Abstract—Today, building automation is advancing from simple monitoring and control tasks of lightning and heating towards more and more complex applications that require a dynamic perception and interpretation of different scenes occurring in a building. Current approaches cannot handle these newly upcoming demands. In this article, a bionically inspired approach for multimodal, dynamic scene perception and interpretation is presented, which is based on neuroscientific and neuro-psychological research findings about the perceptual system of the human brain. This approach bases on data from diverse sensory modalities being processed in a so-called neuro-symbolic network. With its parallel structure and with its basic elements being information processing and storing units at the same time, a very efficient method for scene perception is provided overcoming the problems and bottlenecks of classical dynamic scene interpretation systems.

Keywords—building automation, biomimetrics, dynamic scene interpretation, human-like perception, neuro-symbolic networks.

I. Introduction

MODERN building automation is advancing from simple monitoring and control tasks (like lightning and heating) to more and more complex requirements. Desired future applications are for instance in the field of safety and security surveillance of public and private buildings and in the observation of the activity and the state of health of persons in homes for elderly people and hospitals [2], [14]. Additionally, it is aimed to enable elderly and disabled persons to live longer independently in their own homes [4], [8], [11] and to increase the comfort of occupants by perceiving their needs.

All these issues require the perception of what is currently happening in a building – they require a dynamic scene interpretation. Classical approaches of scene interpretation are generally only based on video data [3]. A major bottleneck in dynamic scene interpretation is the search that is required through a database to find a model that best matches the observed data [19]. Scene perception today only achieves acceptable results for well defined and constrained surroundings. When considering real world situations, the performance is still very limited and can in most cases not substitute a human observer with his cognitive capabilities.

As humans can perceive and interpret their environment that efficiently, the human perceptual system seems to be a good archetype for developing a model for dynamic scene perception and interpretation. To develop such a technical system was the aim of the project *NeuroSym*. This article gives an overview about this bionic model and points out the used information processing principles.

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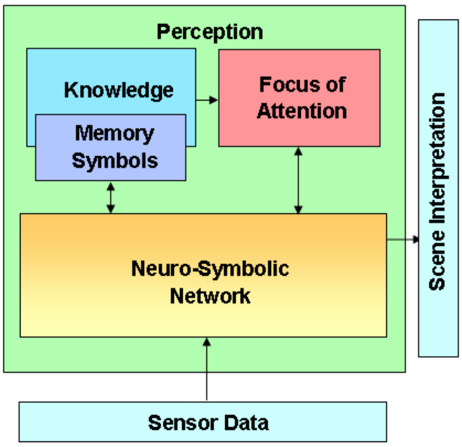

Fig. 1. Overview of Perceptual Model

II. Bionic Model for Dynamic, Multimodal Scene Perception and Interpretation

With the model proposed in this section, it is aimed to provide technical systems with similarly effective and efficient perception abilities as humans have in order to be capable of dynamic scene interpretation in buildings. In figure 1, an overview about the developed model is given. The model is based on neuroscientific and neuro-psychological research findings about the perceptual system of the human brain.

Input data for the model are sensor data. Unlike in classical technical approaches [18] but similar as in human perception, the detection of objects, events, and situations is not only based on data from one sensor type (mainly vision) [12] but on a larger number of different sensor types. The sensor values are processed by a so-called *neuro-symbolic network* [16] and result in a perception of the environment – the scene interpretation. Additionally, the perception process is facilitated by mechanisms called *memory symbols*, *knowledge*, and *focus of attention*. In the following, the different modules of the model are described.

A. Neuro-symbolic Network

The central element of the model is the neuro-symbolic network responsible for neuro-symbolic information processing. Its basic information processing units, its structure and information flow, and its learning principle are described in this section.

