# An Artificial Mind via Cognitive Modular Neural Architecture

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**Abstract**

The author proposes that an artificial mind should be able to duplicate the processes of the human mind, i.e. inner imagery, inner speech, sensations, the cognitive functions like introspection, perception, attention, match, mismatch and novelty detection, learning, memory, reasoning, planning, emotions and motivation, perhaps even consciousness. Furthermore, the author proposes that a cognitive system's ability to perceive and report its inner imagery as such should be taken as a test for machine self –consciousness.

An artificial cognitive system based on modular neural architecture is presented here. This non-numeric system utilizes distributed signal representation, sensory preprocessing into feature signals, processing of information associatively with meaning and significance and a modular reentrant architecture that allows the establishment of inner imagery and speech as well as introspection. Match, mismatch and novelty signals are derived from neuron-level signal relations and they are used to effect sensory and inner attention. Pleasure/displeasure conditions are also modelled and they contribute to the reactive state of the system.

This cognitive system is simulated by a PC with real digital camera and text input. The simulated system architecture consists of perception/response reentrant loop modules for linguistic, visual and gaze direction subsystems as well as subsystem modules for pleasure/displeasure and match/mismatch evaluation. The perception/response reentrant loop realizes sensory perception primed by prediction and inner evocations, introspective perception and the establishment and the grounding of meaning for inner imagery and inner words. Additionally the reentrant loop acts as a reverberating short-term working memory. In-loop associative neuron groups facilitate associative cross-connections to other modules. Learning and long-term memory are realized via synaptic strength modifications.

The system can learn to recognize figures, learn the meaning of concrete words by ostension and via correlation, learn certain abstract words and rudimentary syntax by examples, learn to recognize new figures by verbal description, learn temporal sequences and predict their continuation, detect affirmation and contradiction, deduct the properties of a given object from evoked inner imagery. Learning is inductive and fast, only few repetitions are needed.

This system has several features that are commonly attributed to consciousness: It is perceptive, it has inner imagery and inner speech; it is introspective, the inner workings are perceived by the system via reentry to perception process; there is attention and short-term memory. However, at this moment the system does neither have a body reference for self-concept nor episodic memory capacity for personal history, these will have to be added later.

## 1. Introduction

The human mind is characterized by the flow of inner imagery, inner speech, sensations, emotional moods and the awareness of these; consciousness. The human mind is imaginative, creative and intelligent, it can produce correct responses from minimal cues. The human mind possesses intentionality; it operates with meanings and significance, it understands what it is doing. The human mind seems to unify effortlessly past experience, present multisensory information, the expected and desired future, the needs, drives and goals, "the own will" and the emotional states, moods, arising from the interaction of the above. While doing this the human mind seems not to be plagued by the combinatorial explosion.

Obviously the above mentioned qualities would be very useful to any robot, agent or personal electronic assistant.

Would it be possible to reproduce these qualities artificially, would it be possible to create an artificial mind, a thinking machine? How should we proceed towards the design of this kind of machine?

Traditionally two different approaches have existed here.

The symbolic, rule-based artificial intelligence (AI) tries to achieve this goal through programmed processes and functions. Ultimate success has been elusive and strong criticism has arisen (E.g. Devlin 1997, Lenat 1995, Searle 1984, Omar 1994).

The connectionist or artificial neural network (ANN) approach was originally inspired by the biological neuron. Ultimate success has again been elusive and nowadays the research in this field has largely been reduced into the production of isolated functions like pattern recognition or classification and artificial neural networks can be seen mainly as another style of numeric computation. However, at the end of last century there were some bold attempts towards actual cognitive neural systems (Aleksander 1996, Trehub 1991, Valiant 1994).

The problem with AI and ANN approaches has been that the programs and computations do not really understand what they are doing. Meaning and significance are not really involved in the process.

On the other hand human cognition seems to operate with meaning and understanding. Therefore the author proposes that human cognition should be taken as a model for thinking machines and furthermore, a complete system with rich interactions and reactions should be considered instead of rather artificial modelling of isolated cognitive functions with the usual arbitrary labelling of said computations with a cognitive name.

Cognitive psychology has identified basic cognitive processes like perception, attention, learning, deduction, planning, motivation, etc. (Aschcraft 1998, Nairne 1997). Cognitive brain research has also been advancing and the functions of various parts of the brain are being modelled and their possible relationship to cognition and consciousness are being evaluated (E.g. Taylor 1999). Consequently, the author presents here another approach towards thinking machines, based loosely on ideas about the architecture of the brain and on the emulation of cognitive functions by modular non-numeric associative neural networks (Haikonen 1999b, 1998a, 1998b).

## 2. The Cognitive Approach

The cognitive approach involves the design of a system that is able to process information with meaning in the style of human cognition. This style would mean the reproduction of the flow of “inner speech”, inner imagery, the basic cognitive processes like perception, attention, learning, deduction, planning, motivation, etc. and ultimately the awareness of these.

Information processing by meaning and significance involves the understanding of the subject matter. Let’s consider the following cases of understanding:

-Scene (image) understanding
-Episode understanding
-Story understanding (narratives, books, movies)

What would constitute understanding in these cases? Obviously *neither* tape recorder type storage and playback *nor* mapping one set of symbols into others *but* the ability to:

-Answer questions about the subject like:
    -what is where
    -what is happening
    -who is doing what to whom, etc.
-Paraphrase; describe with own words
-Detect contradictions
-Predict what happens next, what is possible
-Give reasons for present situation
-Evaluate significance, good/bad/urgent

Accordingly the system requirements for understanding would be:

-Recognition of components; objects, sounds, words, etc.
-Detection of their relationships; spatial, temporal
-Learning and evocation of relevant associations as the story evolves; meanings, context, background
-Prediction
-Deduction, reasoning
-Match/mismatch detection, contradiction detection
-Significance evaluation good/bad, urgent
-Suitable working and episodic temporary memories
-Suitable long term memories
-Avoidance of combinatorial explosion by sensory and inner attention guided by significance etc.
-Information representation and manipulation methods that allow these operations fluently.

"Understanding" involves the evocation on the relevant meanings among all the possible meanings for the subject representations; purpose, relations, names, etc. These meanings and significance are acquired by the system via learning.

Distributed signal representation (Hinton et al. 1990) and non-numeric associative processing with necessary controlling mechanisms are seen here as the methods that allow the realization of the above.

## 3. The Associative Neuron

Processing with distributed signal representations calls for the ability to connect representations to each other so that one representation can be evoked by another. Individual signals are the basic components of distributed signal representation. Therefore the processing with distributed signal representations involves operations with individual signals. A signal derives its meaning from the point of origin and can be either on or off. Therefore the basic signal processing unit, the neuron, shall switch a signal on or off while preserving the point-of-origin-path and learn when to do the switching. The point-of-origin-path can be preserved if the neuron is configured so that the signal passes through it.

The author has designed a non-numeric associative neuron along the above principles (Haikonen 1999a). This neuron preserves the meaning of signals and thus allows consistent internal representations in suitable network architectures.

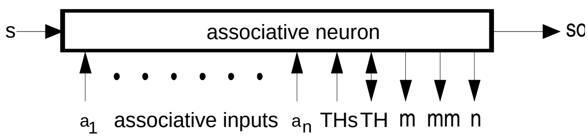


Fig. 3.1. The associative neuron

The associative neuron has one main signal input *s*, a number of associative input signals $a_i$, a synaptic learning fixation threshold control input *THs*, a neuron output bi-directional threshold control *TH* and the output signals *so*, *m*, *mm* and *n*. The point-of-origin meanings of the *s* and *so* signals are the same. *m*, *mm* and *n* signals represent match, mismatch and novelty conditions. The number of associative input signals $a_i$ is not limited or need to be fixed as their synaptic weights are not adjusted against each other. All signals are assumed to have values between zero and one only.

Synaptic learning is correlative and depends on repeated *s* and $a_i$ signal coincidences (modified Hebbian learning). Each coincidence increases the respective synaptic strength and each missed coincidence decreases it. When the so-called learning fixation threshold is achieved, the synaptic weight turns to one and the associative connection between the main signal *s* and the associative signal $a_i$ is established. Thereafter a number of these associatively connected $a_i$ signals may evoke the output *so* alone (associative evocation) and they may amplify the output if the main signal *s* is present (priming function).

Associative evocation as described here can only switch on the *so*-signal. Sometimes switching off or inhibition is needed. This can be effected via the threshold control.

