

## NEUROCOMPUTATIONAL MODELLING OF DISTRIBUTED LEARNING FROM VISUAL STIMULI

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## ABSTRACT

**Objective:** Neurocomputational modeling of visual stimuli can lead not only to identify the neural substrates of attention but also to test cognitive theories of attention with applications on several visual media, robotics, etc. However, there are many research works done in cognitive model for linguistics, but the studies regarding cognitive modeling of learning mechanisms for visual stimuli are falling back. Based on principles of operation cognitive functionalities in human vision processing, the study presents the development of a computational neurocomputational cognitive model for visual perception with detailed algorithmic descriptions.

**Methods:** Here, four essential questions of cognition and visual attention is considered for logically compressing into one unified neurocomputational model: (i) Segregation of special classes of stimuli and attention modulation, (ii) relation between gaze movements and visual perception, (iii) mechanism of selective stimulus processing and its encoding in neuronal cells, and (iv) mechanism of visual perception through autonomous relation proofing.

**Results and Conclusion:** The contribution of this research modelling data of neurophysiological studies and provide collective evidence for a distributed representation of visual stimuli in the human brain. The outcome of this study will enable health institute in diagnosing brain disorders related with perception development

**Keywords:** Neurocomputational modeling, Machine vision, Artificial intelligence.

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## INTRODUCTION

Visual perception is one of the fundamental tasks in machine vision. Many recognition algorithms have been proposed in computer science area [1-5]. While the central processing unit processing speed can now be reached at 4.5 GHz, the human brain has a limited speed of 100 Hz at which the neurons process their input. However, compared to state-of-the-art computational algorithms for object recognition or visual perception, human brain has a distinct advantage in object recognition, i.e., human being can accurately recognize one from unlimited variety of objects within a fraction of a second, even if the object is partially occluded or contaminated by noises. Objects in real world space project natural color images on the retina in the human vision system, which has normal visual acuity and normal color vision. The information of stimuli is transformed to the visual cortex, in which a two-stream hypothesis is widely accepted [6]. The dorsal stream from V1 to intraparietal areas solves the problem of where the object is located. The ventral stream goes through V2 and V4 to inferior temporal areas solves the problem of what the object is. According to this hypothesis, temporal cortex is involved in object recognition task. Based on the cognitive mechanism in the human vision, this proposal presents the novel approach to model the cognitive phenomenon behind the visual perception and to utilize it for a neurocomputational cognitive model for object and scene recognition. Thus, it is much desired to explore computational cognitive models of how human brain recognizes objects to develop visual perception, in both areas of computer vision and cognitive computation.

## Problem statement

To specify the mechanism of visual perception the, we make distinctions between object perception and object recognition. Object perception concerns how the shapes of objects are perceived by controlling stimuli presented to the sensory receptors. Object recognition, in addition to seeing an object, concerns about seeing an object as something that has been seen before. Thus, object recognition involves memory and learning. Based on this perspective, we study object recognition

in the process of perception, memory, learning, and judgment [7]. There are many factors affecting the object recognition, including size, illumination, viewpoint, orientation, and so on. This proposal tends to study these factors and organize them into a single cognitive model after a systemic modeling of gaze-stimuli relationship and neurophysiological signaling, with collective evidence of distributed learning.

Based on the summarized cognitive model, the computational implementation of the cognitive model for object recognition of complex stimuli will be generated. A computational model of human cognition can be defined in several different senses. This work presents a model, which is computationally perceptive. By utilizing cognitive functionalities in the human brain, the proposed model is distinct from existing computing algorithms in computer science research field. Test datasets such as McGill 3D shape benchmark [8] will be used to demonstrate that the presented computational cognitive model outperforms state of the art computer vision algorithm. The study makes the following two contributions in this proposal:

- Systemically study psychological and neurophysiological studies with converging evidence, to uncover distributed learning of cognitive and neural mechanisms for object recognition in the human brain.
- Based on these cognitive mechanisms, a computational cognitive model for object recognition will be generated. The proposed model utilizes distributed local features which are defined as activation patterns and are similarity-invariant. By utilizing a learning process characterized by a reinforcement-learning model, the features are clustered into abstract representations stored in memory traces, which form the partial representations of the object.

The objective of this research is to carry out systematic neurocognitive experiments to model:

- i. Segregation of special classes of stimuli and attention modulation;
- ii. Relation between gaze movements and visual perception;
- iii. Mechanism of selective stimulus processing and its encoding in neuronal cells;

- iv. Mechanism of visual perception through autonomous relation proofing.

Based on the above experiments, the data generated will be modeled into single modified neurocomputational model of cognition. The neurocomputational model will be used to generate an algorithmic visual perception framework for solving real-world problems associated with machine vision.

#### Related work

The mysteries of the human mind have attracted considerable attentions in natural sciences. For nearly half a century, cognitive science has emerged as a new discipline that focuses on the various scientific issues of the human mind. Cognitive science is the interdisciplinary scientific study of human perception and thinking process, which includes all of cognitive processes from sensory input to complex problem solving, individual human being to the intelligent activity of human society, as well as the nature of human intelligence and machine intelligence. Cognitive science research not only promotes the understanding of the nature of the human mind but also promotes the development of modern science and technology. Recently, computer science has become increasingly prominent in cognitive science, and the knowledge of theoretic computer science provides a solid basis for considering the functional architecture of a computational brain [9].

The visual media, including digital images, video and three-dimensional models, contains superfluous visual information. Since the intelligent processing of visual media utilizes a combination of cognitive mechanism and computation, visual media is a good example to integrate cognitive mechanism into an intelligent computation [10-12]. Marr's visual computing theory is the most representative cognitive computing model, which plays an important role in guiding intelligent computer image processing [13]. The algorithm Marr proposed was not only in line with the results of neurophysiology experiments conducted in primate animals, but also explains the characteristics of the human visual system [14]. Marr's model was the most successful model that combined human cognitive mechanisms and computer algorithms. However, with the rapid development of science and technology, the pending visual media information from the Internet is massive, unordered, uncertain, and interactive in social groups. Thus, it is imperative to propose new theories and methods to process massive amounts of visual media.

Over the past decade, a large number of neurophysiological and cognitive neuroscience researches have provided in-depth and detailed experimental data and theoretical models to reveal the brain's information processing mechanisms. Because of the complexity of information processing in the human brain, cognitive scientists recognize that computational models can enhance our understanding of the cognitive system functions and provide a theoretical foundation and technical support [15]. For example, science, nature, and neuron recently published a series of studies [16-21] that showed the role of the bottom-up and top-down visual attention selection in the process of human visual perception. Different neural pathways, as well as corresponding computational models that successfully simulated their neural mechanisms, were discussed. Further neurophysiology research and computational modeling research indicated that the perceptual significance of stimuli depends on the background information in the environment [22]; background information is also shown to be very important in object recognition process [23]. Poggio and Bizzi proposed a systematical computational model based on the perception principles of biological visual system [24-26]. However, the researches on the neural mechanisms of visual information processing still lack a quantifiable cognitive model and a corresponding mathematical theory to explain the internal mechanism clearly. All of these problems obstruct the practical applications in engineering. How could cognitive mechanisms and computational models simulating human cognitive functions be applied to the intelligent sensing and machine perception in the natural environment? How could they be applied to solve

practical problems of intelligent computing? All of these questions would be answered by the fundamental scientific exploration of intelligent computing.

The past studies include exploring an uncharted area of modeling various aspects of cognitive function for facial recognition information in identifying individuals [26]. The objective was to identify the factors from parahippocampal place area (PPA) with means of a computational method that trigger the recognition process, which constitutes facial encoding by measuring the selectively responses in PPA to images of objects. The synthetic intelligent computer model is used to enable categorization of feature selectivity in brain patterns and simultaneously training it as a building block for the visual system, which mimics and categorized shape selective responses in PPA. Another work includes the exploring the mechanism of interconnected neural networks by plasticity mechanisms to bring out intelligence, consciousness, and emotions by a collective firing of sets of neurons operating at different time delays and oscillations [27]. The nature of our study was to computationally test a mathematical model to mimic neurological events in general and provides a theoretical and experimental framework that links neural function to model-based learning and theory of cognitive control; which in turn has bridged the junction of biology and computer science. This had allowed us to sculpt such neural networks into effective data processor. Moving further in our past research accomplishments, we have shown the neural mechanism with which complex computing problems deals with multidimensional signals is usually experienced as unitary precepts [28]. A neuronal spike pattern is used to determine the synchronization dynamics of neuronal activity for computer-generated color patterns in aid of synchronization of neuronal activity for memory formation in autistic subjects. In particular, this gives functional organization of neuronal circuits and interesting relationships between these oscillations and interneuronal coupling that suggest an enhanced mechanism for effective learning of visual patterns by autistic brain.

#### METHODOLOGY: GLOBAL AND NODAL PROPERTIES OF COACTIVATION AND CONNECTIVITY NETWORKS FOR COGNITIVE VISION AND FEATURE LEARNING

The coactivation network was topologically complex in several ways. The nodal degree distribution was fat-tailed with high-degree hub nodes to be located in proposed polymorph neural network using a sequence of information to excite the necessary regions and assess the information in an associative form (Fig. 1). This enables the machine not only to learn, but it enables it to embark the cross relationship between various data for prediction or simulation based logical conclusion. Physically, this topology was embedded parsimoniously, in terms of the connection distance between coactivated nodes (Fig. 2). Most connections or edges were separated by short sequence of excitatory data, significantly shorter than random networks; with  $p < 10^{-3}$  in the permutation test. Relatively few edges were long distance, and these were often interhemispheric projections between bilaterally homotopic regions where 14% of longest connections

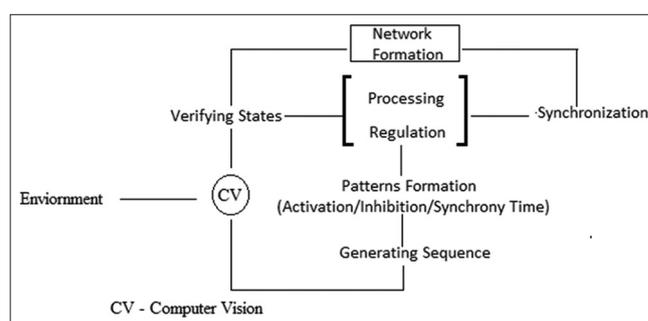


Fig. 1: Structural network of cognitive vision based learning mechanism in the proposed model

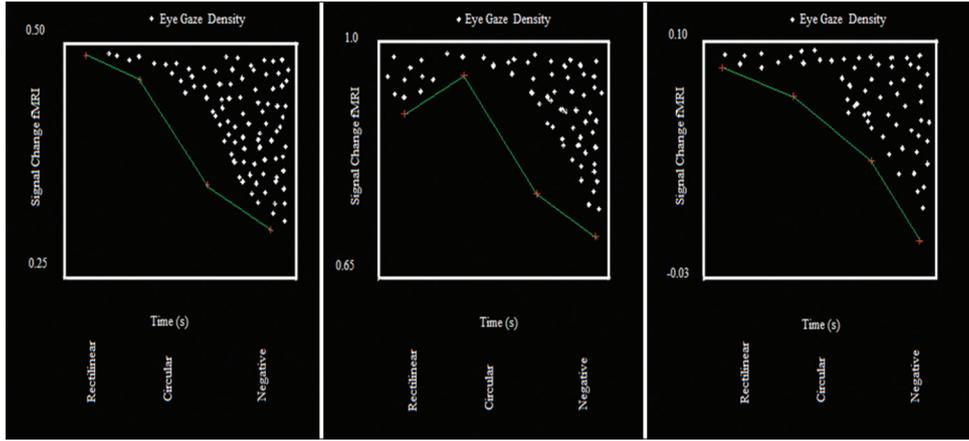


Fig. 2: Stimuli results for arrays of rectilinear shapes with rounded and negative images while depicting the eye gaze density for each of the images

(defined as top 10 percentile) were homotopic; significantly more than random.

The artificial neural rule-based system used in the experiment employs the concept of neural network as well as fuzzy logic. The neural network used in work contains an input layer and an output layer [29,30,31]. The number of neurons in hidden layers decides the objects to be classified. Output layer of the network is used to replicate the recognition process by carrying out the same task as the similar data to the subject is fed into the system. At time, each of the two elements of the focusing factors is processed within the layers (using matrix representation) that are related to the classes of rectilinear and curvilinear objects, and the output is manifested in the form of the step-by-step identification process. The fuzzy learning mechanism is used between the weights of the input and middle layer to detect how often the outputs win the competition. Multilayer feed forward neural network is used in the first step during examination. The input layer of neural network has M number of neurons, and the hidden layer has  $N_g$  neurons. The output layer of the network has N neurons. Training of artificial neural network is done using Backpropagation (BP) algorithm as modeled below:

- Step 1: Develop a network with suitable number of neurons and other parameters as per the value of I and M supplied.
- Step 2: Analyze input image and map all detected and segmented objects and numbers into linear arrays.
- Step 3: Read desired output converting each segmented object to a binary unicode value. Characters are individually stored.
- Step 4: Generate arbitrary weights within the interval [0,1] and assign to all neurons in hidden layers and also output layer. Maintain a unity value weight for all neurons of the input layer.
- Step 5: For each segmented object:
  - i. The output of the feed forward network is calculated.
  - ii. A comparison is made with the desired output corresponding to the symbol and computer error.
  - iii. Errors are propagated back across each neuron in previous layers to adjust the weights.
- Step 6: The training dataset I is fed to the classifier and determine BP error by:

$$BP_{err} = C_{tar} - C_{out} \quad (1)$$

Where  $C_{tar}$  is the desired target output, and  $C_{out}$  is the actual network output. The value of  $C_{out}$  is determined as:  $C_{out} = [Y_2^{(1)} Y_2^{(2)} \dots Y_2^{(N)}]$  where  $Y_2^{(1)}, Y_2^{(2)}, \dots, Y_2^{(N)}$  are the network outputs of each neuron. The individual network outputs can be computed as:

$$Y_2^{(1)} = \sum_{r=1}^{N_g} w_{2r1} Y_1(r) \quad (2)$$

$$Y_1(r) = \frac{1}{1 + \exp(-w_{1r1} \cdot C_{in})} \quad (3)$$

Where  $w_{2r1}$  is the weight of the connection from the  $2r_{th}$  input element to the  $1^{th}$  hidden unit. equation 5.18 and equation 5.19 are activation functions of output layer and hidden layer respectively.

- Step 7: Adjust the weights of all neurons by  $w = w + \Delta w$ , where  $\Delta w$  is the change in weight estimated as:  $\Delta w = \gamma \cdot Y_2 \cdot BP_{err}$ , where  $\gamma$  is the learning rate. In general, the value of learning rate is between 0.2 and 0.5.
- Step 8: The hidden layer outputs are computed as:

$$O_j^h = \frac{1}{1 + e^{-a \sum_{i=1}^m W_j^i x_i}} \quad (4)$$

Where  $x_i$ , the net input to the  $i_{th}$  input unit;  $O_j^h$ , the output of the  $j_{th}$  hidden layer neuron and  $W_j^i$  is the weight on the connection from the  $i_{th}$  input unit to the  $j_{th}$  hidden unit. The actual output  $k_{th}$  hidden layer is:

$$O_k^h = \frac{1}{1 + e^{-a \sum_{i=1}^n W_k^i U_j}} \quad (5)$$

Where  $O_k^h$  is the actual output for the  $k_{th}$  unit and  $W_k^j$  is the connection weight from the  $j_{th}$  hidden unit to  $k_{th}$  output unit. The error term between output layer neuron and hidden layer neuron is:

$$\delta_k^o = O_k (1 - O_k) (T_k - O_k) \quad (6)$$

Where  $T_k$  is the target output for the  $k_{th}$  output unit and  $\delta_k^o$  is the error term for the  $k_{th}$  output unit.  $\delta_j^h$  is the signal error for the  $j_{th}$  hidden unit, given as:

$$\delta_j^h = O_j (1 - O_j) \left( \sum_{k=1}^p \delta_k^o W_{jk} \right) \quad (7)$$

The weights on the output layer are adjusted by:

$$W_{jk}^o(t+1) = W_{jk}^o(t) + (\mu \cdot \delta_k^o \cdot O_j) \quad (8)$$

Where  $\eta$  is learning rate of output layer. The weights of hidden layer neurons are adjusted as:

$$W_{jk}^h(t+1) = W_{jk}^h(t) + (\eta \cdot \delta_k^o \cdot X_j) \tag{9}$$

Final error is calculated (if  $(T_k - O_k) \geq 0$ ):

$$\delta_k^o = (1 + e^{(T_k - O_k)^2}) O_k \cdot (1 - O_k) \tag{10}$$

Otherwise

$$\delta_k^o = -(1 + e^{(T_k - O_k)^2}) O_k \cdot (1 - O_k) \tag{11}$$

Now, the rules are generated in the form of fuzzy error classifiers and these fuzzy rules are generated to recreate the recognition process and train the artificial neural system for visual recognition. Major steps of the system are:

- Repeat the process until the BP error is minimized as  $BP_{err} < 0.1$ .
- Check for next segmented objects and repeat until recognition of all objects is over.
- The average error is computed for all object which are in correlation with other segmented ones a supposed to be  $< 40\%$  the total error.
- Finally, the above process has to be repeated till specified number of epochs.
- Once error threshold is reached, the object recognized is displayed.

Although the network cost was overall low, as measured by the distance of connections, the network topology still managed to balance integration and segregation between all topological artificial neural regions: The clustering of the network threshold at sparse levels was much higher than random, while retaining a similar path length, i.e., it was small world. The illustration of the so formed weighted perception values from distributed stimuli is shown in Fig. 3. In all these respects, the organization of the coactivation network was convergent with properties of a comparable functional connectivity network generated from resting-state of excitatory sequences. As known from prior study, and reproduced here, a recognition state polymorph neural networks for feature extraction and encoding of it for both the grayscale and negative images (which is an example of small world encoding), with fat-tailed degree distributions and parsimonious distance distributions.

Thus, it seems reasonable to say that the proposed research has firm prominence with its scope fulfillment and will be relatively specialized for action, the occipital module for perception, and the default-mode module for emotion. Action and cognition tasks accounted for approximately the same proportion of intramodular edges in the other already cited software AI modules (96.6% and 98.2%, respectively), and therefore we described it as specialized for other executive functions. This research assumes the development of a prototype of cognitive

vision based visual systems, which shall boost the application of open sourced Intelligent Framework.

**RESULTS AND DISCUSSION**

As shown in Fig. 2, the dotted region of the selectivity of the geometric shapes in the brain regions is represented for the magnified antirational responses resultant from rectilinear versus circular visual object stimuli.

Thus, from this viewpoint, the procedurally created viewership of the certain images with specific properties of being rectilinear or curvilinear or negative object images that there is significant bias for the rectilinear images than with the circular or rounded or curvilinear images. Finally, the negative images did not preserve the object size thus having a hard time recognizing those images by the subject. The imaging results demonstrate marked neural response which tends to serve to complement the behavioral findings of the significant restoration of the ability to recognize for such visual images. Altogether, these causes to give an explanation on the long-standing question of why photographic negatives are hard to recognize. This result suggests that the difficulty in analyzing negative images is driven in significant parts by dissolving the geometric shapes in 2D contrast polarity relations between a essential regions of the face defined by a combination of rectilinear and circular shaped objects. The special significance of eye gazes is that it perceives objects differently in the collection of segmented order (for a fractal image) overlaid in the neighborhood which gives out the data from the same experiment conducted with different diameters of the circular aperture (Fig. 2). Thus, this finding explains the perceptual significance of reconciliation of photometric relationships with human's ability to identify and recognize line drawings of faces rather easily than circular ones. Evidently, line drawings mainly contain contour information and very little photometric information which is held responsible to define luminance relation. However, when it comes to facial recognition or of fractal images, the density and weight of the lines affect the relative intensity of different regions. Thus, the contour lines included in such depictions corresponds not only to low-level edge maps instead it embodies the images' photometric structure. It is the skillful inclusion of these photometric cues by the overlapping of contour lines which in our experiment make the human subjects more prone to easily recognize line-drawings which is latter replicated by the computer algorithm as shown in Fig. 3.

This research work addresses the intelligent processing of massive amounts of visual media and makes the processing of perception, memory, and judgment (PMJ) in cognition correspond to the steps of analysis, modeling, and decision in computing, respectively. Here, the computational cognition model of PMJ is proposed, consisting of three stages and three pathways integrating cognitive mechanism and computing in its framework based on the basic mechanisms of human

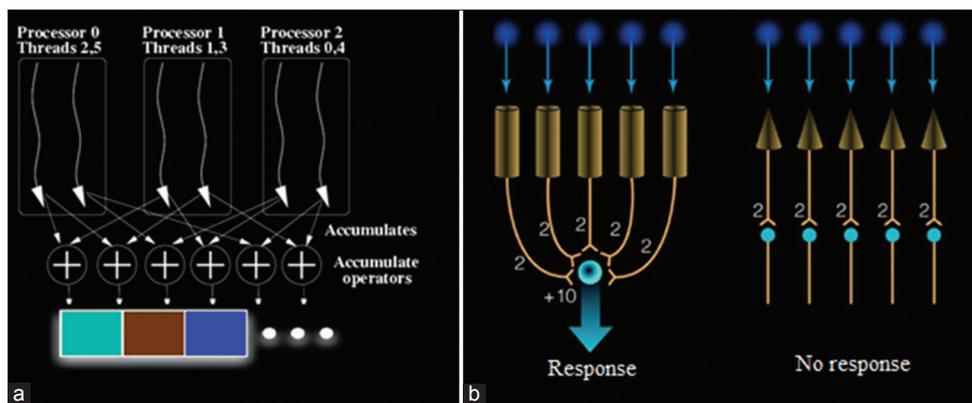


Fig. 3: (a) Formation of patterns with the perception of object based on the proposed model, (b) Region of input responses for perception development from polymorph neural networks

cognition. In the framework of PMJ model, the important cognitive mechanisms of human information processing were studied on mass visual media, build a neural network model based on PMJ model, achieve a quantitative description of the visual cognition load, and further explore the mathematical formulation of the model. Finally, the model will be applied in the field of affective forecasting based on Internet images and image retargeting. PMJ model would provide the realizable cognitive basis for improving the efficiency of mass visual media processing from the Internet and realizing visual media interaction, integration, and presentation in accordance with human perception and cognition. Furthermore, the model would effectively promote cognitive computing from qualitative research to quantitative research, and enhance the research level of intelligent processing of Internet visual media.

Computation a lists from cognitive psychology proposed that cognition is a kind of computational form [32], and the primary function of the brain is to process information [22]. The received information can be represented in the brain. If such a representation of the brain is absent, it is impossible for the brain to communicate with the world [1]. Representations of the brain are functioning homomorphisms; that is, there are structure-preserving mappings (homomorphisms) from states of the outside world (the represented system) to symbols in the brain (the representing system) [9]. Symbols are the physical manifestation of computation and representation in cognitive processes. They carry information and embody the results of those computations [9]. Therefore, it is essential to understand that the symbols of the brain are physical entities and cognition is the computation of symbols and the information processing of the brain [9]. Good symbols in a computational system must be distinguishable, constructible, compact, and efficacious [9].

The computability of cognition could bind the mechanism of human cognition and computational models realized by computers. It is the theoretical foundation for the research in which human behaviors could be explained by computational processes, and the basic principles of cognitive modeling for instructing engineered computing (categorization, identification, and encoding) based on cognitive hypotheses. The computability of cognition not only makes the quantification of cognitive properties possible but also serves as the basis for quantified data to be computed in the computing processes of modeling and judgment.

## CONCLUSION

The contribution of this research is of two folds. Firstly, the systematic cognitive experiments are designed for modeling data of neurophysiological studies, which provide collective evidence for a distributed representation of visual stimuli in the human brain. Secondly, a computational technique to model and simulate the distributed mechanism of visual learning is implemented. Research outcome presented in this study will be used for developing better artificial intelligence to solve societal problems such as AI for identifying theft, mugging, and other criminal actions from surveillance feed. The outcome has enabled us to develop a cognitive model of visual computing to understand the information processing for shape selective objects. The model will be used in conjunction with several health institutes in diagnosing several brain disorders, which are associated with perception development.

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