A Bionic Approach for High-Efficiency Sensor Data Processing in Building Automation

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***Abstract*-Today's building automation shifts from simple applications like controlling illumination and temperature towards complex applications like the observation of buildings for safety and security reasons or increasing the occupants' comfort. Complex applications require more and more sensory information. Existing approaches of sensor data processing cannot cope with these demands. In this article, we present a new, bionically inspired approach for coping with such a huge amount of diverse sensory information. For this purpose, an information processing principle called neuro-symbolic information processing is introduced which bases on neuroscientific and neuro-psychological research findings about the perceptual system of the human brain.**

I. INTRODUCTION

Today, building automation is mainly concerned with simple monitoring of the environment (e.g., temperature) and controlling simple systems in order to adjust those values to predefined value ranges targeting comfort and energy preservation. However, as outlined in [2], [7], and [8], in future, this will shift towards applications like safety and self-learning environment control. More and more sensory information will be necessary and available for processing. Existing approaches cannot cope with this abundant amount of data and the way in which it shall be responded to them. There will be a need to introduce new concepts for handling the demands of the upcoming future.

For this purpose, an interdisciplinary operating team of scientists was formed at the Institute of Computer Technology of the Vienna University of Technology, which attends all its focus on developing next generation intelligent building automation systems [3].

This article has the aim to describe one of the outcomes of these research efforts: a bionically inspired system for human-like sensor data processing applicable in buildings and interactive environments in order to perceive effectively what is going on in the building and environment, respectively. This approach is inspired from neuroscientific and neuro-psychological research findings about the perceptual system of the human brain, which allows it to process sensory data in a very efficient manner. By integrating this system into private and public buildings like airports, train stations, stadiums, or museums, they can be observed automatically for safety and security reasons and to increase the comfort of the occupants. Furthermore, this allows the monitoring of activities and the state of health of persons in retirement homes and hospitals to detect critical situations like that an elderly person has collapsed and cannot get up any more, or that a confused and disoriented person does not find his room or leaves the building unattended. Such systems could also make it possible that elderly people live longer independently in their own homes.

II. A BIONIC MODEL FOR HUMAN-LIKE SENSOR DATA PROCESSING

A. The Challenge of Emulating the Brain

As just mentioned, the model introduced in this article is based on neuroscientific and neuro-psychological research findings about the perceptual system of the human brain. The inspiration for using the human brain as archetype for model development came from the fact that humans generally perceive their environment most efficiently. Although the approach to use the perceptual system of the brain as archetype for machine perception seems to be quite obvious, no convincing approach of this kind has been suggested until now. Fact is that emulating the brain for technical purposes bears a range of challenges: One problem is the different way of thinking of brain researchers and engineers. Brain researchers generally just give verbal descriptions of their research findings, often only in form of case studies. A systematic analytical thinking with function blocks, interfaces, and information flows can in most cases not be expected. Furthermore – because of the complexity of the brain – existing models are always incomplete and in many cases also contradicting. Therefore, the challenge that has to be faced is to derive a unitary, functional, and technically implementable model from these incomplete and contradicting verbal descriptions about the brain. How such a model can look like is described in the following.

B. Model Overview

Figure 1 presents an overview about the developed model. Perception always starts with sensor values. These sensor data are then processed in a so-called neuro-symbolic network and result in the perception of what is going on in the environment. This perception process is additionally assisted by mechanisms called memory, knowledge, and focus of attention. For the current article, the focus is laid on the neuro-symbolic network, which is the central element of the model and is concerned with the so-called neuro-symbolic information processing. For a description of the other model parts it is referred to [11].

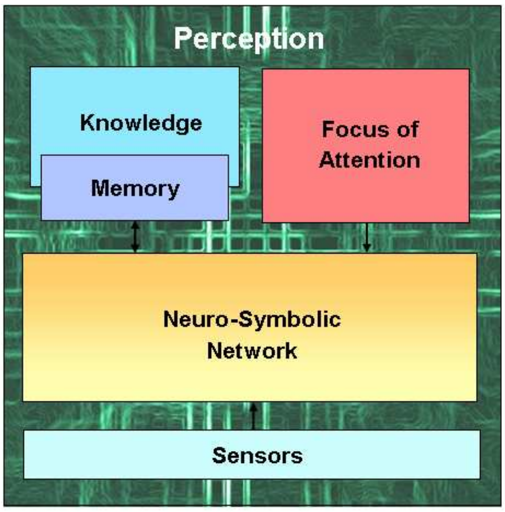

Fig. 1. Model Overview.