The output signal duration is normally limited by a decay process. This decay is followed by a short refractory period during which no output is possible. Decay is not applied to direct sensory signals.

Distributed main signal arrays are processed with blocks of these neurons in parallel, usually with common associative inputs. “Winner-Takes-All” (WTA) thresholds at the neuron outputs may be used to select the strongest signals. Sequential circuits may be assembled by using additional short-term memories, delay-line type or other. Strategies to eliminate associative interference e.g. the exclusive-or problem exist (Haikonen 1999b).

## 4. Perception/Response Reentrant Loop

A cognitive system uses perception processes to access information about its environment and its own physical states via sensors. The perception of an entity in the cognitive sense does not primarily involve the recognition of a pattern; it involves the evocation of the purpose, significance, name, etc. potentially everything that is associated to the sensed signal arrays. The interpretation of these sensed signals to represent one object and not another, to have one set of associations win over others, perhaps equally or even more probable from the sensory point of view, depends on the experience and contextual state of the cognitive system. Thus the whole cognitive capacity of the system is available to assist the perceptive recognition process.

The Perception/Response Reentrant Loop is devised by the author as the basic system module that performs the functions of sensory perception, establishment of inner representations; inner imagery, inner speech etc., introspection, reverberating short-term working memory and the generation of response.

The perception/response reentrant loop consists of a feedback neuron group with output threshold, association neuron blocks and a related Winner-Takes-All neuron group. The signal array at the output of the feedback neuron group is labelled as the percept. It is the official output of the loop and is broadcast as such to other loops and to the pleasure/displeasure system. The percept may be the preprocessed input signal array as such, input signal array primed by the feedback signal array, feedback signal array as such or a combination of the sensory input signal array and feedback signal array.

The feedback neuron group consists of one neuron for each input line. Each neuron has one associative input that receives its signal from the respective association neuron block output WTA neuron so that the inherent meaning of the main signal and the associative feedback signal are the same.

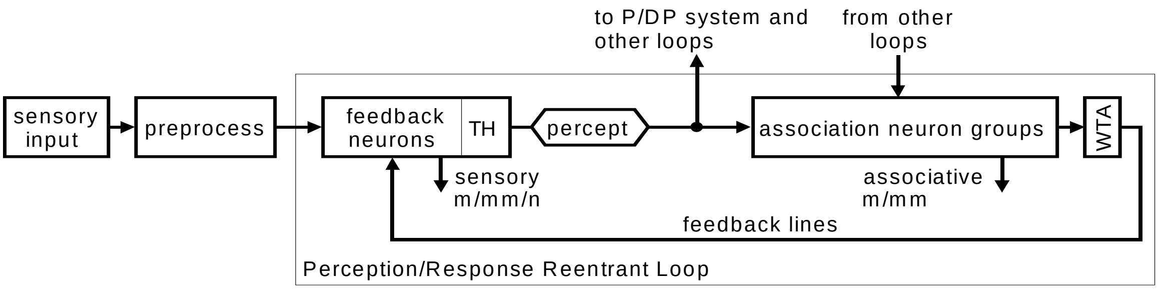


Fig. 4.1. The Perception/Response Reentrant loop

*Perception process* combines the effect of sensed distributed signal representations and internally generated representations. This can be achieved by inserting neurons into the attribute signal lines and using the associative inputs as reentry points for feedback signals from the system. Initially when the system is in unlearned state, there is no feedback and the sensed distributed signal representation passes through the feedback neurons as such and will be the percept for the system. However, when the system is learned, feedback signals may be generated. In this case *perception with priming* takes place. The percept will now be a non-linear sum of the sensed signals and the feedback. Thresholds may now be applied at various points within the system so that only the thus amplified part of the sensed signal array will have effect.

Two cases of perception with priming can be distinguished. *Predictive perception* occurs when the feedback signals represent a prediction or expectation of the input. This prediction may arise due to associations to previous percepts within the system. What is expected will be more likely perceived. Match/mismatch states derived from the feedback neurons indicate the accuracy of the prediction. *Searching perception* occurs when the feedback signals are an internally evoked representation of a desired entity to be found or distinguished. In that case the match/mismatch states indicate the successful/ unsuccessful status of the search.