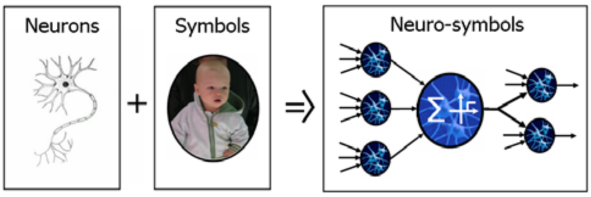

Fig. 2. Neuro-symbols Combine Neural and Symbolic Information Processing Principles

1) Neuro-symbols – The Basic Information Processing Units: The basic information processing units of the neuro-symbolic network are so-called neuro-symbols. From the fact that neuro-symbols are the basic elements of the model, the project *NeuroSym* – the abbreviation for *NeuroSymbols* – got its name. The idea for using neuro-symbols came from the following consideration: In the brain, information is processed by neurons, which are interconnected and therefore interact with each other. However, we do not think in terms of action potentials and firing nerve cells but in terms of symbols [17]. Examples for symbols are a color, a shape, a person, a face, a sound, a voice, or a melody. Neural and symbolic information processing can be considered as information processing in the brain at different abstraction levels. An interesting and important question is if there exists a connection or interface between the neural and symbolic level. Considering neuroscientific literature, we suggest to answer this question positively. There have actually been found neurons in the brain which react for example exclusively to the perception of faces [7], [10]. This fact allows the conclusion that there must exist a connection between the neural and the symbolic information processing level. This was our inspiration to design neuro-symbols as basic information processing units of the model. Neuro-symbols combine characteristics of neural and symbolic information processing (see figure 2).

Neuro-symbols represent perceptual images – symbolic information – like for instance a color, a shape, a person, a face, a sound, a voice, or a melody. Furthermore, neuro-symbols show a number of analogies to neurons. Each neuro-symbol has a number of inputs, one output, and a so-called activation grade *AG* with a value between 0 and 1. The activation grade indicates if the perceptual image the neuro-symbol represents is currently present in the environment or not.

Via the inputs, among others, information about the activation grade of other connected neuro-symbols is collected. These activation grades are then summed up and normalized to the number of inputs *n* resulting in the activation grade of the current neuro-symbol (see equation 1).

$$AG = \frac{1}{n}\sum_{i=1}^{n} AGofInput_i \qquad (1)$$

If this sum exceeds a certain threshold value, the neuro-symbol is activated meaning that the perceptual image it represents was perceived in the environment. In contrast, an activation grade value below the threshold value indicates that the particular perceptual image has not been perceived. Information about the activation grade of a neuro-symbol is transmitted via its output to other connected neuro-symbols whenever its value changes:

```
if (changeInActivationGrade)
  if (ActivationGrade>=ThresholdValue)
    Activation of Neuro-Symbol
    Transmit ActivationGrade
  else if (ActivationGrade<ThresholdValue)
    No Activation of Neuro-Symbol
    Transmit ActivationGrade
  end
end
```

Activation grades coming from different inputs can also be weighted differently. Unlike in neural networks, for neuro-symbols, the weights of different inputs represent the reliability of the sensory modality (or cognitive unit) they come from in comparison to the other inputs. This concept is in accordance with the neuroscientific concept of perceptual dominance of a certain sensory modality (most times vision) over the others [5]. Neuroscience is not yet sure whether perceptual dominance is inborn or formed by experience. In the current version of the model, the reliability of different units is predefined in accordance with the suggestion from neuro-science that perceptual dominance is inborn. However, for later versions, it could be acquired by evaluating the outcome of the perceived data. In case that the weights of the inputs of a neuro-symbol differ, equation 1 has to be changed to equation 2. In this formula, the sum of the activation grades is normalized to the sum of the weights of all inputs.

$$AG = \frac{1}{\sum_{i=1}^{n} Weight_i} \bullet \sum_{i=1}^{n}(Weight_i \bullet AGofInput_i) \qquad (2)$$

Weights of inputs can be positive or negative, depending on the source they come from (see section II-A3).

By a neuro-symbol, it cannot only be processed information that is received via the inputs concurrently, but it can also be processed information which arrives asynchronously within a certain time window or in a certain temporal succession. Furthermore, a neuro-symbol can comprise so-called properties, which specify it in more detail. One property of neuro-symbols is the location property, which indicates where in the environment a perceptual image was perceived. The usage of properties corresponds to the principle of population coding [7] according to which related perceptual images are not represented always by separate neurons, but by a group of neurons. For details about the processing of asynchronous information, temporal successions, and of properties, see [15].

2) Modular Hierarchical Interconnection of Neuro-symbols: For performing complex tasks, a single neuro-symbol is not sufficient. Neuro-symbols have to be interconnected and need to exchange information. The question that has to be answered is how these interconnections shall look like. For this purpose, the structural organization of the perceptual system of the human brain is taken as archetype. According to [10] and [13], the perceptual system of the human brain is organized as illustrated in figure 3.