C. Basic Information Processing Units

The basic information processing units of the neuro-symbolic network are so-called neuro-symbols. The inspiration for using neuro-symbols as elementary information processing units came from the following observation: In the brain, information is processed by neurons. However, humans do not think in terms of action potentials and firing nerve cells but in terms of symbols like a face, a person, a melody, or a voice.

Neural and symbolic information processing can be regarded as information processing in the brain on two different levels of abstraction. The interesting question is whether there exists a connection or interface between these two levels. Considering latest neuroscientific research findings, this question can be answered positively. Actually, there have been found neurons in the brain which react for instance exclusively if a face is perceived in the environment [4], [5], [6]. This fact was the motivation for introducing neuro-symbols as basic information processing units. Neuro-symbols show certain characteristics of neurons and others of symbols (see figure 2).

Neuro-symbols stand for perceptual images – symbolic information – like a person, a face, a voice, or a melody. Each neuro-symbol has an activation grade, which indicates whether the perceptual image it represents is currently present in the environment. Neuro-symbols have a number of inputs and one output. Via the inputs, information about the activation grade of other neuro-symbols with which they are connected is received. These activation grades are then summed up and normalized by dividing this value by the number of inputs a neuro-symbol has. If this normalized sum exceeds a certain threshold value, the neuro-symbol is activated and information about its activation grade is transmitted via the output to other neuro-symbols.

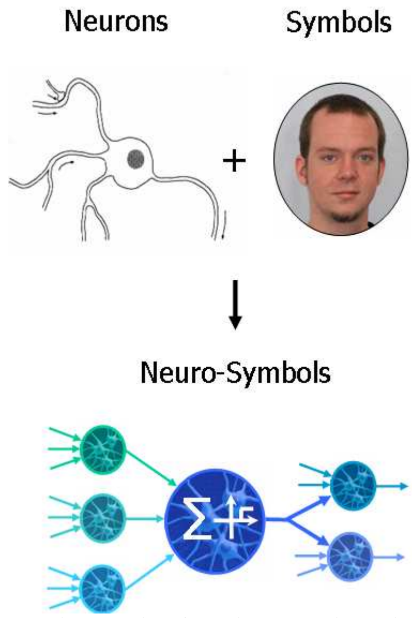

Fig. 2. Basic Information Processing Units.

D. Cerebral Organization of Perception

To perform complex tasks, neuro-symbols have to be combined to neuro-symbolic networks. A crucial question is how this interconnection of neuro-symbols shall look like, because a random connection of neuro-symbols will not lead to the desired result. To answer this question, the structural organization of the perceptual system of the human brain is taken as archetype. According to [6] and [9], the perceptual system is organized as depicted in figure 3.

Starting point for perception are the sensory receptors of different modalities (visual, acoustic, somatosensory, gustatory, and olfactory perception). This information is then processed in three different levels. In the first two stages, the information of each sensor modality is processed separately and in parallel. In the third level, the information of all sensory modalities is fused and results in a multimodal perception of the environment. In the first level, simple features are extracted from the data coming from sensory receptors. Giving an example for the visual system of the human brain, in this first level, neurons would fire to features like edges, lines, colors, movements of a certain velocity and into a certain direction, etc. In the second level, a combination of extracted features results in a quite complex perception of all aspects of the particular modality. For the visual system, perceptual images like faces, a person, or other objects would be perceived.

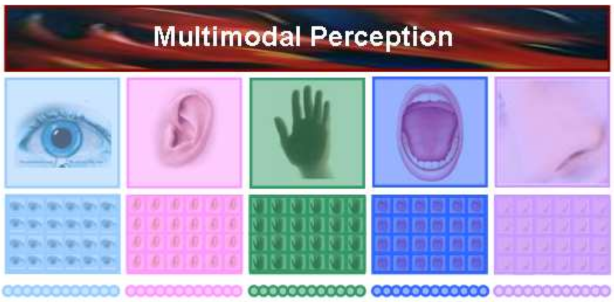

Fig. 3. Cerebral Organization of Perception.

Finally, on the highest level, the perceptual aspects of all modalities are merged. An example would be that a person, looks like this, talks like this, smells like this and that all these sensory impressions belong to one and the same person with all these characteristics.