The reentry mechanism facilitates also introspection. *Introspective perception* of inner imagery or other inner representations takes place when the percept is due to the feedback signals only, when there is no sensory input or the input is subdued.

The use of the terms *inner imagery*, *inner speech* etc. can be justified as follows. In introspective perception the feedback signals are translated into the percept signals. These signals have the same point-of-origin meaning as the sensory attribute signals, which in turn are in causal connection to the sensed external world. In visual domain these signals represent visual attributes or features and the percept signals represent a sensed image of the external entity. Therefore, whenever any percept signals are evoked internally, it is as if the respective visual attributes were sensed; from the system’s point of view the situation is equivalent to that when an image is sensed. However, in this case there is no sensed external entity, the image is internally evoked. These inner images may not necessarily contain all the attributes of sensed external world, they may not be as vivid. These images are not necessarily those sensed before, instead novel images are possible due to the nature of distributed representation. Therefore the term "inner imagery" may be used here. The same line of arguments applies to other sensory modalities as well.

Eventually the system must be able to distinguish between true sensed imagery and internally generated inner imagery, otherwise it would react to internally generated imagery as if it were of external origin. The following cues are available: The activity status of sensory preprocess, *mm*-signals, intensity, vividness.

## 5. The Cognitive System

A modular system architecture that is based on the previously presented principles is described here. This system architecture consists of perception/response reentrant loop modules for linguistic, visual and visual attention focus position (gaze direction) subsystems as well as subsystem modules for pleasure/displeasure and match/mismatch evaluation. The modules are associatively crossconnected so that the percepts from individual modules can be globally broadcast allowing cross-associative operations.

The linguistic system perceives input words, associates percepts from other units to words, associates words to words, evokes inner representations for words and perceives them as words via the reentrant feedback and enables the flow of inner speech. Words are represented as distributed letter signals so that each individual letter is represented by one on/off signal. As words are, in principle, temporal sequences of phonemes or letters in this case, the letter signal representations are transformed into parallel form so that the letters of the represented word always set in fixed positions and are available simultaneously.