The starting point for perception are sensory receptors of different sensory modalities. This information is then processed in three stages. The primary cortex is responsible for the first stage, the secondary cortex for the second, and the tertiary cortex for the third one. Each sensory modality has its own primary and secondary cortex. This means that in the first two steps, information of different modalities is processed separately and in parallel. In the tertiary cortex, the information of all modalities is merged, which results in a unitary multimodal (modality-independent) perception of the environment.

The primary cortex has a topographic structure. This means that spatially neighboring receptors of sensory modalities project their information on neighboring neurons in the primary cortex. Perceptions on this level are highly location dependent. Examples for perceptual images perceived in the primary cortex of the visual system would be simple features like edges, lines, colors, or movements of a certain velocity and in a certain direction. Results of information processing in the primary auditory cortex are sounds of a certain frequency.

Neurons in the secondary cortex fire as reaction to the perception of complex images independent of the location of the images in the perceptual field. A perceptual image of the secondary visual cortex is for example a face. Perceptual images of the secondary auditory cortex could be a voice or a melody. Considering the somatosensory system of the brain – in common parlance also referred to as tactile system – this system consists in fact of a whole group of sensory systems like the actual tactile sense, the body sense, the temperature sense, etc.

On the multimodal level, the complex modality-specific perceptions of the different secondary cortices are merged and result in a unified perception. An example would be the assignment of the visual image of a face to the acoustic perception of a voice resulting in the perception that a person is currently speaking.

In analogy to this modular hierarchical organization of the perceptual system of the human brain, neuro-symbols are structured to so-called neuro-symbolic networks (see figure 4).

In the first level, feature symbols are extracted from sensory raw data. Information processing in this level has its analog in the processing performed in the primary cortices of the different sensory modalities. This layer has a topographic structure and is therefore highly location dependent. It can in fact consist of a number of sub-layers representing increasing complex features from level to level. For more details about the information processing principles of this layer see [15].

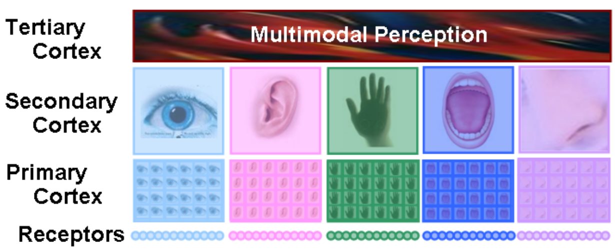

Fig. 3. Modular Hierarchical Structure of the Perceptual System of the Human Brain

In the next two processing stages, sub-unimodal and unimodal symbols are derived from feature symbols. These two layers correspond to the functions of the secondary cortices of the brain. For the somatosensory system it was mentioned that sensory modalities can consist of a number of sub-modalities. Similarly, there can exist a sub-unimodal level between the feature symbol level and the unimodal symbol level. On the sub-unimodal levels, all perceptual aspects of the particular sub-modalities are processed. The unimodal level of each modality then combines these aspects to a unitary unimodal perception.

The multimodal level and the scenario level correspond to information processing taking place in the tertiary cortex of the human perceptual system. In the multimodal layer, information of all unimodal neuro-symbols is combined and merged to multimodal symbols. On the scenario symbol level, sequences of multimodal symbols are combined to scenario symbols to represent longer temporal sequences of events in scenes. The multimodal level and the scenario symbol level provide the output information of the system. An activated neuro-symbol of these levels corresponds to a detected scene.

Neuro-symbols of a lower level can be considered as symbol alphabet for the next higher level. One and the same neuro-symbol of a certain level can contribute to the activation of different neuro-symbols of the next level. The higher the level, the more comprehensible and interpretable the meaning of the neuro-symbols gets for a human interpreter.

As already mentioned, the presented bionic model for dynamic scene perception and interpretation bases on information from different sensory modalities. Concerning the sensory modalities, there can be used sensor types that have their analogy in the human sense organs like video cameras and microphones for visual and auditory perception, tactile floor sensors, light barriers, or motion detectors for tactile perception, or chemical sensors for olfactory perception. Furthermore, there can be used sensor types which have no correspondence to human sense organs like sensors for perceiving electrical energy consumption, electro-magnetism, ultrasound, and infrared radiation.

