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The Mechanism of Orientation Detection Based on Artificial Visual System for Greyscale Images

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Abstract: Human visual system is a crucial component of the nervous system, enabling us to perceive and understand the surrounding world. Advancements in research on the visual system have profound implications for our understanding of both biological and computer vision. Orientation detection, a fundamental process in the visual cortex where neurons respond to linear stimuli in specific orientations, plays a pivotal role in both fields. In this study, we propose a novel orientation detection mechanism for local neurons based on dendrite computation, specifically designed for grayscale images. Our model comprises eight neurons capable of detecting local orientation information, with inter-neuronal interactions facilitated through nonlinear dendrites. Through the extraction of local orientation information, this mechanism effectively derives global orientation information, as confirmed by successful computer simulations. Experimental results demonstrate that our mechanism exhibits remarkable orientation detection capabilities irrespective of variations in size, shape, or position, which aligns with previous physiological research findings. These findings contribute to our understanding of the human visual system and provide valuable insights into both biological and computer vision. The proposed orientation detection mechanism, with its nonlinear dendritic computations, offers a promising approach for improving orientation detection in grayscale images.



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MSC: 68T07

1. Introduction

Between 1950 and 1980, neurophysiologist David Hubel and neuroscientist Torsten Wiesel conducted a series of scientific studies on vision, focusing on cortical cells in rabbits and monkeys [1,2]. Their experiments revealed several important biological phenomena: first, visual cortical cells are highly sensitive to rectangular spots and slits; second, there are simple cortical cells that respond only to stimuli at specific angles, a property known as orientation selectivity [3–5]. Orientation detection is a crucial function of the visual system, allowing us to recognize and interact with our surroundings [3]. However, little is understood about how orientation selectivity contributes to the global orientation detection of objects with varying sizes, shapes, and positions. To address this issue, we proposed a novel mechanism in a previous paper [6]. Our approach involves local orientation selection neurons that can detect an object's orientation angle, and infer global orientation from this information.

Despite progress in understanding the visual computations performed by V1 and other areas of the cortex, important questions remain. For instance, it is unclear how computations in V1 relate to those performed elsewhere in the cortex, and whether V1 contains

unique mechanisms for computing orientation from retinal images [7–9]. Recent studies suggest that dendrites play a critical role in visual computing, particularly in invertebrates. These studies use Boolean logic to represent the nonlinear interactions of dendritic trees, using operators such as “and,” “or,” and “not” rather than softer alternatives like minimum or maximum. Additionally, experiments have demonstrated that single dendrites in neocortical pyramidal neurons can perform computation on input that was traditionally thought to require multilayer networks, such as linearly indivisible classification [10–12].

The retina is a crucial structure in the visual system, serving as a specialized component of the central nervous system. It plays a vital role in converting photoelectric signals, processing them, and transmitting visual signals to the cerebral cortex. The discovery of retinal receptive fields and orientation-selective ganglion cells (OSGCs) in the retina marked a critical milestone in the study of biological orientation detection [13]. In vivo and in vitro studies have extensively explored the properties of orientation-selective ganglion cells (OSGCs) in the mammalian retina. These studies, particularly in mice and rabbits, have identified OSGCs as a significant component of the output layer of the retina, specifically the retina ganglion cells [14–19]. However, like other neural systems in the brain, OSGCs cannot perform complex visual tasks independently. The frontal neural pathway of OSGCs spans the entire retinal layers, forming the “OSGC vertical pathway,” the ganglion cell layer of the retina comprises various cell types, including photoreceptor cells (PCs) in the outer nuclear layer (ONL), horizontal cells (HCs), bipolar cells (BCs), amacrine cells (ACs), and orientation-selective ganglion cells (OSGCs) [19–22]. These layers interact through synapses, enabling intercellular information sharing and cooperation to constitute a functional vertical pathway. While photoreceptors are not orientation-selective, downstream OSGCs exhibit orientation selectivity [23,24]. The neural computational processes underlying this selectivity, as well as the associated neural circuits and membrane biophysics, have been a classic example of neural computation and the focus of decades of research. Figure 1 illustrates these concepts:

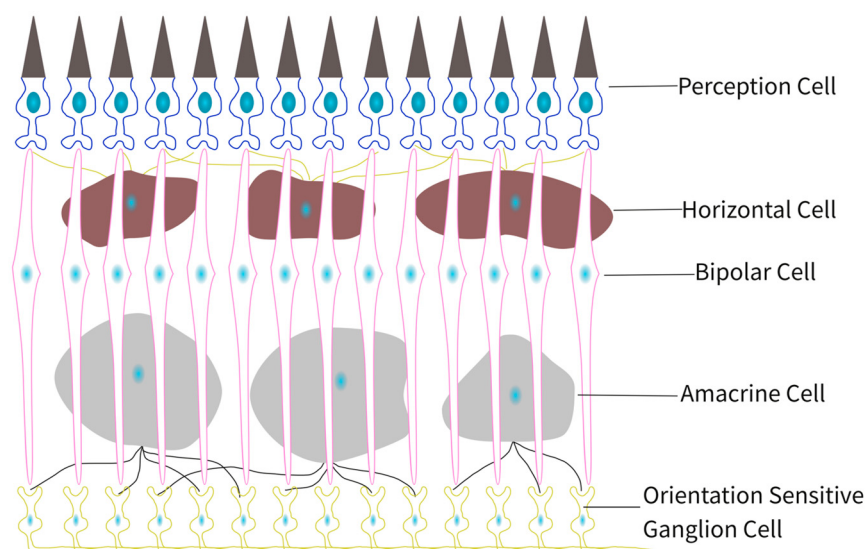


Figure 1. Retinal cell model.