E. *Neuro-symbolic Networks*

In analogy to the modular hierarchical structure of the perceptual system of the human brain, neuro-symbols are combined to neuro-symbolic networks (see figure 4). Again, sensor data are the starting point for perception. These inputs are then processed in different hierarchical levels to more and more complex symbolic information until they result in a multimodal perception of the environment. Neuro-symbols of different hierarchical levels are labeled differently according to their function. Neuro-symbols of the first level are called feature symbols, neuro-symbols of the next two layers are labeled sub-unimodal and unimodal symbols, and the neuro-symbols of the highest level are referred to as multimodal symbols. Concerning the sensor modalities, there can be used sensor types, which have an analogy in human sensory perception like video cameras for visual perception, microphones for acoustic perception, tactile sensors for tactile perception, and chemical sensors for olfactory perception. Additionally, there can be used sensors, which have no analogy in the human senses like the meters for electricity or magnetism. What sensor data trigger which neuro-symbols and what lower-level neuro-symbols activate which neuro-symbols of the next higher level is defined by the connections between them. There exist forward connections and feedback connections. These connections are no fixed structures, which have to be predefined at initial system startup, but they can be learned from examples. Learning allows great flexibility and adaptation of the system. A short introduction into the used learning concept will be given in section G. For more details about the learning process [10].

F. *Concept Clarification*

To clarify the concept of neuro-symbolic information processing, it is illustrated by means of a concrete example, which is intentionally kept simple. In the example, a person walking around in a room should be detected. For this purpose, a room is equipped with a number of sensors: a video camera, a microphone, a motion detector, and tactile floor sensors (see figure 5).

How the corresponding neuro-symbolic structure can look like is illustrated in figure 6. From the camera data, a person can be perceived. From the microphone data, steps can be detected. From the motion detector, motion can be perceived, and from the tactile floor sensors, it can be detected whether an object is present at a certain location. The data from the motion detector and the tactile floor sensor are then combined and result in the detection that an object moves within the room. Finally, the information of all sensor modalities is merged and results in the detection that a person walks around in the room. One question that might come up is why so many different sensor types are necessary for perceiving only one single situation. A single sensor type might be sufficient for this purpose. However, for realistic applications,

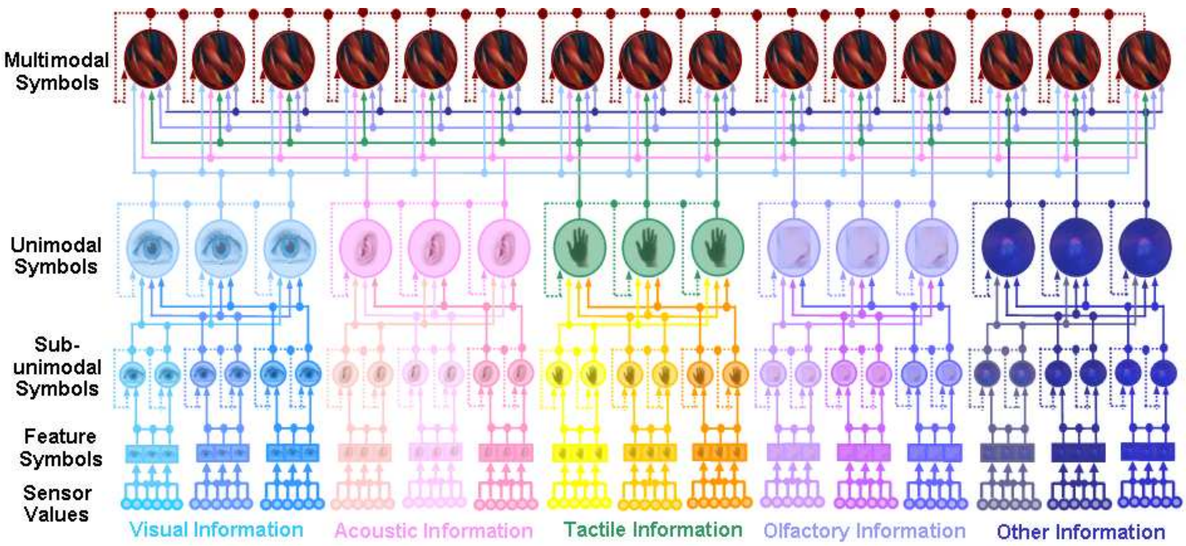

Fig. 4. Neuro-symbolic Network.