3) Neuro-symbolic Information Flow: Having explained the modular hierarchical organization of neuro-symbolic networks, it is now about to described how the flow of information between neuro-symbols looks like. Similar as in the human brain, in the model, it is differentiated between bottom-up information flow, feedbacks, and top-down information flow.

Bottom-up information processing is depicted in figure 5. Connections are directed from lower-level to higher-level neuro-symbols. Processing starts with sensor data, which are then processed level by level to more and more complex neuro-symbolic information until they result in the activation of multimodal symbols and scenario symbols, which are the outputs of the system. Weights of bottom-up connections are always positive.

Additionally, there exist feedback connections within neuro-symbolic levels (see figure 6). In neuroscience, the function of

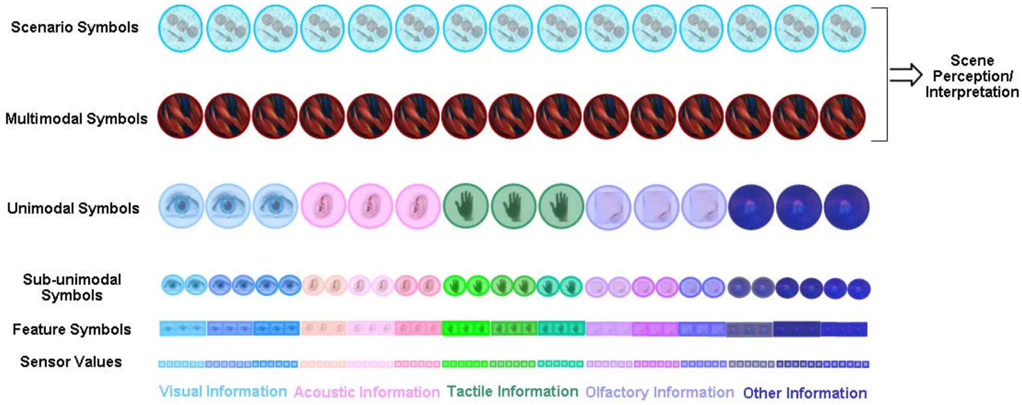

Fig. 4. Modular Hierarchical Structure of Neuro-symbolic Network

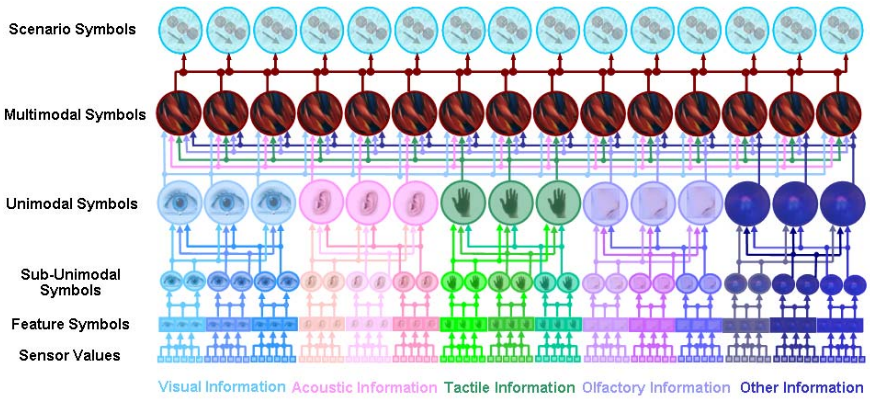

Fig. 5. Bottom-up Information Flow in Neuro-symbolic Network

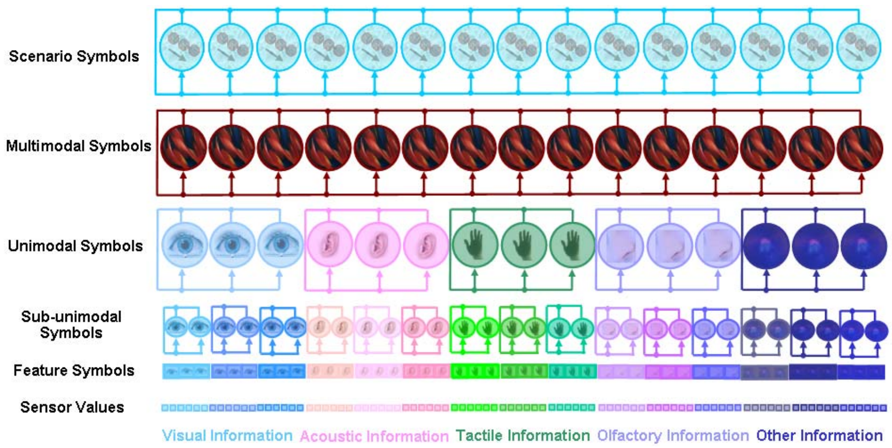

Fig. 6. Feedbacks within Neuro-symbolic Network

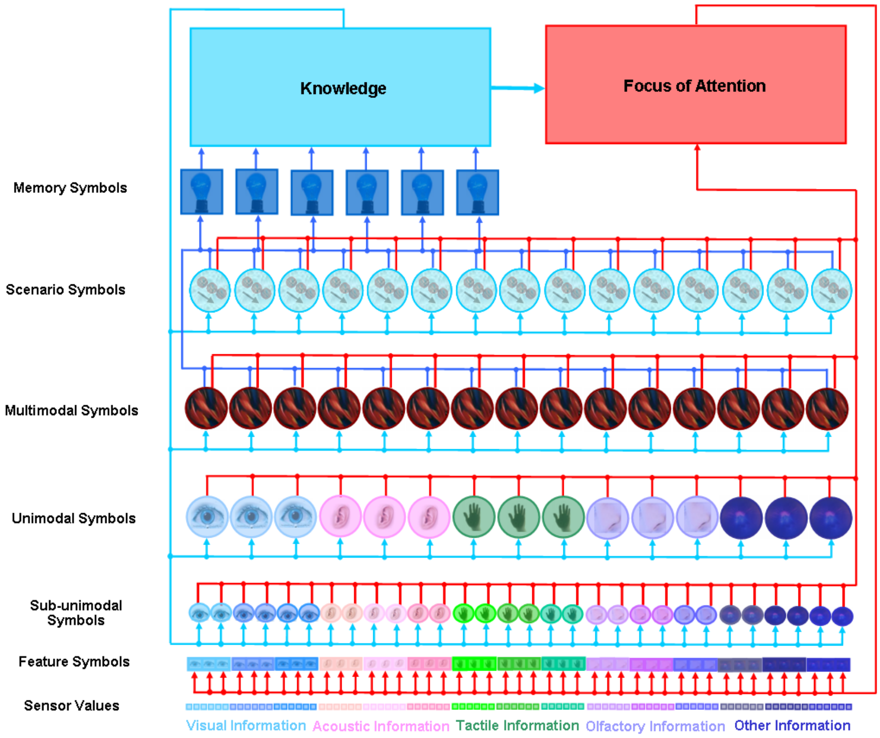

Fig. 7. Top-down Information Flow in Neuro-symbolic Network

feedbacks within in the brain is still not very well understood. In the suggested neuro-symbolic model, feedback connections are necessary to inhibit the undesired activation of neuro-symbols. It is very likely that in the brain – besides other functionalities – the inhibition of undesired neural activations is one utility of feedbacks. In order to have an inhibitory function, weights of feedback connections are always negative. For a more detailed explanation of the function of feedbacks see [15].

Top-down information processing is based on stored *knowledge* and *focus of attention* (see figure 7). These mechanisms can influence the activation of neuro-symbols in a top-down manner. A more detailed description of these two mechanisms will be given in section II-B and section II-C. Top-down connections can principally be either positive or negative.

The connections between neuro-symbols depicted in figure 5 to 7 show what interactions between neuro-symbols and other modules, respectively, are principally possible. The connections are depicted only schematically in a bus-like way. In fact, however, they are point to point connections between different units. In a configured system, depending on the application domain, there will not exist all the depicted connections but only a subset of them.

4) Learning in Neuro-symbolic Networks: Neuro-symbolic networks are no rigid structures but offer the possibility to learn correlations and connections between the different neuro-symbols from examples. For this purpose, again, the perceptual system of the human brain is taken as archetype. According to [1], certain neural structures need to be already connected at birth, because it is not possible to start from a “tabula rasa”. Furthermore, it is described in [10] that higher neural levels can only evolve after lower levels have already developed.