About 60 years ago, Hubel and Wiesel observed that certain cortical cells responded selectively to certain orientations of visual stimuli, but the precise mechanisms underlying this selectivity remain unknown. This paper proposes a novel mechanism for generating orientation selectivity in V1 cortical anatomy. We hypothesize the existence of locally directed detection neurons that selectively receive neighboring photoreceptor inputs and compute the direction to which they respond. Using a dendritic neuron model, we extend this mechanism to multi-orientation detection neurons. We conducted experiments on a dataset comprising 252,000 images with varying shapes, sizes, positions, and orientations

to validate the effectiveness of our mechanism. The results of our experiments clearly demonstrate that our approach is highly effective in accurately detecting object orientation direction. Furthermore, computer simulations of our mechanism confirmed its reliability and robustness across a range of orientation scenarios. This study may shed some light on the exact mechanism of selectively to certain orientations of visual stimuli.

Therefore, we propose an orientation detection mechanism based on the OSGCs for grayscale images. Building upon this mechanism, we also propose an artificial visual system (AVS) for planar orientation detection and other visual information processing. To verify its validity, we compared it with other models in the Related Works section and obtained satisfactory results. This demonstrates that our proposed model in the paper can effectively perform orientation detection in grayscale images and outperforms the current mainstream models in many aspects.

The principles and mechanisms of the model are described in detail in the Mechanism section, the accuracy of the model is verified experimentally in the Experiment section, and finally the model is compared with the mainstream models currently used for orientation recognition in the Related Works section.

2. Mechanism

2.1. Dendritic Neuron Model

Artificial neural networks (ANNs) have been a prominent research area in the field of artificial intelligence since the 1980s [25,26]. By mathematically modeling brain synaptic connections and information processing mechanisms, neural networks have become indispensable in various fields such as medical diagnosis, stock index prediction, and autonomous driving, exhibiting remarkable performance [26–28]. This section will provide a detailed description of the neuron's structure and its orientation detection mechanism. Our hypothesis proposes that simple ganglion neurons detect orientation information by sensing light signals within and around their receptive fields.

While many of these networks rely on the traditional McCulloch-Pitts neuron model as their basic computing unit [29], this model fails to capture the nonlinear dendritic mechanisms that are crucial for information processing in biological neurons [30]. Recent research on dendrites in neurons, however, has revealed their crucial role in overall calculations, providing strong support for future research [31–38]. Koch, Poggio, and Torre proposed that the interaction between synapses on the adendritic branch of retinal ganglion cells can be regarded as a logical AND operation, where excitatory synapses are intercepted if activated inhibitory synapses are closer to the cell body [39–41]. The current from the dendritic branch is summed up at the branch node, which can be modeled as a logical OR operation [42–44]. The outputs of the branch nodes converge at the cell body, or soma. Upon surpassing the threshold, the neuron fires and transmits a signal through its axon to other neurons. In Figure 2a, the ideal δ cell model is illustrated. If the inhibition interaction is modeled as a NOT gate, the output of the δ cell model can be expressed as follows:

$$Output = X_1 X_2 + \bar{X}_3 X_4 + \bar{X}_5 X_6 X_2 \quad (1)$$

Excitatory inputs X_1 , X_2 , X_4 , and X_6 are denoted by logical 1 signals, whereas inhibitory inputs X_3 and X_5 are denoted by logical 0 signals. The cell body (soma) signal produces a logical 1 signal only in three scenarios: (i) $X_1 = 1$ and $X_2 = 1$; (ii) $X_3 = 0$ and $X_4 = 1$; and (iii) $X_5 = 0$, $X_6 = 1$, and $X_2 = 1$. In contrast, the γ cell model receives input from both excitatory and inhibitory synapses, as shown in Figure 2b. Its output can be expressed as follows:

$$Output = \bar{X}_1 X_2 X_3 \quad (2)$$

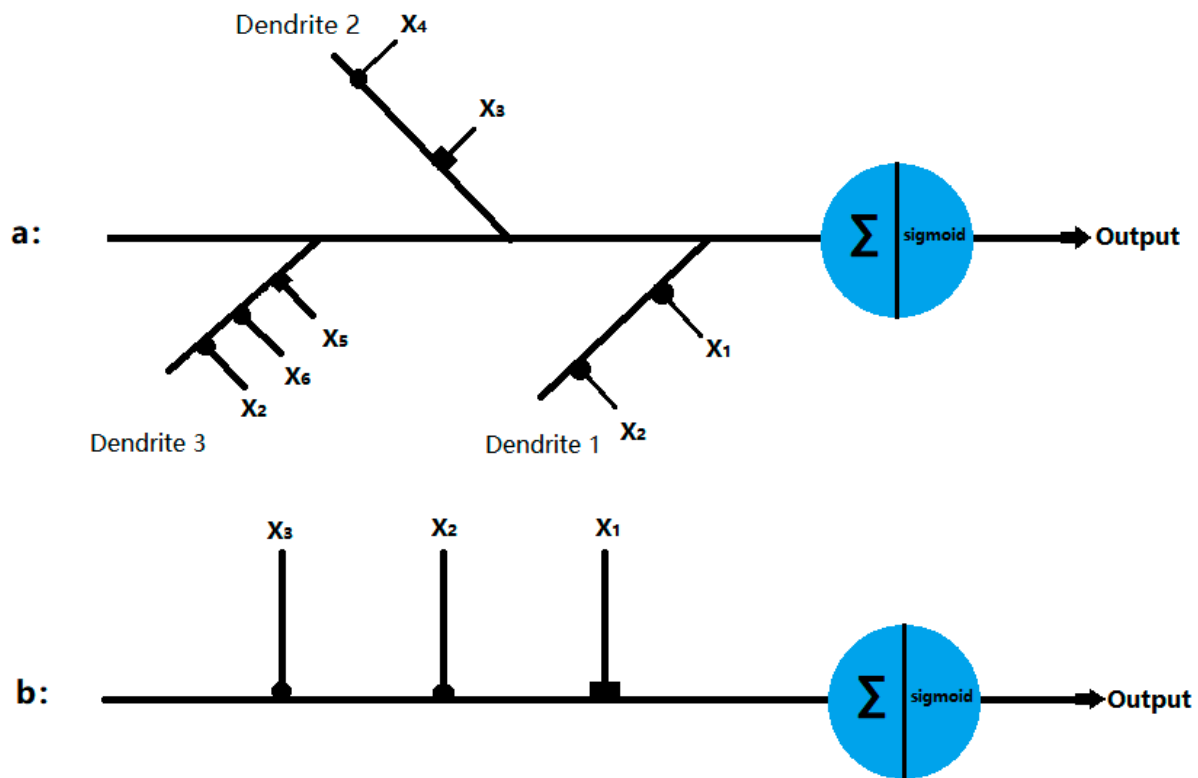


Figure 2. The dendritic neuron model with inhibitory inputs (■) and excitatory inputs (●) consists of two distinct structures: (a) δ cell and (b) γ cell.

2.2. Local Orientation Detection Neuron

This section will provide a detailed description of the neuron's structure and its orientation detection mechanism. Our hypothesis suggests that simple ganglion neurons detect orientation information by sensing light signals within and around their receptive fields.

The visual system's primary pathway for transmitting visual information occurs from photoreceptors to bipolar cells, then to ganglion cells, the lateral geniculate nucleus (LGN), and ultimately to the primary visual cortex [45]. Assuming a 2D visual field or receptive field, we can divide it into $M \times N$ regions, with each region corresponding to the smallest visually distinguishable area. When light falls on a region, the corresponding photoreceptor or a cluster of photoreceptors converts the light signal into an electrical signal, which is transmitted to the ON-OFF response bipolar cells. For simplicity in neural computation, we utilize only the ON-response mechanism. Thus, if a photoreceptor receives light, its corresponding ON-response bipolar cell outputs 1; otherwise, it outputs 0. The input signal is represented by X_{ij} , which indicates the position of the 2D receptive field. Prior to this, horizontal cells intervene to identify color in grayscale, with an excitatory input color chromatic difference threshold set to θ . If the color difference between adjacent pixels is less than θ , the neuron receives excitatory input; if the color difference is greater than θ , it receives inhibitory input. The input signal is processed as follows:

$$HC = \begin{cases} 0, & |x_{ij} - x_{i-1j-1}| < \theta; \\ 1, & |x_{ij} - x_{i-1j-1}| \geq \theta. \end{cases} \quad (\theta = 3) \quad (3)$$

which is described in Figure 3:

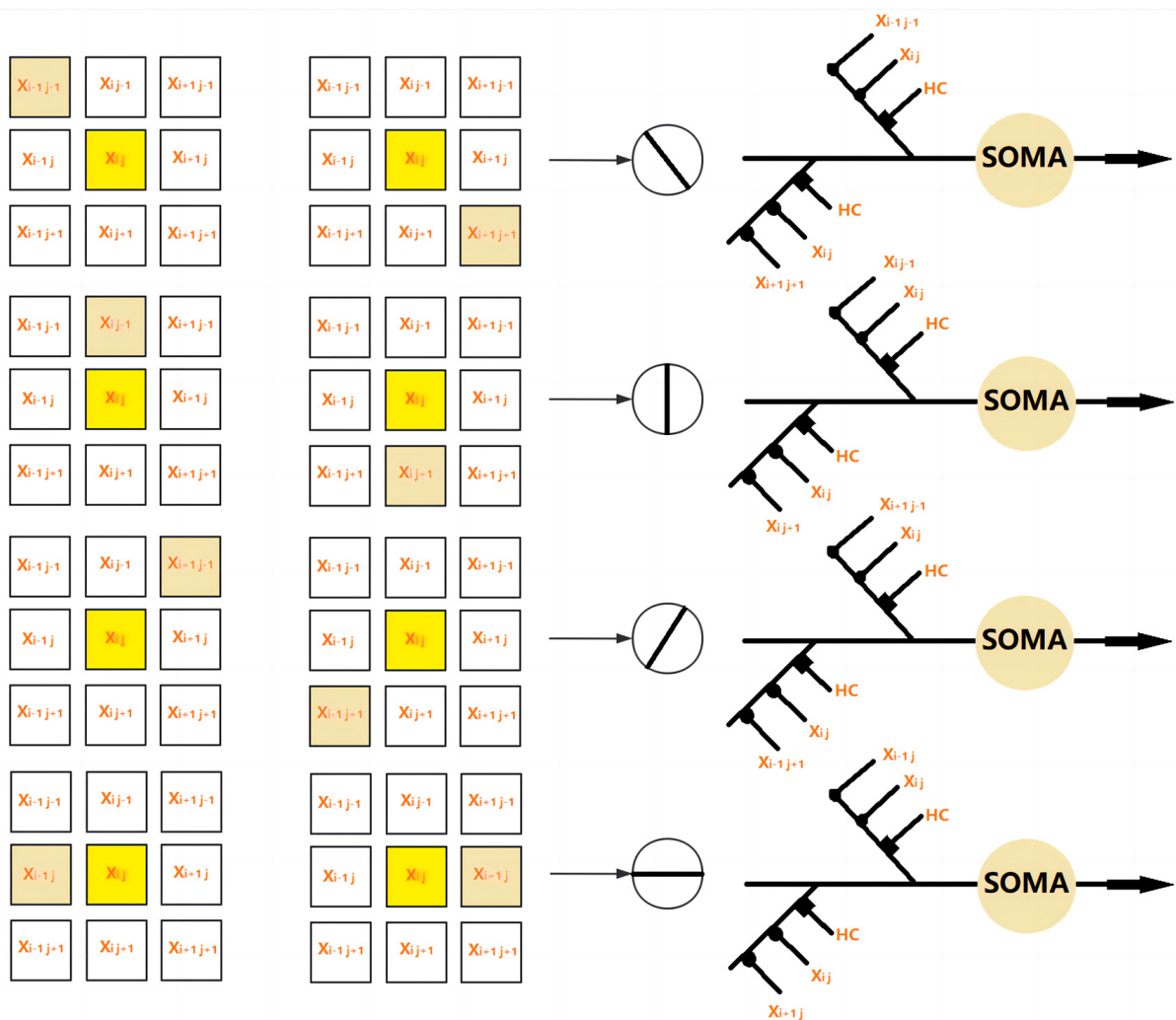


Figure 3. The local orientation detection neurons for four different angles: 0 degrees, 45 degrees, 90 degrees, and 135 degrees.

For this study, we set the receptive field to a 3×3 matrix, enabling us to obtain the active states of eight neurons corresponding to four different orientation angles. These include 135° and 315° for 135° inclines, 90° and 270° for vertical, 45° and 225° for 45° inclines, and 0° and 180° for horizontal. Furthermore, increasing the size of the receptive field allows for the extraction of more orientation information.

2.3. Global Orientation Detection

As previously mentioned, the locally directed detection neurons interact through the reception of light in their respective fields. We posit that local orientation information can be used to infer global orientation. By measuring the intensity of neuronal activity in all local orientations of the receptive field, we can make orientation assessments by summing up the neuronal output in different orientations.

There are four possible solutions for measuring the activity intensity of local orientational detection neurons in the two-dimensional receptive field ($M \times N$): (1) Single-neuron scheme: This involves assuming the existence of only one local orientation detection retinal ganglion neuron that scans eight orientations for each location. (2) Multi-neuron scheme: This involves assuming the existence of eight different neurons that scan eight adjacent positions in different orientations to provide local orientation information. (3) Neuron array scheme: This involves assuming the existence of multiple non-overlapping neurons that slide across the receptive field to provide orientation information. (4) All-neuron scheme:

This involves assuming that each photoreceptor corresponds to a 3×3 receptive field with its local orientation in eight positions. In each receptive field, local orientation detection neurons can extract basic orientation information. The local orientation information is used to infer the global orientation.

To illustrate the orientational detection mechanism, we employ a simple 5×5 two-dimensional image with a target angle of 45 degrees, as depicted in Figure 4. Without loss of generality, we utilize the first solution, which involves the local detection of retinal ganglion neurons scanning each position from (1, 1) to (5, 5) on the receptive field to generate local orientation information. Figure 4 demonstrates that the activation level of the 45° neurons is the highest, indicating consistency with the target orientation.

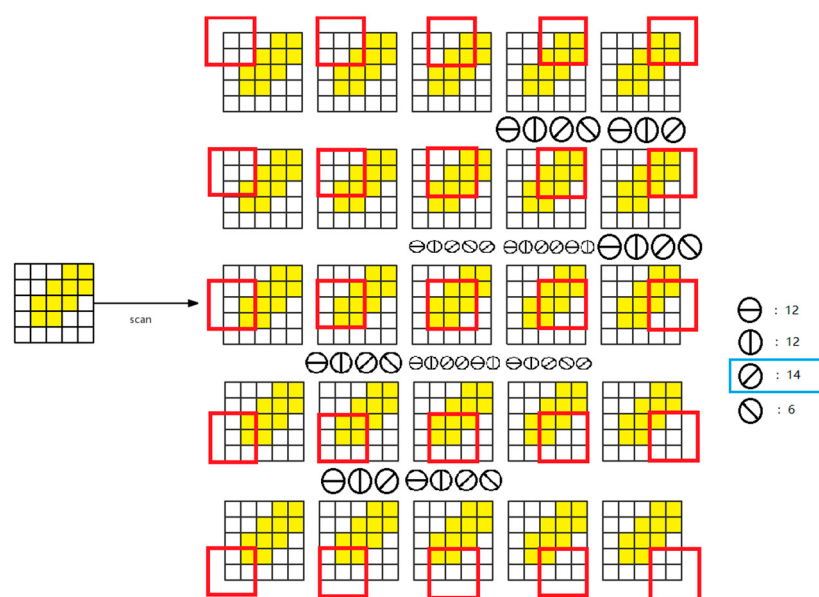


Figure 4. An example of the global orientation detection.