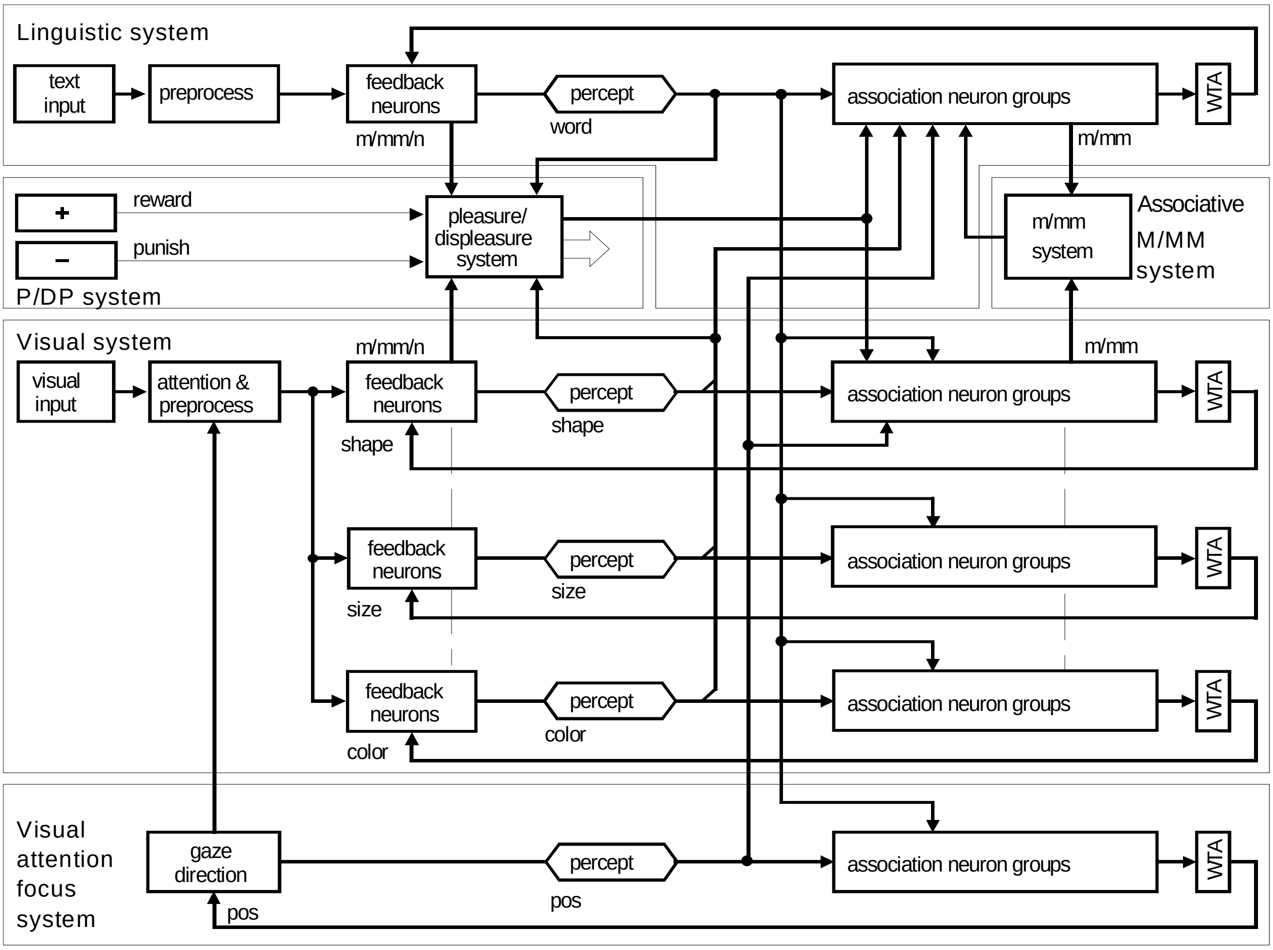


Fig. 5.1. The Artificial Cognitive System

The visual system perceives sensed visual objects; patterns with color and size, associates percepts from other modules to visual objects, associates visual objects to other visual objects, evokes representations of visual objects internally by percepts from other modules and perceives them via associative feedback and in this way enables the flow of inner imagery. The visual system supports the two-way meaning process for concrete words, perceived words with visual meaning evoke the inner representation of the respective visual object.

The visual system preprocesses images into distributed feature signals for shape, color and size. Each of these features has its own perception/response reentrant loop. Images are not reconstructed at any point, the system does not internally operate with actual images. The binding of the features of each recognized entity takes place automatically via associative amplification and thresholding.

The visual attention focus position system controls the focus position and temporarily associates visual objects to their positions. Visual attention focus position is determined by visual change and internally by associative evocation. Visual change is detected by the visual preprocessor.

The associative neuron groups generate match/mismatch signals that indicate the match/mismatch relationship between percepts and evoked representations. These signals are used for learning control and the indication of affirmative and contradictory states, which is important for deduction and reasoning.

The pleasure/displeasure system (P/DP system) associates good/bad significance to percepts and guides judgement, motivation and attention. There are two input sources for the P/DP system. 1.) External reward and punishment signals are accepted, 2.) Match-states from feedback neurons generate pleasure and mismatch-states generate displeasure.

Reward- and punishment-related pleasure and displeasure can be associated to percepts so that later on similar percepts will evoke respective pleasure/ displeasure signals. These percepts are now said to have p/dp significance (functionally more or less similar to emotional significance in biological systems). This significance will translate into signal intensity whenever the said percepts arise again. This signal intensity in turn will guide attention via WTA-circuits and other thresholds so that the significant signal arrays will gain priority (focussing of attention and priming of perception due to emotional significance.)

Linguistic input and visual percepts may be associated together by repeated coincidences. Thereafter sensed visual features will evoke the best matching word, which in turn will evoke the respective visual feature signals at the visual association neuron groups. These will be then prime the visual perception process via the reentry loop and those sensed visual feature signals that belong to the evoked visual entity will be amplified. The same amplifying process can be due to the p/dp significance and other possible sensory modalities. In this way the perception process is primed by the system's knowledge and instantaneous state. In the same way words will evoke respective visual feature signals even if nothing is visually sensed. These evoked inner representations will be sustained by the visual reentrant loops for a while thus enabling introspection so that e.g. questions about them may be answered by the linguistic system. In this way via the cross-associative links the loop modules have access to the other reentrant loops and are thus able to report the contents of the other loops in their own terms –words, imagery, etc. and are also able to affect the contents of the other loops.