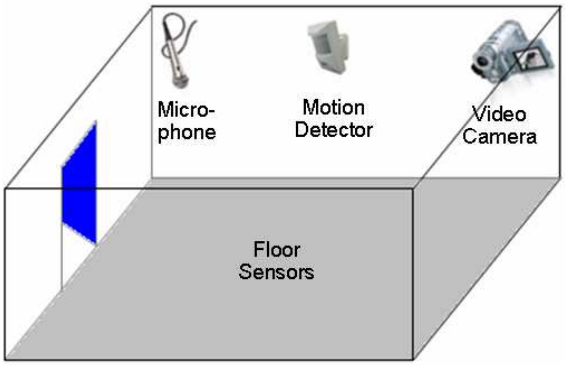

Fig. 5. Room Equipped with Different Sensors.

where not only one but thousands of different situations have to be perceived, a larger number of different sensor types is necessary in order to make a distinction between different situations. Additionally, by using diverse sensor types with a certain amount of redundancy, fault tolerance can be achieved (see [11] for more details).

G. Neuro-symbolic Learning

As already outlined briefly in section E, neuro-symbolic networks are no fixed structures but offer the possibility to learn connections and correlations between neuro-symbols from examples. The used learning concept is inspired from insights about the learning processes taking place in the human brain. In the brain, certain neural structures, especially structures on the lower neural levels, are already connected at birth. In contrast, correlation to and within higher neural levels are subject to learning. A next-higher level can only evolve if the levels below have already developed. Similar to this, in the proposed neuro-symbolic network, the lowest levels are predefined. This means that their correlations and connections are already fixed at initial system startup. In the brain, the "knowledge" how to predefine structures is stored in genes. For a technical system, this task has to be taken over by an engineer and system designer. Higher neuro-symbolic levels are however subject to learning. Learning takes place stage by stage starting at the lowest initially not connected layer and proceeding with the next higher one until all connections have formed. For each stage, there are learned forward connections and feedback connections. Additionally, redundant neuro-symbols can be identified and eliminated or a splitting and necessary extension of neuro-symbolic structures is feasible to distinguish information in more detail.

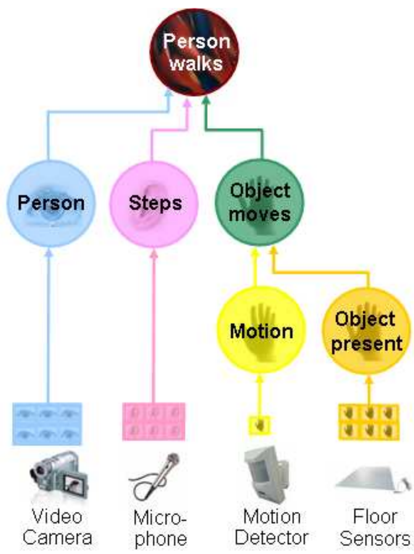

Fig. 6. Neuro-symbolic Structure for Perceiving a Walking Person.

The learning principle used for deriving correlations between neuro-symbols is a supervised learning process, which extracts correlations between data from examples consisting of input data and target data pairs. Input data are data from the sensors that are triggered when a certain object, event, or situation takes place in the environment. The target data of an example describe the meaning of these input data and assign it to a particular neuro-symbol of a certain level.

To learn correlations, examples are needed that represent each object, event, and situation that shall be perceived later on by the system. To allow generalization, not only one but a certain number of examples has to be presented to the system for each object, event, and situation to be perceived. This is because of the fact that a certain object, event, or situation might not always trigger exactly the same sensors. Coming back to the simple example of figure 6 in which a person walks around in a room, different tactile floor sensors are triggered depending on where in the room the person walks. Nevertheless, the meaning of the situation remains the same independent of the actual positions of the person.

In figure 7, the learning principle is clarified by means of the tactile modality of the unimodal level. For other modalities and other levels, the same learning method is applicable. As already mentioned, the input data for learning are sensor data of sensors that are triggered when certain objects, events, or situations occur in the environment. As for the learning phase of a certain layer the lower-level connections have already been set, certain lower-level neuro-symbols are activated based on these sensor data. These activated neuro-symbols serve as actual input data for the learning process.

The target data specify the meaning of the input data – the object, event, or situation that is currently occurring – and assign them to a certain neuro-symbol of the current higher level.