2.4. Artificial Visual System (AVS)

The visual system includes sensory organs (eyes) and pathways connecting the visual cortex with other parts of the central nervous system. Local visual feature detection neurons within the visual system can extract fundamental local visual characteristics, such as local orientation information, which are subsequently combined by subsequent layers to detect higher-order features. Expanding upon this mechanism, we have created an artificial vision system (AVS) depicted in Figure 5. The Local Feature Detection Neuron (LFDN) layer corresponds to neurons in the V1 region of the cerebral cortex, such as Local Orientation Detection Neurons, and is utilized to extract fundamental local visual features. The extracted features are then transmitted to the subsequent layer, known as the global feature detection layer neurons, which correspond to the primate brain in the temporal region (MT), this layer detects higher-order features, such as the global orientation of an object. The neurons in this layer can be a sum of the output of simple layer 1 neurons, including direct detection, motion orientation detection, motion speed detection, binocular vision perception, or a single layer, two layers corresponding to V4 and V6, three layers corresponding to V2, V3, and V5 network, or even multilayer networks for pattern recognition. Notably, AVS is a feedforward neural network that can be trained by error backpropagation. In contrast to traditional multi-layer neural networks and convolutional neural networks, the local feature detection neurons (LFDN) in AVS layer 1 can be designed in advance based on prior knowledge and do not typically require learning. Even if learning is necessary, AVS is a good starting point that can greatly improve learning efficiency and speed. Additionally, AVS has a simpler and more efficient hardware implementation

compared to Convolutional Neural Network (CNN). In addition, most applications only require simple logical calculations.

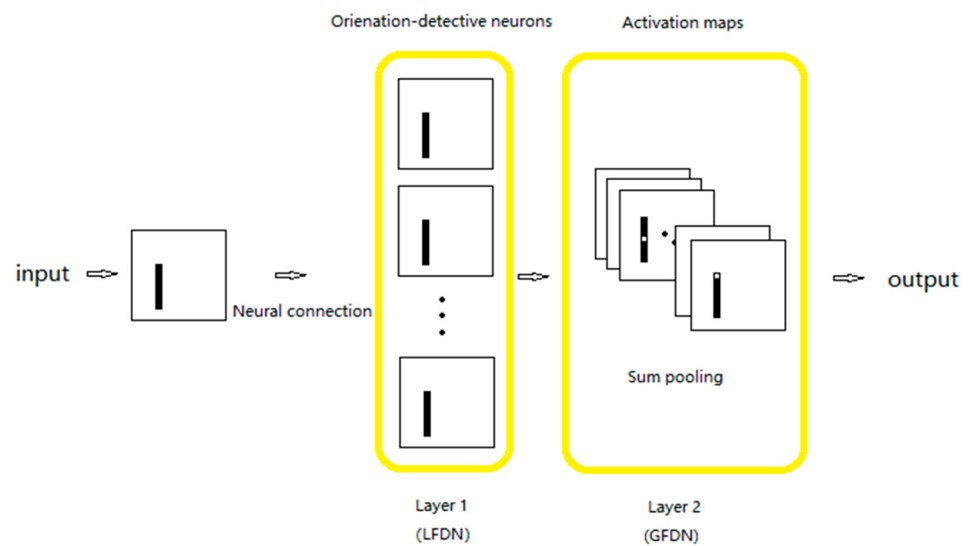


Figure 5. Artificial Visual System (AVS).

3. Experiment

The effectiveness of our proposed mechanism and mechanism-based AVS was validated through the generation of a large dataset of 32×32 grayscale pixel images for testing purposes. We used a 3×3 window to scan each pixel of the two-dimensional image, extracted the local position information of each pixel using eight orientation detection neurons, and derived the global position information from the local information. We created ten sets of random graphs with varying widths and positions in four orientation for the dataset. For all experiments, we used a 3×3 receptive domain with a step size of 1 and set the color chromatic difference threshold to 10.

Figures 6 and 7 depict objects at 135° angles of varying sizes, while Figures 8 and 9 depict objects oriented horizontally and vertically, respectively. We tallied the number of activations in all orientations and selected the orientation with the strongest signal as the output result. The experimental results are presented in Figures 6–9.

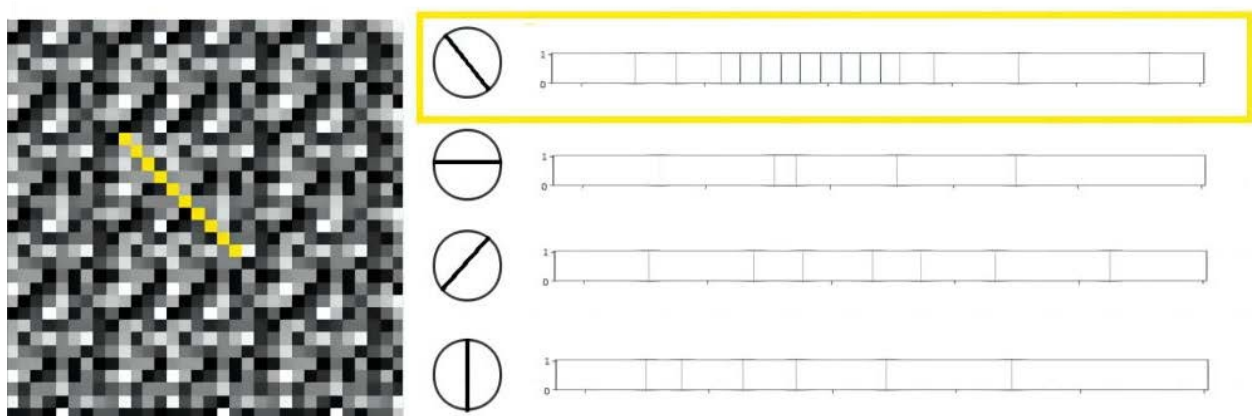


Figure 6. Experimental result of detecting a 135° bar with a width of 1.

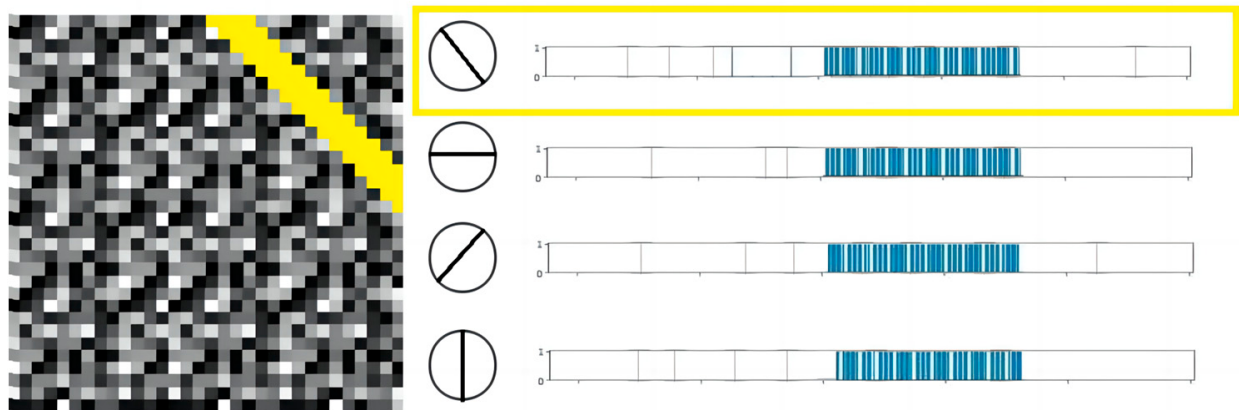


Figure 7. Experimental result of detecting a 135° bar with a width of 4.

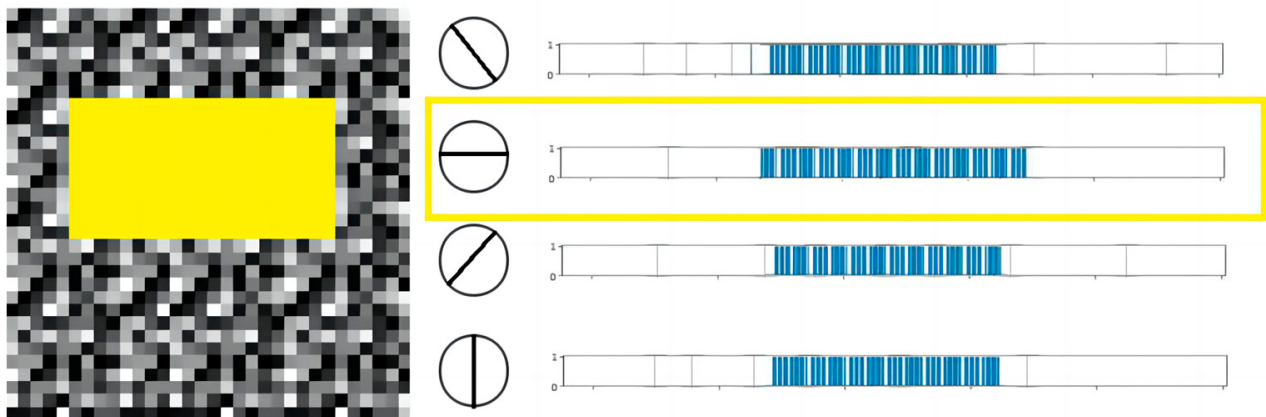


Figure 8. Experimental result of detecting a horizontal (0°) bar.

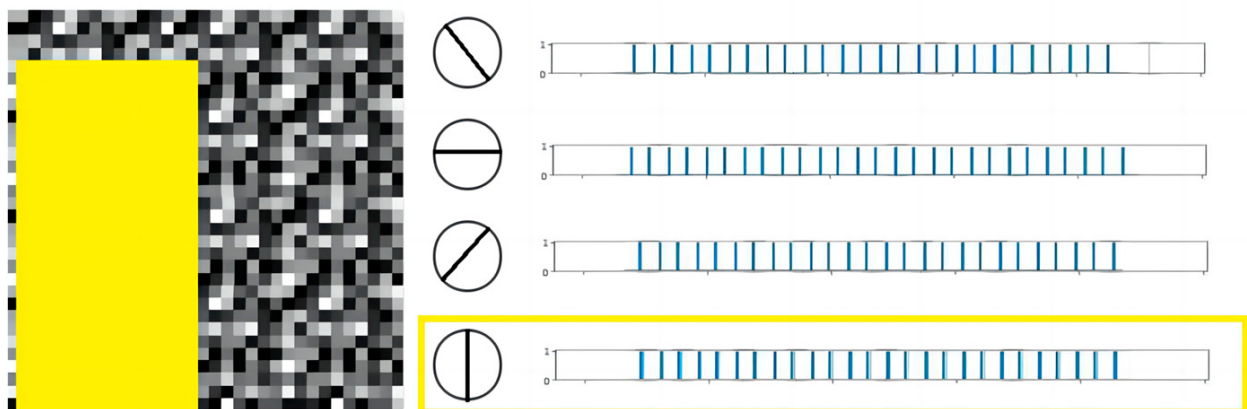


Figure 9. Experimental result of detecting a vertical (90°) bar.

The above is only a representative part of the experimental results, after a large number of experiments show that AVS can give accurate judgments of orientation regardless of the color and size of the target in the grayscale map.

4. Related Works

To compare our AVS's global orientation detection performance with other methods, we chose CNNs because of their widespread use and success in object detection, segmentation, and image recognition. Figure 10 shows the CNN architecture used in our experiments, which is a typical architecture for handwritten character recognition [46]. It includes seven

layers: (1) a convolutional layer with 30 3×3 filters producing 30 32×32 feature maps; (2) a 2×2 max pooling layer; and (3) An Affin layer, also known as a fully connected layer in neural networks, was used with a full network architecture consisting of 8192 ($30 \times 16 \times 16$) input nodes, a hidden layer of 100 nodes, and an output layer of 4 nodes. The CNN received 1024 (32×32) inputs for a 32×32 pixel image and produced 30 32×32 feature maps after convolution and pooling. In contrast, our AVS only had two layers: (1) A perceptron layer consisting of 4096 ($4 \times 32 \times 32$) local orientation detection neurons was used to generate four 32×32 local orientation feature maps for the AVS.; and (2) a summing pooling layer that produced four outputs by summing the four local orientation feature maps. Compared to the CNN, which had a much larger number of parameters (820,004), our AVS had only 12 parameters for local orientation detection neurons (4×3), leading to a significant reduction in the number of parameters and computation cost.

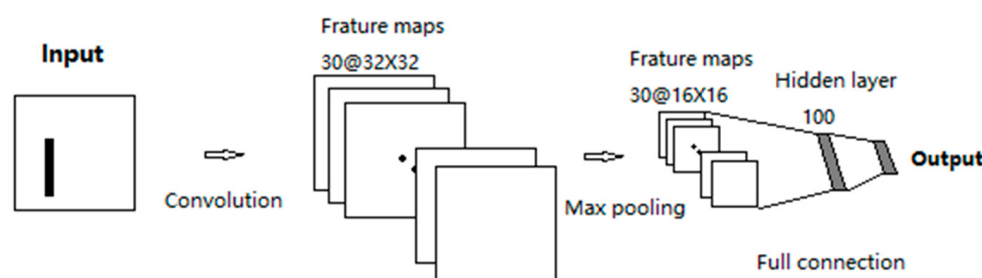


Figure 10. The architecture of CNN used in experiments.

Furthermore, while CNN requires hundreds of layers, AVS only requires two layers. Therefore, the hardware implementation of AVS is significantly simpler and more efficient than CNN. Table 1 summarizes the comparisons between CNN and AVS.

Table 1. Comparison between CNN and AVS.

Metrics	CNN	AVS
Layers	>7	2
Parameters	820,004	12
Reasoning	Black Box	Reasonable
Bio-Soundness	Low	High
Noise Resistance	Low	High
Learning Cost	High	No

To compare the anti-noise ability of AVS and CNN, we added random noise to the non-object area, which was independent of and not connected to the object. The Figure 11 shows the added noise levels of 0.1%, 0.5%, 1%, 2.5%, 5%, and 10%. To detect the planar orientations of these object images with noise, we utilized AVS and CNN. Table 2 presents the identification accuracy of both AVS and CNN on object images with added noise, with the corresponding data presented in the table. However, we can see that the identification accuracy of CNN drops to 97.86% even if noise level is 0.1% (only one pixel is added). As the noises level increases to 10%, CNN's identification accuracy drops sharply. In contrast, AVS consistently maintains 100% identification accuracy, demonstrating excellent noise resistance performance.

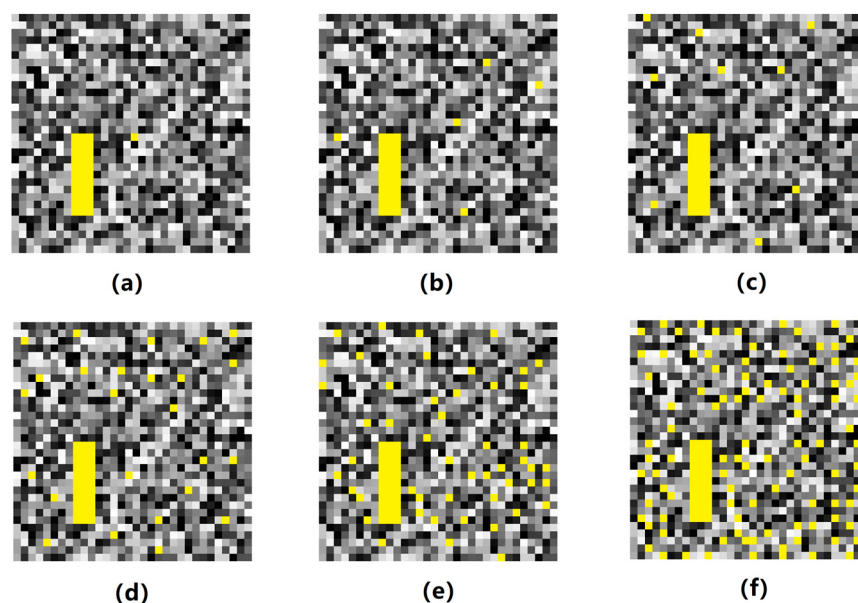


Figure 11. The example images with noise levels of 0.1% (a), 0.5% (b), 1% (c), 2.5% (d), 5% (e) and 10% (f).

