Modeling Peripheral Blurring in Visual Processing

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***Abstract*—Individuals with autism spectrum disorder (ASD) have been found to have abnormalities in visual processing, which lead to not only disabilities in facial recognition but also surprising strengths in object finding. Global connection sparsity and local connection density in the visual pathway of those with ASD have been implicated in producing these abnormalities. We evaluate computational models of the visual pathway with this sparsity of connections through the method of blurring. Our work demonstrates the wonderfulness of variation in the design of the human eye and visual pathway, as well as the viability of biologically-inspired, specifically *autism*-inspired, computer vision systems and camera lens designs for enhanced object detection.**

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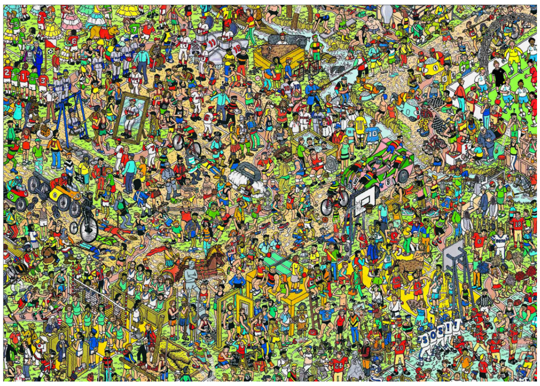


Figure 1: This is an example of a "Where's Waldo?" puzzle. How long does it take for you to find Waldo? