THE EXPERT NEURON

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The paper presents an original concept of artificial neuron, called the Expert Neuron (XN). The approach is aligned with similar approaches intending to build a hybrid neural - expert system, based on both Expert System and Neural Network theories. The originality consists in the creation of a neuron that acts as a small expert system at micro level and can be integrated in several layers of neural networks. The neuron has been integrated in a hybrid neural-expert system called CHILDREN – Computer Human Interface for Learn, Detect and Reasoning with Expert neurons that emulates the visual and cognitive processes of the human brain, starting from the eye and the visual cortex areas and ending with the frontal areas that are responsible with consciousness processes – memory, diagnose, recognition.

Keywords: Expert system, neural network, visual system, pattern recognition

1. Introduction

The paper presents a new concept of artificial neuron called the expert neuron. In the following pages I will make a review of the research context, the directions that converged to the creation of the expert neuron, followed by a presentation of this new type of neuron. In the second part I will describe aspects linked to the research results. Based on the expert neuron concept I have build a software system that is specialized in image learning and recognition, called CHILDREN – *Computer Human Interface for Learn, Detect and Recognition with Expert Neurons*. The system proposes an original approach for image processing, learning and recognition following the biological processes of the human visual system, from the retina to the visual cortex. The system capabilities of modeling the human visual perception are emphasized during the presentation, by making a parallelism between the artificial neural networks implemented with the expert neuron cells and the biological neural layers that are responsible for image processing.

The main objective of the study was to take a step back and make an analysis of the existing artificial intelligence paradigms, with an accent on the expert systems [1], trying to find better ways of modeling the human biological processes. As already known, the expert systems were created as an attempt to simulate high level human brain processes, like diagnose, reasoning, deduction, and so on [2]. During the last years the expert systems continue to be a technique

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used for solving problems in different domains: engineering, business, management, medicine, and many more [1]. However the study intended to analyze what is the gap between these systems and the biological processes. The hypothesis was that the current methodologies and techniques related to expert systems have drifted somehow from their initial purpose of modeling the biological processes. This is due mainly to three factors: first, the biological research has greatly evolved during the last years. Without responding to all questions linked to human perception, there is however a lot of new information that may not be considered in the expert systems (ES) paradigm, which hasn't changed a lot during the last years. Second, the evolution in the ES domain was biased by the need to provide commercial systems, favoring the tradeoffs in the implementations that did not follow anymore the biological processes, but the expected results of these systems. Finally, the last factor that must be considered is the technology evolution that can offer new tools and more possibilities in software modeling.

Therefore, the study was to build a system that implements a better model of the biological processes linked to vision and reasoning. The biological and ES elements that were merged in the expert system elaboration as a new concept are presented in [3]. A brief summary of this research results on the biological direction were [4], [5], [6]:

1) The retina performs an image compression of 130:1 on the input image
2) The retina does not send to the brain the entire input image, but only 10 – 12 sketchy representations
3) During the visual path the image processing is split in two parts, the magnocellular path, specialized in processing large areas of the input image, and the parvocellular path, specialized in processing image details
4) At visual cortex level there are several layers specialized for detection of specific image characteristics. These layers are interconnected and hierarchical. Image processing increases in complexity from one layer to another [7].

As we will see the implemented system follows these three main characteristics of the biological visual processing system. It contains several neural layers; each layer is specialized in processing a specific pattern in the input image and sends the processing result to the next layer. The system receives as input a sketchy representation of an image. The image processing complexity increases from one layer to another, converging in the end and producing the complex shape that has to be recognized or learned.

The research results on the ES direction discovered that this paradigm is the one that provides the best modeling approach for the high level biological processes, like reasoning and diagnose [1], [8]. However at this moment there were not found a lot of references about expert systems involved in image processing. So in general the domain addressing image recognition is addressed by other techniques, like neural networks. On the other hand the expert systems and the neural networks can be seen as complementary techniques, each has its advantages and disadvantages [9]. This is why today there is an increased tendency to build hybrid neural – expert systems, that integrate neural networks and specific ES modules, like knowledge base, inference engine, and so on. An example of such neural expert system is MACIE (Matrix Controlled Inference Engine) proposed by Stephen I. Gallant [10].

However there is a gap that is difficult to cross: while the expert systems process symbolic representations for hypothesis, facts, observations, etc, the neural networks work usually with numerical data [9], [11]. This is not necessary a disadvantage and one of the integration strategies, called *divide and conquer [9]*, works by dividing the problem in several sub-problems and treat each problem based on its nature either by an expert system or by a neural network. However during the study, after analyzing the evolution and specificities of the classical neural network processing paradigm, that have little similarities with the human neuron processing, it was considered that this paradigm has somehow drifted away from the biological processes modeling.

The biological and ES directions research provided the following assumptions on a system that should better model the human biological perception [3]:

1) The system should be based on several successive neural layers
2) The system should process sketchy images, extracted from the original
3) Processing should increase in complexity from one layer to another
4) The processing should separate the detail processing from the global processing

All these considerations generated several attempts in building a system that should model both the image processing specific to the visual cortex and the high level processing specific to the frontal brain. The final result was the expert neuron. As we will see, the final system can be considered as a hybrid neural expert system that implements the strategy of *transforming explicit knowledge in neural networks* [9], [11]. However the approach is extended, the expert neuron is practically an atomic micro-expert system, he can take the activation / deactivation decision based on the embedded knowledge base and inference rules, on one hand, and on the other hand based on the set of facts received from the previous layers.

2. The expert neuron (XN)

The architecture diagram of the expert neuron is presented in Fig. 1:

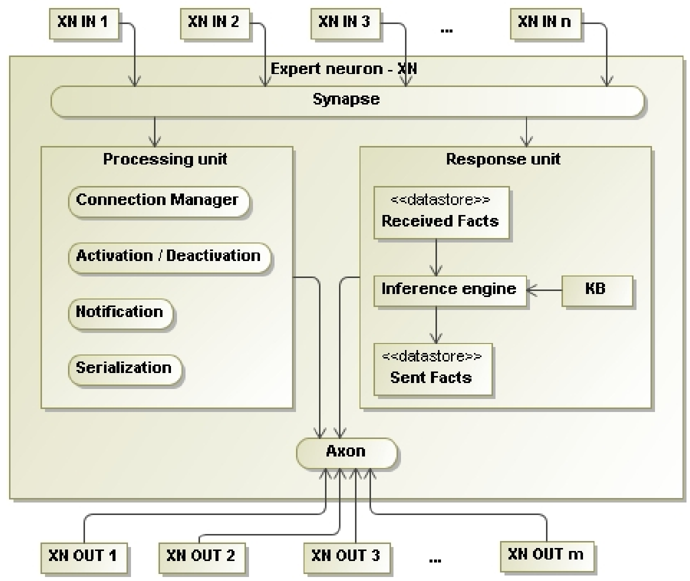


Fig. 1. XN architecture

The expert neuron (XN) has basically the same behavior as a classic NN neuron. This neuron has a synapse, that allows sender neurons connections, and an axon, that allow this neuron to connect to the next neural layers. This basic behavior is of course the same as the biological neuron behavior. Another similitude is the activation that is based on processing the responses of the sender neurons. In the modelling it was considered that the neuron response is not just the sum of the input potentials, but a logical processing of the received facts.

The main difference between the XN and the classic neurons is that the XN is a small unit that acts as an expert system. It contains the main modules that compose an expert system, the inference engine and the knowledge base. The XN modules are:

1) The inference engine and the knowledge base – these modules have a similar behavior to the ones in the ES theory
2) A processing unit, that is responsibile for implementing the processes required by the good functioning of the neuron: allow external neurons to connect to the current neuron, trigger the recomputation of the neural response based on the received input, manage data exchange between different internal modules, serialize the neuron
3) The synapse and the axon are software components allowing the neuron connection with other neurons.

The XN implements a two channel communication [3]. The functional diagram of the neuron is presented in Fig. 2:

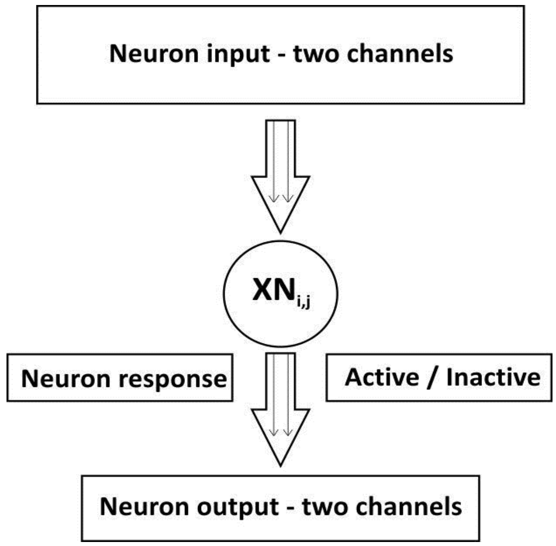


Fig. 2. XN – Functional diagram

The first channel is the activation / deactivation channel, responsible for transmitting the neuron activation / deactivation in the network, similarly to the classical artificial neuron [12]. This channel is called the **status change channel**. The input status change notification received by the neuron from the sender neurons travels trough the internal communication bus and reaches the processing unit. The processing unit will then trigger the recomputing of the neuron response. The neuron response is computed based on the inference rules contained in the inference engine applied to the received facts. In other words, the input neurons will send facts to the current neuron, not simple values as in the classical approach, and the current neuron will compute its response based on the received facts, the existing facts from the knowledge base, and the applied rules. The response will also be a set of facts that will be sent via the axon to the next level of neurons on a separate channel, called the **response channel**. Together with the response, the neuron will determine a change in the current state (active / inactive). The processing unit is responsible for changing the state.

During the implementation, as it will be explained in the next chapter, two additional types of neurons were developed, that have an architecture slightly different from the one presented in Fig. 1. These architectures were needed due to the specific function that these neurons implement. The first type of architecture was the **sensitive neuron**. The biological equivalent of this neuron are the neurons that allow transforming the neural signal into input or output information related to the outside world. Examples of such neurons are the retina photoreceptor cells [5], that are responsible for transforming the light rays into neural impulses during the *transduction* process [5], [6], and the motor neurons that carry signals from the spinal cord to the muscles to produce movement. The architectural representation of the visual sensitive neuron is presented in Fig. 3:

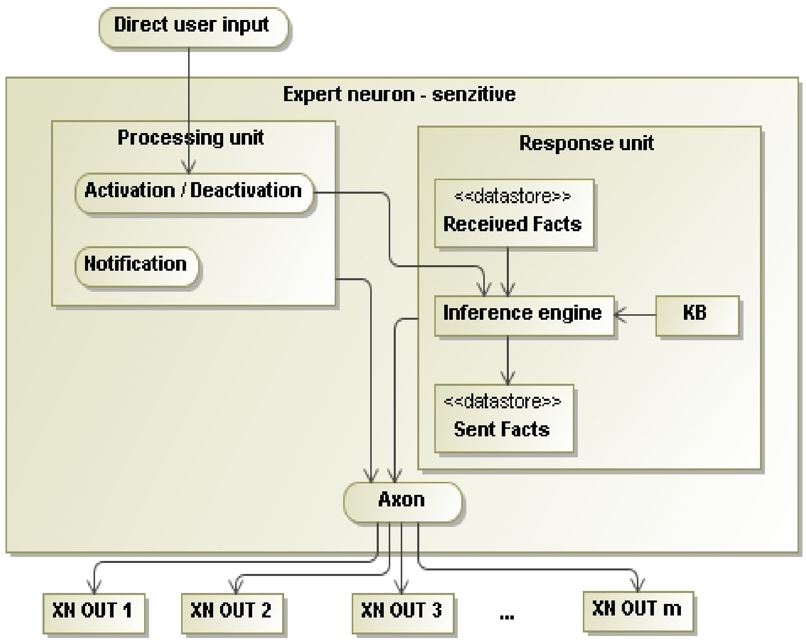


Fig. 3. Sensitive Neuron

The difference between the sensitive neuron and the expert neuron is that the senzitive neuron does not have a synapse. The input signal is taken directly from the user and transformed internally into neural data.

The second type of neuron derived from the expert neuron was the **declarative neuron**. This architecture is characteristic to the high level neurons, like the entity neurons presented in the next chapter. They have a dedicated synapse connection that allows organising these neurons in open world representations [1], [2]. The architecture of these neurons is presented in Fig. 4:

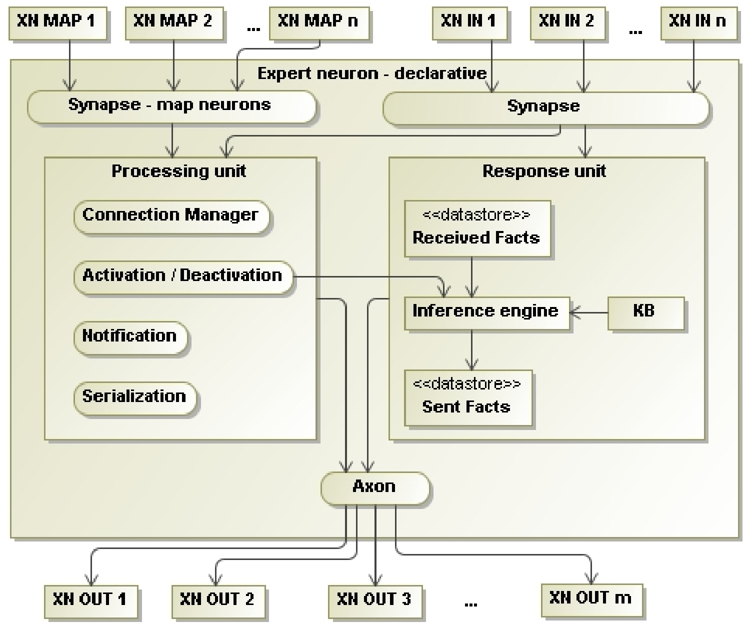


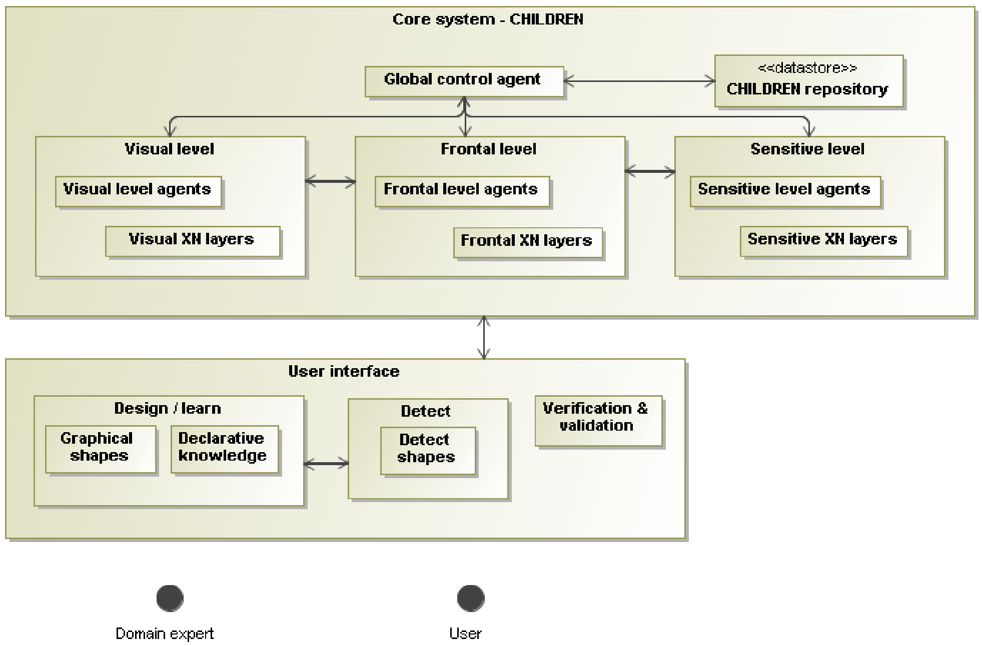
Fig. 4. Declarative Neuron

As the image shows, the additional synapse is dedicated to a specific neuron called **map neuron**. The map neurons will be described in chapter 3. They have the role to control the declarative neuron activation / deactivation based on the user choice.

3. CHILDREN system

The expert neuron has been integrated in a software system called CHILDREN – *Computer Human Interface for Learn, Detect and Recognition with Expert Neuron*. The system is a proof of concept that presents an original way of simulating the biological processes linked to vision and reasoning. The implemented neural layers follow closely the biological patterns of the layers existing in the visual path, from the retina to the visual cortex [5], [13].

The system architecture is presented in Fig. 5:



Fig, 5. High level architecture of the system

The system architecture can be decomposed in three vertical directions:

1) The visual system – part of the system that handles visual representation of image patterns

2) The frontal system – part of the system that handles high level representation of explicit data

3) The sensitive system – part of the system that handles neurons similar to the biological perception neurons

As one can see from Fig. 5, the system consists from two tiers, the user interface and the core tier. The user interface implements functions dedicated to two types of users. The **domain expert** is able to design and trigger learning of new graphical shapes and also explicit data in the frontal neurons (design / learn module). The **user** is able to trigger the detect and recognition process, which consists in the system analyzing input data and recognizing images in a pattern similar to classical expert system processing (reasoning module). At core level the system consist in the three vertical directions mentioned above. Every vertical slice is composed from an agent, responsible for integrating the system processing in the global context, and from the neural layers, responsible for the actual expert processing. The global process is managed by a transversal agent, responsible also for saving the system state (i.e. the neural layers created by the user or domain expert). Fig. 6 details the three neural levels:

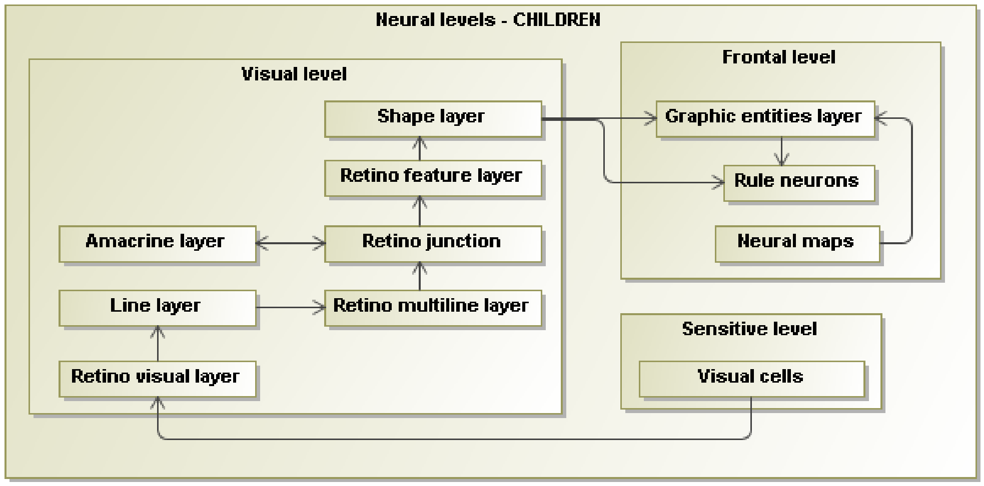


Fig. 6. Neural levels – details

The **sensitive level** contains neuron layers allowing the system to interact with the outside world. These neurons are called **visual graphical cells**. Their architecture has been presented in Fig. 3. The **visual cells** correspond to the biological visual cells in the eye [3]. They have a dual behavior; they act as a neuron and as an input/output cell, transforming the user input in neural activation response.

The **visual level** contains neuron layers dedicated to image processing, learning and recognition [3]. An important aspect of the process is the fact that the neuron response calculation is based also on the topological connections between each neuron and the previous layers. We present a short description of each visual layer [3].

1) The visual neurons – the topological organization of the visual neurons, connected to the graphical cells, is shown in Fig. 7:

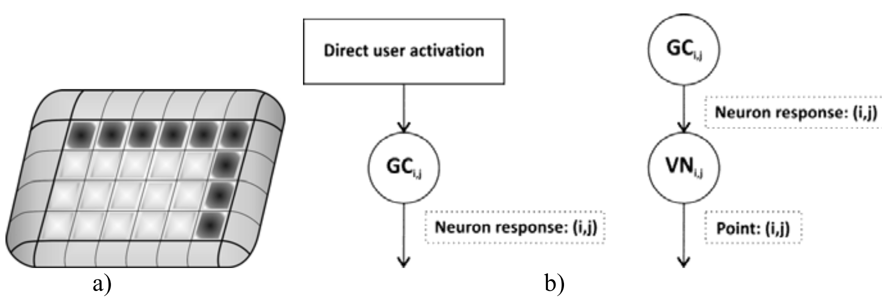


Fig. 7. a. Input graphical cells; b. Graphical cells and Visual cells – topological organization

The graphical cells (GC) represent the first neural layer, allowing the user to draw input test images in an 8X6 or 8X8 matrix - Fig. 7.a.. Each cell in the matrix is a sensitive neuron that transforms the user input in neural activation, similar to the retina transduction process [4], [5]. The graphical cell is activated if the cell is activated by the user. The next layer, the visual neurons (VN), has a similar behavior; a visual neuron is activated if the sender neuron, the graphical cell, is activated. The neuron response for both graphical cell and visual neuron is the coordinate of the cell activated by the user.

2) The line neuron and its connections to the previous layer are presented in Fig. 8:

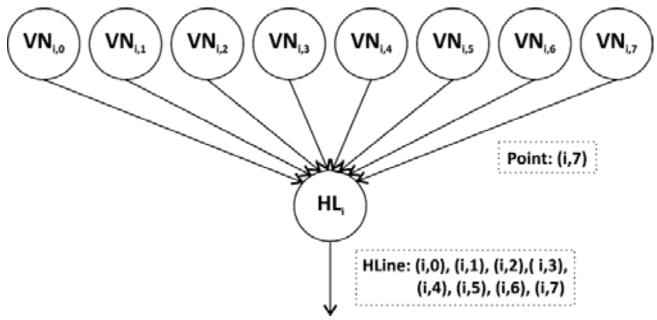


Fig. 8. Line neuron

There are two types or line neurons, for horizontal and vertical line detection. The neuron response is computed based on the topological connections to the previous layer and the activation of the sender neurons. The line neuron response is an active line from the input image. The line neuron biological equivalents are the visual cortex simple cells that have receptive bands sensitive to rays of light with specific orientation [7], [13].

3) The multiline neuron and its connections to the previous layer is presented in Fig. 9:

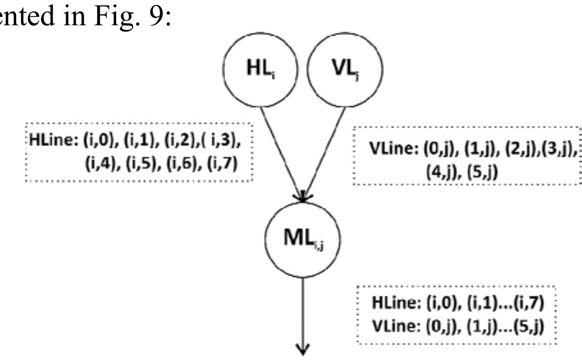


Fig. 9. Multiline neuron

The multiline neuron layer has a retinotopic structure, meaning that there is a multiline neuron corresponding to each visual point of the input image, i.e. to the coordinate of each visual point. The multiline neuron is activated if the associated point in the input image belongs to one or more active lines. The neuron response is the list of lines associated with the neuron coordinates.

4) The junction neuron connections and response are presented in Fig. 10:

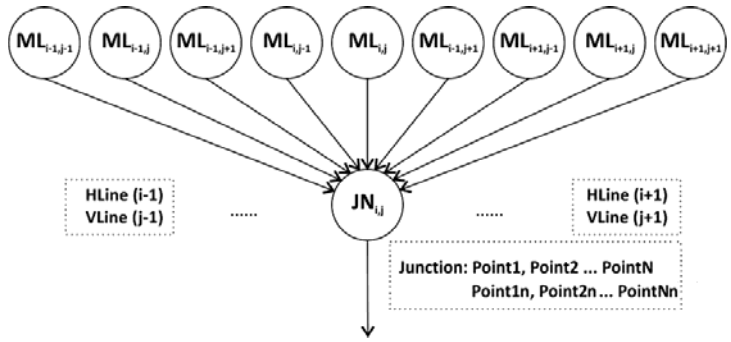


Fig. 10. Junction neuron

The junction layer has also a retinotopic structure [5], [7]. Its connections to the previous layer consist in a central neuron and more neighbor neurons. Due to this type of connection the junction neuron detection field is a rectangular window, formed by the association of the detection fields from the previous layers. This way of creating a rectangular detection field is also a biological characteristic of some visual cortex types of neurons (simple cells) [7], [13]. The junction neuron will be activated if the central point belongs to a junction. A junction is formed from a set of points that link two lines from the input image. The neuron response is the junction points. The neuron performs also a normalization of the detected junction by performing a translation of the junction points in the origin of the axes of the input field, which is the top left cell of the receptive field.

5) Amacrine neuron connections are presented in Fig. 11:

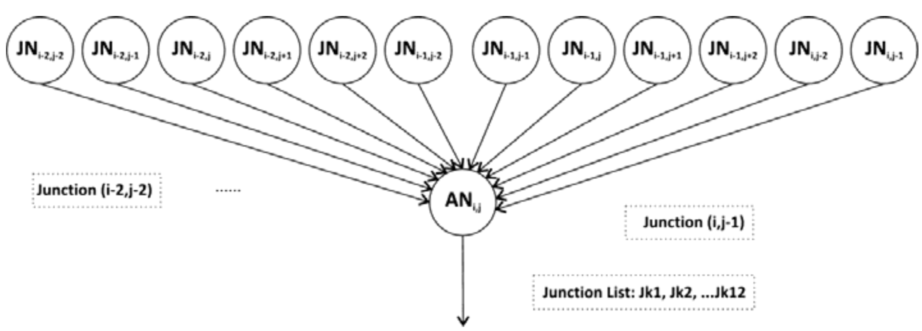


Fig. 11. Amacrine neuron

The amacrine layer is a layer of XN that has a similar behavior with the amacrine layer in the biological retina [4], [5]. At this moment the precise role of the biological amacrine cells is not fully established. However, during the implementation of the system emerged the need to eliminate duplicate junctions detected in the image. This required the implementation of a neural horizontal layer that is connected to several neighbors from the junction layer. Each time a duplicate junction is detected the associated amacrine neuron will activate. The receiving neural layer, the feature layer, will process the information from both the junction layer and the amacrine layer, selecting only the non identical junctions from the image – Fig. 12.

6) The feature neuron is presented in the image bellow:

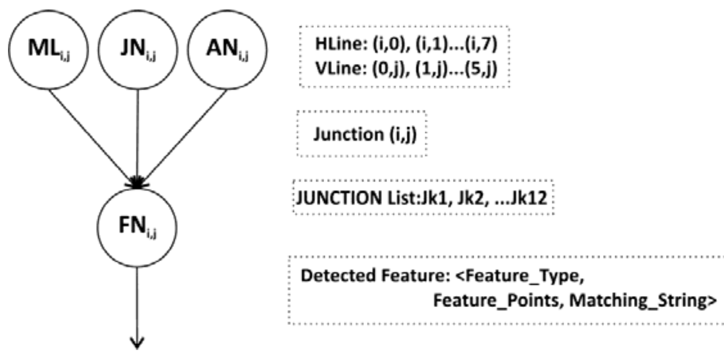


Fig. 12. Feature neuron

As already explained, the feature neuron will receive the response from the multiline layer, the junction layer and the amacrine layer. Based on this input it will create an object of type DetectedElement. This is a generalization of an image graphic feature. The detected element can be: horizontal line, vertical line, or junction. Each detected element will have associated a corresponding matching string, respectively: “LH”, “LV”, {Junction points}. This string will be later used during learn and recognition process. The feature neuron response consists in the graphical feature associated with a specific point in the input image. Also at feature neuron level the duplicate junctions are eliminated.

7) The shape neuron:

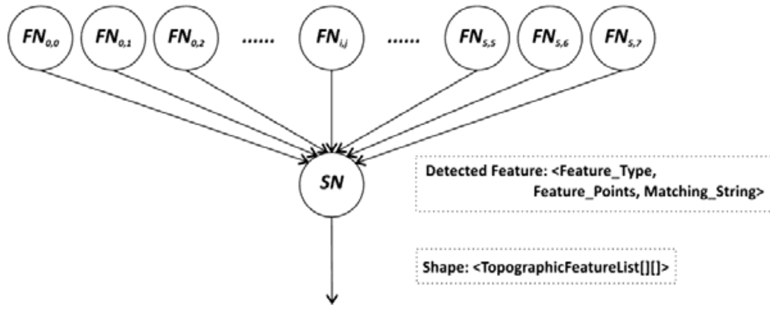


Fig. 13. Feature neuron

The shape neuron creates a topographic feature list based on the responses from the previous layer. For an input image corresponding to number "Seven", like the one in Fig. 7.a., the response will be similar to:

< LH, JUNCTION> (1)
< 0, LV >

This response means that the input image can be characterized by a horizontal line, a junction, and a vertical line.

8) The entity neuron is practically part of the frontal level, because he is responsible of high level processes, like learn and recognition; however this neuron performs the last part of the image processing, so it will be presented at this stage – Fig. 14:

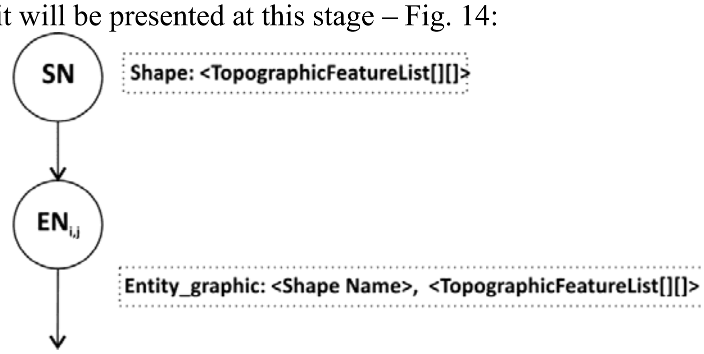


Fig. 14. Entity neuron

The entity neuron receives from the shape neuron the shape detected from the image. Based on the current operation, learn mode or recognize mode, the neuron will behave differently. During the learn operation the system creates dynamically a new entity neuron. This entity neuron will contain in the knowledge base the current shape and a label provided by the user, that represents the learned image. During the recognition process the neuron will perform a matching algorithm per each line and feature, between the learned shape and the shape currently detected.