Table 2. Comparison of identification accuracy between CNN and AVS.

Noises Level	0.1%	0.5%	1%	2.5%	5%	10%
CNN	97.86%	59.26%	51.38%	37.98%	35.24%	30.32%
AVS	100%	100%	100%	100%	100%	100%

To facilitate a fair comparison, we trained a Convolutional Neural Network (CNN) for global orientation detection. The training and testing data sets consisted of 15,000 and 5000 samples, respectively. The objects varied in size from 2 to 256 pixels and were randomly placed with diverse shapes. The CNN was trained using the backpropagation method with the Adam optimizer. The performance of the trained CNN for orientation detection was impressive, achieving a recognition accuracy of 99.997%. This performance is remarkable, although slightly lower than the untrained AVS, which achieved 100% accuracy.

While the AVS does not typically require learning for most applications, it does possess advantages over CNNs. Firstly, the AVS requires significantly fewer parameters to train compared to increasingly deep CNN architectures with millions of optimized parameters. Secondly, the AVS can leverage a priori knowledge of the system and task to start learning from a well-informed initial value, whereas CNNs rely on random initial values. Thirdly, the convergence of AVS is guaranteed within a certain number of iterations [47], while CNNs often require more training time and can be prone to local minima. Importantly, the learning process of AVS is controllable and its results are interpretable, in contrast to the black box nature of CNN learning where results can be opaque and untraceable to humans.

Furthermore, the hardware implementation of AVS is notably simpler and more efficient compared to CNNs, as CNNs may require hundreds of layers while AVS only requires two layers. Additionally, while CNNs claim similarity to Hubel and Wiesel's AVS in terms of connecting units to local receptive fields [26], they fail to fully incorporate the crucial concept of locally sensitive, direction-selective neurons. Hence, CNNs can be referred to as convolutional networks rather than convolutional "neural" networks. On the other hand, the AVS is built upon Hubel and Wiesel's visual system concept, effectively utilizing local receptive fields and orientation-selective neurons. It not only integrates these concepts but also introduces a novel mechanism for inferring global orientation, resulting in successful global orientation detection.

In light of the research conducted by David Marr and James Albus on the cerebellum being a perceptron [48,49], as well as the discovery of long-term inhibition at synapses supporting the cerebellar perceptron theory by Masao Ito et al. [50], we can confidently state that the AVS surpasses CNNs in terms of orientation for biometric recognition.

Overall, the AVS demonstrates superior performance and alignment with the principles of the visual system compared to CNNs, particularly in the realm of orientation detection for biometric recognition.

Finally, based on the above experiments in order to compare the noise immunity of CNN and AVS, we remove the restriction on noise in the previous experiments and observe their noise immunity. Table 3 presents a summary of the noise resistance results for CNN and AVS. Notably, when 5% of noise was added, the recognition accuracy of CNN decreased to 90%, while AVS exhibited a slightly higher accuracy of 96%. As the amount of noise increased to 30%, the recognition accuracy of CNN significantly declined, reaching as low as 35%. In contrast, the single-layer perceptron AVS maintained a recognition accuracy of 43%, demonstrating remarkable noise resistance.

Table 3. Compare the recognition accuracy of the learned CNN and AVS when responding to unconditional noise.

Noises Level	0	5%	10%	15%	20%	25%	30%
CNN	99.887%	90.682%	74.433%	59.112%	47.563%	39.864%	35.351%
AVS	100%	96.571%	85.562%	71.490%	59.716%	49.924%	43.452%

These results clearly highlight the superior noise immunity of the single-layer perceptron system compared to CNN. Even in the presence of substantial noise, the AVS model managed to preserve a substantial portion of its recognition accuracy, showcasing its robustness in challenging conditions.

5. Conclusions

This paper introduces local plane orientation detection neurons to calculate the local plane orientation and describes a global plane orientation detection mechanism for Greyscale Images along with a global plane orientation judgment scheme based on local plane orientation information. The local plane azimuth detection algorithm is used in the local receiving field to extract basic visual features such as plane orientation, which are then passed to the next layer to detect higher-order features, such as global plane orientation. The proposed mechanism exhibits desirable properties that render it a valuable component of any visual sensory system. Furthermore, it appears to play a crucial role in the human visual system. The proposed mechanism is not only useful for the detection of local orientation information but can also be applied to many other basic visual perceptual phenomena, such as the perception of movement direction and speed, as well as binocular perception. It also sheds light on how functions are partitioned among different elements of the visual circuit. Based on this, we developed an artificial vision system, specifically for Greyscale Images. We conducted plane orientation detection experiments using AVS without learning and CNN with learning to compare the performance of AVS and CNN. Our findings revealed that AVS outperforms CNN in accuracy and noise resistance, as well as other aspects. AVS has the potential to be easily applied to other visual perceptions. Therefore, we anticipate that AVS is likely to surpass CNN in the future. Since the proposed model is highly simplified, it still requires further optimization and research to cope with complex image recognition. This will be the focus of our future work, with the aim of achieving more effective applications in complex and color images. Although based on a highly simplified model, the proposed mechanism and AVS provides a mechanism that can quantitatively explain many known neurobiological visuals and could lead to further exploration of neurophysiology and neuroanatomy to review their observation and find

the corresponding function and structure. Furthermore, advances in biological science may lead to a elaborate and modified mechanism.

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