Similarly, in the proposed bionic model, the lowest neuro-symbolic levels have to be predefined. This means that the correlations between sensor data and feature symbols and for certain modalities also connections between feature symbols and sub-unimodal symbols (or unimodal symbols if there exist no corresponding sub-unimodal levels) are fixed before system start-up. Correlations between higher levels are learned in different stages during a number of learning phases. At initial system start-up, neuro-symbols of these levels are unconnected. During different learning phases, forward connections are first learned between feature symbols and sub-unimodal symbols. Secondly, feedback connections between sub-unimodal symbols are learned. Next, forward connections between sub-unimodal symbols and unimodal symbols are determined followed by feedback connections between unimodal symbols. Afterwards, forward connections between unimodal symbols and multimodal symbols and feedback connections within the multimodal layer are set. Finally, there are established connections between multimodal symbols and scenario symbols and feedbacks within the scenario symbol level.

In the following, the learning principle used for deriving correlations between neuro-symbols from examples will be explained by means of the unimodal tactile modality (see figure 8). For the other modalities and other hierarchical levels, the same principle is applicable. To learn correlations,

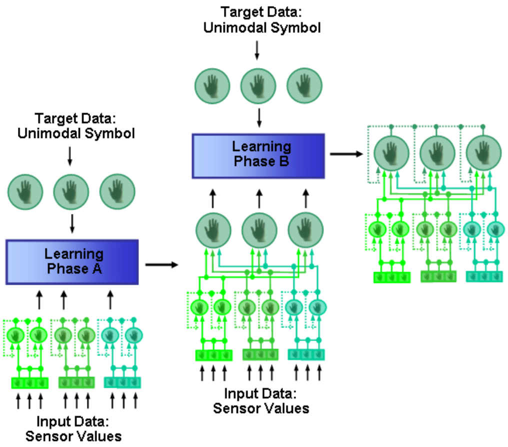

Fig. 8. Learning in Neuro-symbolic Networks

examples have to be available that comprise all objects, events, and situations that shall be perceived by a certain modality and level. To allow generalization, not only one but a certain number of examples has to be available for each particular object, event, and situation. The used learning concept is a supervised learning principle. Examples include input data and target data. Input data are sensor data of sensors that are triggered when certain objects, events, or situations occur in the surrounding. Before the learning phase of a certain layer starts, the lower-level connections have already been set. Therefore, certain lower-level neuro-symbols are activated based on these sensor values. These activated neuro-symbols serve as actual input data for the learning process. The target data indicate the meaning of the input data. They specify the object, event, or situation that is currently occurring and assign it to a certain neuro-symbol of the current level.

For each neuro-symbolic level, the learning process consists of two phases: learning phase A and learning phase B. For the unimodal tactile modality, in learning phase A, forward connections between sub-unimodal and unimodal symbols are determined. After that, the same input-target-data-pairs as used in learning phase A are presented to the system a second time in learning phase B to determine feedback connections. In learning phase B, a comparison is made between what unimodal symbols are activated based on the sensor data and forward connections set in learning phase A and what unimodal symbol should actually be activated according to the target data. To avoid undesired activations, feedback connections are set between unimodal tactile symbols accordingly.

During the learning phases, besides forward and feedback connections, there can also be determined values of properties, location information, and temporal correlations between data from examples. Additionally, the used learning algorithms offer the possibility to eliminate redundant neuro-symbols and to detect perceptual images, which are represented by one and the same neuro-symbol but should better be further distinguished and therefore assigned to more than one neuro-symbol.

The pseudocode below shows the basic steps of the learning algorithm of learning phase A. For details about its underlying mathematical principles and a systematic formulation of the algorithm of learning phase B it is referred to [15].

```
For each modality
    Determine which neuro-symbols occur
    most often
If one neuro-symbol of one modality occurs
in more than c1 percent of all cases
    Set connection
If two neuro-symbols of one modality occur
in more than c2 percent of all cases
    Use two separate higher-level
    neuro-symbols and set connections
For each neuro-symbol type connected
    Calculate average x- and y-location
    Calculate average x- and y-location-
    deviation
    Determine property values
Calculate x- and y-inter-modality location
deviations between neuro-symbols
If necessary
    Consider temporal character of data
```

B. Memory Symbols and Knowledge

The focus of the description of the bionic model was so far set on the explanation of the sensory information processing within the neuro-symbolic network. However, in the brain, perception does not only base on sensor information but also on stored knowledge. This knowledge can be factual knowledge like that objects generally fall down, context knowledge like that certain objects and events generally occur at certain places or at a certain time of day, or the expectation that certain events and situations are likely to happen after particular other events and situation. The influence of knowledge on perception is considered as a top-down process. To make such predictions, a mechanism is needed to store what happened in the past to use this information later on.

To realize the principles just mentioned, so-called memory symbols interact with stored knowledge. Memory symbols have the function to store information about occurring events or consequences of events that are relevant for future perceptions. Memory symbols are needed, because neuro-symbols only represent what is going on in the environment at a particular moment or within a certain time interval. As soon as the sensors that trigger this information are deactivated again, also the corresponding neuro-symbols are deactivated. An example would be to memorize that when a person entered a room, because it means that from now on a person is present in the room. In the knowledge module, a reasoning process is taking place based on stored knowledge, activated memory symbols, and activated neuro-symbols. It is decided what neuro-symbols to influence in what way (increase, decrease, or inhibit the activation grade and activation of neuro-symbols). By means of stored knowledge, it can for instance be concluded that a person cannot carry out activities in a room if there has not entered a person before. In figure 7, it is depicted on which levels the interaction between neuro-symbols, memory symbols and knowledge takes place. Neuro-symbols of the multimodal level and the scenario level can activate and deactivate memory symbols to store information about perceptual images or their consequences, respectively, to facilitate future perceptions. Memory-symbols tightly interact with the knowledge module, which can send information to neuro-symbols from the sub-unimodal level upwards in order to influence their activation grade.

C. Focus of Attention

A second top-down process involved into perception is focus of attention. Like in every information processing system, also in the brain, the processing capacity is constrained. This can pose a problem if too many different events happen at the same time. To overcome this problem in the brain, focus of attention restricts the spatial area that is considered when binding sensory information [6]. In [9], it is described that focus of attention inhibits the further processing of information, which has no relevance in the current situation. Accordingly, in the model, focus of attention influences the activation of neuro-symbols on the feature symbol level (see figure 7). This level is topographic in structure meaning that feature symbols have a strong correlation to the position of the sensors they are derived from. On the feature symbol level, different events happening concurrently in the environment are represented by feature symbols of different locations. From the sub-unimodal level upwards, location information is contained only as property of neuro-symbols and the number of concurrent events that can be coded is restricted. By focus of attention, feature symbols are bound to higher-level neuro-symbols that lie within the focus of attention. The activation of feature symbols is reduced in a way that they get below the threshold value of activation if the perceptual images they represent lie outside the spatial area that is currently covered by the focus of attention. With this method, the number of concurrently activated neuro-symbols can be reduced.

After information within a certain spatial area has been processed, the focus of attention has to switch to another area to process the information of feature symbols being active at the same time. This "switching" of the focus of attention requires a certain steering and control process to decide what to focus on. In the model, information from the sub-unimodal level upwards as well as the knowledge module can provide input information for the focus of attention module for this purpose (for more details see [15]).

III. Implementation and Use Cases

To evaluate the developed model, it was implemented in the simulation environment AnyLogic and tested with a number of use cases. The use cases were different activities going on in a building. For this purpose, an office building was equipped with different sensors.

Figure 9 shows one of the rooms of the building and the sensors, which were installed in it. There are used 416 tactile floor sensors, three motion detectors, two light barriers, a door contact sensor, a video camera, and a micropohne.