## 6. Simulation System

The artificial cognitive system has been simulated with a system consisting of a computer program and a digital camera.

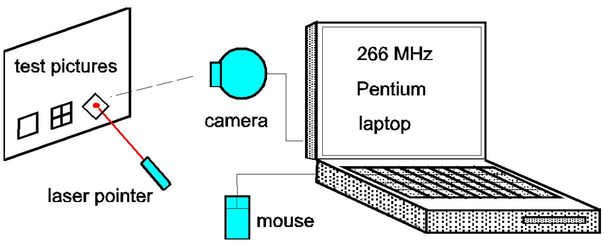


Fig. 6.1. The simulation system

The simulation system hardware consists of a 266 MHz Pentium II laptop computer with mouse, digital color camera and laser pointer to point test figures. The computer operating system is Microsoft NT 4.0. The software consists of a C-language interface for the camera control and a Visual Basic language program for the modular neural system simulation and the user interface. These programs communicate via dynamic link library (DLL) functions.

The camera view is processed into a total visual area and a much smaller visual attention focus area which can move within the total area. Illumination change is detected within the total visual area and actual imagery is detected within the visual attention focus area. The position of the visual attention focus area is determined either by an illumination change (illumination by the laser pointer) or by an internal command from the neural network.

In order to limit the number of required neurons the total visual area is limited to 66 x 66 pixels and the visual attention focus area to 16 x 16 pixels.

When a figure is detected the preprocessing program fine-tunes the visual attention focus area position so that the figure is centered automatically.

The visual object perception and recognition is based on detected features. As a rather limited recognition power is enough for the demonstration of cognitive principles, the number of derived signals is reduced in order to limit the number of required neurons. However, the derived features must enable size invariant recognition, for instance a square must be identified as a square regardless its size. Also minor distortions in the figures must be tolerated.

For the purpose of feature detection the visual attention focus area is divided into four quadrants and a center cross area. Four features; one horizontal, one vertical and two diagonal short lines can be detected within each quadrant. In addition two horizontal and two vertical lines can be detected within the center cross area. Each feature is represented by one signal, visual figures are represented as arrays of feature signals.

Words and sentences may be entered from the keyboard at any time. Each word may contain up to six letters. Each individual letter is represented by one on/off signal. No words are stored at any point as alphanumeric strings.

The simulation program starts in unlearned condition, therefore usually some figures, sizes, colors and their names are taught first by ostension and then higher concepts are taught by example sentences. Thereafter simple conversation is possible. The simulation program learns fast, e.g. the meaning for a word can be taught in few seconds. When the desired effect has been completed the cognitive processor window and the camera window may be captured by the print screen command for documentation.

The following cognitive functions and processes have been demonstrated among others:

*Perception with priming; predictive perception*. This involves the evocation of a continuation to the perceived state of affairs, a rudimentary deduction process. The generation of prediction match/mismatch value and corresponding match/mismatch pleasure/ displeasure is also included.

*Perception with priming; searching perception*. This involves the priming of perception with the representation of the searched item and the generation of match signal when the item has been found.

*Introspective perception*. This involves the perception of the system's inner responses.

*Visual sensory attention*. The ability to focus the gaze on individual visual objects. In this simulation gaze direction is controlled by external stimulus, i.e. visual change caused for instance by a laser pointer, and by internal command. Additionally visual sensory attention is related to the perception of individual visual feature signals. The attended signals will be the strongest ones, due to external or internal causes.

*Inner attention*. Inner attention is based on the operation of the various WTA neuron groups that pass the strongest signals. Priming, decay etc. affect the strength of individual signals.

*Learning concrete words by ostension*. Ostension involves the pointing out the intended item and associating a word to it. This is also a two-way process, afterwards the item must be able to evoke the given word and the given word must be able to evoke the inner representation of the respective item.

*Learning concrete words via correlation*. Sometimes the item to be named cannot be pointed out exclusively. In that case different items with the desired attribute as common can be used as examples.

*Learning by examples*. Learning category names by example question-answer pairs ("what color red", "what name candy" etc.) and learning the meaning of "yes" and "no" and to recognize a question to which yes or no is expected as an answer, again by example question-answer pairs ("is this square yes", is this candy no") has been demonstrated. There is also some inductive power, the learned examples can be used in different context.