The **frontal level** contains an additional layer that may be considered also as being part of the image processing. This is the **rule layer**. The system allows the domain expert to define new rules by implementing an interface. The rules are dynamically loaded at runtime, and their role is to allow refining the graphical detection by using classical matching algorithms. An example of such rule would be “Select best match”. If during the graphical shape detection the system detects two graphical entities as valid response (i.e. two graphical neurons are activated), the rule is applied and the neuron with the highest number of features matching the graphical shape is activated.

The last neural layer contained in the frontal level is the **neural map layer**. This layer allows defining more open worlds in the system [1], [2]. The biological equivalent would be the neural map, i.e. structures of neurons associated with different activities. Another example can be the **grid cell**, a type of neuron found in brains of rats and mice [14]. The map neuron has the role of commanding the neural response for the entity neurons to which it is connected. During the computation of the neural response the entity neuron will first verify if there is a map neuron connected on the dedicated synapse (Fig. 4). If there is no map neuron connected, the entity neuron response is processed normally, by applying the defined inference rules. If the entity neuron has a map neuron connected as sender the processing unit will first check if the map neuron is active. If the map neuron is active than once again the entity neuron response will be computed normally, by applying the inference rules. If the map neuron is not active than the entity neuron will remain also deactivated, even if the set of facts received through the “functional” synapse (the neuron response channel) would require neuron activation.

The domain user can define different worlds or sub-domains in the system by defining neural map neurons and connecting the neural map neurons to the already defined entity neurons. This is a way of grouping entity neurons into problem sub-domains. The user can create different worlds specific for each set of recognized input images, for instance letter detection map, number detection map, and so on. Such separation will allow better recognition results due to the narrowing of the result set.

4. Conclusions

The paper presented an original alternative to the classical type of neural networks and neurons. Based on the human biological processes related to vision and reasoning, on one hand, and on the other hand based on the expert system and neural network theories a new type of neuron has been developed, called the Expert Neuron. Using this neuron an expert system has been developed, that simulates as close as possible the human biological system characteristics related to vision and reasoning. The CHILDREN system integrates the common concepts of the expert system paradigm and implements several common processes of any expert system: learn, diagnose, and reasoning.

As mentioned in chapter 1, the main objective of the study was to analyze the gap between the existing artificial intelligence paradigms and the latest research studies related to the biological processing in the brain, and to find ways of modeling more accurately the human biological processes linked to vision.

The results obtained have a high level of similitude with the human visual path, different from the existing approaches. They also prove the feasibility of an expert system based on expert neurons for different types of reasoning, including shape detection. Up to this date references about expert systems used for image recognition could not be found, and this is a direction that was insufficiently explored. However obtained results are promising. There are also additional elements that should be taken into account, like modeling uncertainty in the XN detection algorithms. At this moment the XN contains such elements, based on the certitude theory [1], [2], [15], however the full mechanism has only been used in some neurons, like the line detection neurons, and was not generalized at system level.

The advantages of this approach, as compared to classical approaches consist mainly from the fact that they are modeling very close the human biological processes. Another major advantage is that the approach provides a way of building a hybrid neural – expert system that removes the barrier between the neural networks and the expert systems, because it transforms the neural image processing using numerical data into expert processing, using explicit information extracted from the image. The expert neuron maintains the advantages of the classic neuron – flexibility, atomicity, autonomy, distributed processing, and so on, but is adapted to a kind of processing that is characteristic to the biological systems, the logical processing. This type of process is currently well modeled by the expert systems for the high level processes, like reasoning, diagnose, deduction [2], [16], but is not successfully addressed by the classical neural networks approach. The expert neuron allows extending the expert system paradigm and methods to any type of processing inspired from the biological systems.

This proof of concept must be extended, of course, and new elements must be added, that would allow processing real images. For this the recommended direction would be the creation of a module based on the local energy model, an image processing technique that allows segmenting and extracting elements from an input image following also the biological models [17]. Another direction may be the enhancement of the sensitive neurons following a similar approach as for the visual neurons, by allowing them to process information received from a sensor.

The final results and applications of the system would be dedicated to real life systems that are involved in complex approaches that require image processing followed by high level operations of reasoning, diagnose, deduction. Such systems can address domains like: video monitoring and surveillance, analysis and processing of video content, and so on.

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