In each level and modality, the learning process actually consists of two phases. For the unimodal tactile modality, in the learning phase A, forward connections between sub-unimodal and unimodal symbols are determined and set. After these connections have evolved, the input-target-data-pairs from the learning phase A are presented to the system a second time in the learning phase B to determine feedback connections. In the learning phase B, it is compared 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. In the next step, feedback connections are set

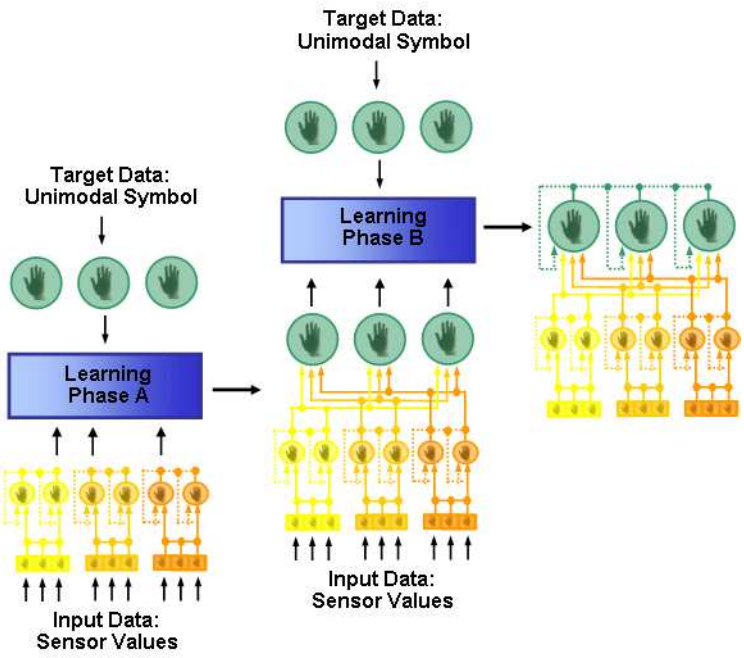

Fig. 7. Neuro-symbolic Learning.

between unimodal tactile symbols accordingly to avoid undesired activations.

III. IMPLEMENTATION

To test the developed model, it was implemented in the simulation environment AnyLogic [1] and tested with a number of test cases. The test cases were different activities going on in a building. For this purpose, the building was equipped with different sensors like video cameras, microphones, motion detectors, light barrier, tactile floor sensory, door contacts, etc.

In figure 8, the activation of different neuro-symbols is shown for the already described case that a person walks around in a room.

The neuro-symbols are shown from the sub-unimodal neuro-symbolic level upwards. Taking a look at figure 8, it catches ones eye that there is depicted one more neuro-symbols than comprised in figure 6. This is for the reason that in the simulation, a larger number of different situations had to be perceived which required a larger number of neuro-symbols. In most cases, different neuro-symbols of a certain level can get information from partly the same neuro-symbols of the level below. This was also the reason why feedbacks had to be introduced into the system. Their function can easily be explained by the example given in figure 8 and will be introduced later on in this section.

As just mentioned, the figure illustrates all neuro-symbols, which are involved in the perception of a walking person from the sub-unimodal level upwards. The neuro-symbol "motion" is activated when a motion is detected in the room. The neuro-symbol "object present" is triggered when tactile floor sensors are activated by an object. Assuming that a moving object is present in the environment, these two neuro-symbols should now activate the neuro-symbol "object moves". At this point, feedback connections come into play. If the neuro-symbolic network shall not only be able to perceive a moving object but also a standing object, a neuro-symbol "object stands" is needed. Looking at the forward connections between the four symbols just mentioned, it turns out that the neuro-symbol "object stands" is activated by a subset of the neuro-symbols, which activate the neuro-symbol "object moves", namely by the neuro-symbol "object present". For this reason, the neuro-symbol "object stands" would always additionally be activated when the neuro-symbol "object moves" is triggered. However, as one situation shall only trigger one neuro-symbol of a certain modality and level, this activation is undesired. For this reason, feedback connections were introduced into the system. Feedback connections have an inhibitory effect on the activation of neuro-symbols. As soon as the neuro-symbol "object moves" is activated, an inhibitory signal is sent to the symbol "object stands" and its activation is suppressed.

As described in section F, the neuro-symbol "person" is activated as soon as a person is detected from the video data. The neuro-symbol "steps" is activated as soon as the steps are detected from the microphone data.