*Learning of rudimentary syntax*. The ability to recognize a question and to answer to it properly involves the learning of rudimentary syntax.

*Learning by verbal description*. Learning by verbal description is one form of social learning and it involves the availability of common language between the learner and the teacher. In this simulation system inner representations for new visual objects can be created by verbal description using already known visual objects as components and a name can be associated to these objects ("small green square dollar"). Thereafter whenever the new object is actually imaged it will be recognized ("what name *dollar*").

*Learning of sequences*. The learning of sequences involves temporal association. This is realized here by sequential predictor circuitry within the association neuron groups and its output is perceived via the reentrant loop.

*Sensory Match/mismatch/novelty signals*. These signals indicate whether there is match or mismatch between the sensed representation and the internally evoked representation or whether the sensed representation is novel.

*Affirmation and contradiction detection*. This function is based on associative match/mismatch detection, which matches representations against each other whether evoked externally or internally. This is a prerequisite for reasoning by inner imagery and is also needed for the grounding of meaning for words like "yes" and "no".

*Pleasure/displeasure function and p/dp significance*. Pleasure and displeasure are system's reactions that try to sustain the prevailing attention and activity or disrupt and refocus them. In this simulation system pleasure/displeasure signals are used to initiate actual reactions. Due to the limited scope of the simulation system the actual reactions are rather limited. E.g. when visually searched object has been found, match pleasure is generated and this in turn will hold the visual attention on that object. *The p/dp-significance* manifests itself in elevated signal levels, which e.g. facilitate the detection of p/dp-significant patterns.

*Short-term memory via loop reverberation*. Short-term memory is needed for working memory. The perception/response reentrant loops are able to sustain representations via reverberation.

*Long-term memory via synaptic weights*. Long-term memory is based on the accumulation and fixation of synaptic weights.

## 7. Conclusions

Do we have here a mind, a mind with its own joys, sorrows, secret desires, perhaps even with existentialist suffering? Definitely not. But we do have an architecture, mechanism and platform that supports some of the prerequisites of the mind; the operation with meaning and significance, unification of information from multiple sensory modalities and internal knowledge, learning, the flow of inner imagery, inner speech, introspection, sensory and inner attention. Cognitive processes involving the utilization of inner imagery and inner speech have been demonstrated.

The demonstration of anything like goal-oriented and emotionally motivated action would necessitate the inclusion of motor output (even if virtual), needs, and provision for system reactions. It remains for future research to see if and how emotional states could be emulated with total system reactions and attention control induced by the P/DP-system.

The author has presented here one possible way how a cognitive neural system can be actually assembled. The simulated system is at this moment admittedly limited in scope but it could be easily expanded. A more complete cognitive system for actual applications (e.g. robotics) would include further sensory modalities (tactile etc.) and motor outputs. Also more extensive serial/parallel capacity should be included in the association neuron groups.

The author's system can be compared to other models of mind and consciousness. Baars' global workspace theory (Baars 1997) proposes a "theater stage" as the site for inner imagery and inner speech. In the author's model the percept locations may be compared to the Baars' "theater stage" as they contain the inner speech and inner imagery and these representations are broadcast to the other parts of the system. Baars proposes that this "theater stage" is located at the sensory projection areas, which is also the case in the author's model and which is also quite necessary for the grounding of the basic meaning for the inner representations. However, Baars does not really explain how information should be represented by neural firings or how actual neurons should be connected into networks that would constitute a complete cognitive system.

How about machine consciousness? Self-consciousness is not yet emulated here, as the simulation system does not have episodic memory for personal history nor body reference for self-concept ("I") and therefore is not able to perceive itself as the executing agent. Even though the system has the flow of inner speech and inner imagery and it operates with them, it is not yet able to report having them. It is not able to produce much towards the response "I have inner imagery" or the consequence "I think – therefore I exist". Obviously this kind of a report would only count as a proof of self-consciousness if it can be seen that the system is producing it meaningfully, i.e. the system would have to be able to perceive its inner imagery as such and it would have to posses the concepts like "I", "to have" and "inner imagery". The mere reproduction of preprogrammed strings like "I have inner imagery" would not count as a proof here. -The author would like to see the Turing test (Turing 1950) be replaced by this one. May the race begin!

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