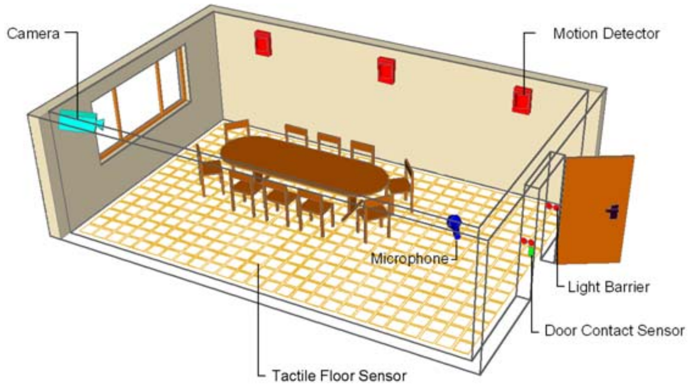

Fig. 9. Room Equipped with Sensors

In figure 10, the neuro-symbolic configuration is depicted for one use case set of this room. In this particular case, different activities of persons in the room have to be perceived. In the picture, the neuro-symbolic network is shown from the sub-unimodal level upwards. Lower-level symbols are not depicted, because in these layers, connections are predefined and not subject to learning and therefore of less interest. Furthermore, these lowest level comprise information that is difficult to interpret for humans. Before learning, none of the depicted neuro-symbols is interconnected. During the learning process, the interconnections are determined and reach a final form as depicted in the figure. Looking at the different connections, it can be seen what neuro-symbols of the different hierarchical levels are finally responsible for the activation of different multimodal and scenario symbols, which provide the output information and constitute the final scene perception.

IV. Results and Conclusion

In this article, a bionic approach for dynamic, multimodal scene perception and interpretation in buildings was presented. The proposed model provides a powerful and flexible tool for information processing of sensor data to perceive and interpret objects, events, scenarios, and situations in an environment. The developed model was inspired by neuroscientific and neuro-psychological research findings about the perceptual system of the human brain. By emulating the organizational structure and the information processing principles within the brain, it was aimed to equip a technical system with similarly effective and efficient scene perception capabilities as humans have. As simulation results show, besides the fact that the proposed system presents a workable solution to dynamic scene perception, the suggested information processing scheme actually proved to be very fast and efficient. This efficiency is achieved by the parallel information processing structure of the neuro-symbolic network and the fact that neuro-symbols are both information storing units and information processing units at the same time. This saves time for explicit memory (or database) access and comparison operations in relation to classical computer architectures. To take advantage of the parallel distributed structure of the model, the next step that has to be taken is to implement the model into a chip to

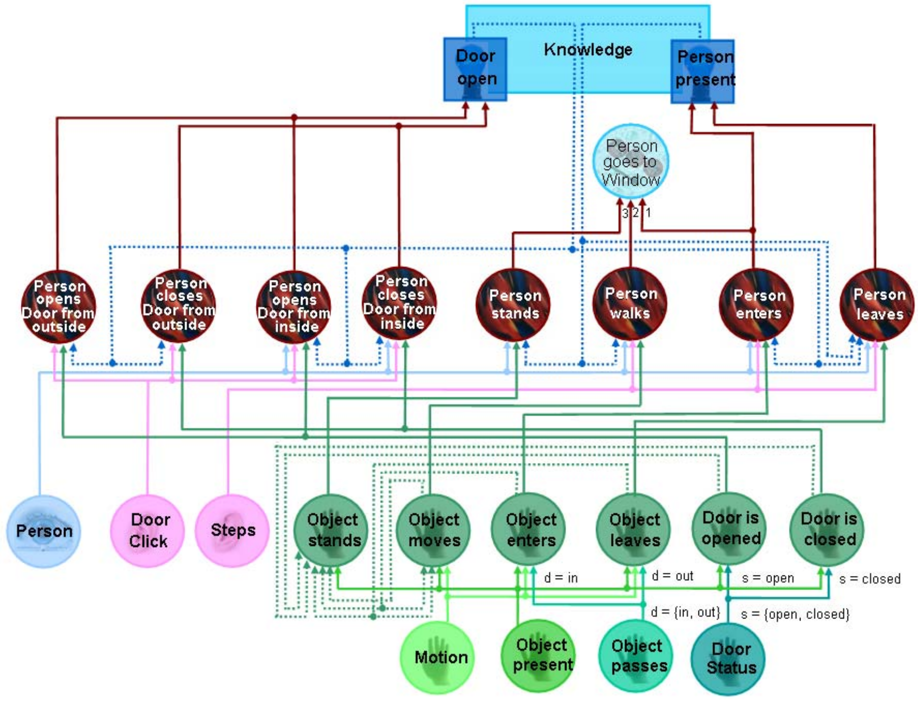

Fig. 10. Neuro-symbol Hierarchy of Test Set after Learning

perform real parallel processing instead of merely simulated parallel processing. Furthermore, it is planned to develop a neuro-symbolic network toolbox to allow fast and comfortable development and testing of neuro-symbolic network structures in order to make this information processing principle attractive to a broader group of users.

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