On the next higher neuro-symbolic level, the activated neuro-symbols "person", "steps", and "object moves" can activate the neuro-symbol "person walks". This layer can be considered as output layer. Activated neuro-symbols of this layer indicate that a certain situation has been perceived in the environment.

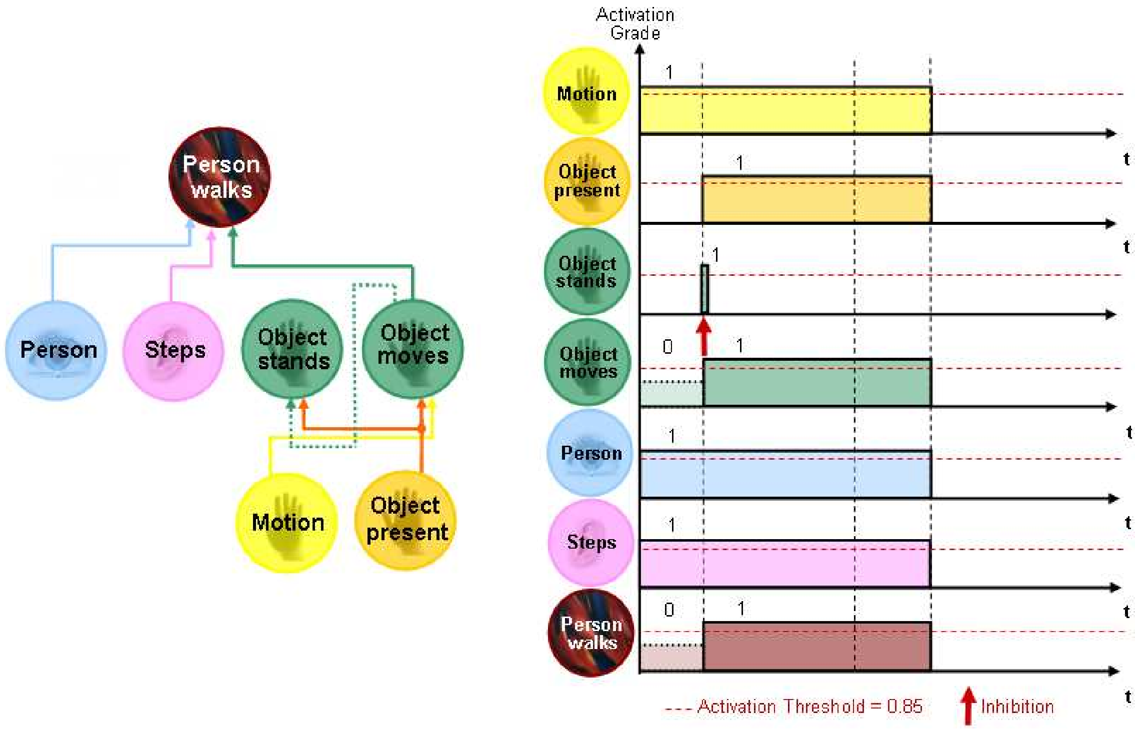

Fig. 8. Neuro-symbolic Activations for Test Case.

IV. 4. CONCLUSION

In this paper, a model was presented for human-like processing of sensory data coming from a huge number of diverse sensory sources. The envisioned application was the autonomous perception of safety and security relevant situations in private and public buildings and to increase the comfort of the occupants. This can help to reduce personal for monotonous observation tasks. Additionally, old and/or disabled persons can get the possibility to live longer independently in their homes. The suggested model was based on neuroscientific and neuro-psychological research findings about the perceptual system of the human brain, which also has to cope with such a huge number of data from diverse sensory receptors.

Besides the fact that the model proved to be functional, it turned out that the derived information processing architecture is very efficient and fast. It allows parallel information processing of a larger number of sensory data. Furthermore, the used information processing units – neuro-symbols – are information processing and information storing units at the same time. Therefore, time can be saved for external memory access and comparative operations.

In addition to this, the usage of neuroscientific and neuro-psychological research findings to design technically functioning and actually implementable technical systems allowed it to discover a number of inconsistencies in existing models of the brain. These gained insights can contribute to a better understanding of the brain, to better brain models, and in further consequence again to more efficient technical systems derived from these insights. In future, cooperation between engineers and brain researchers might help us to make a leap forward not being possible as long as both disciplines work in isolation.

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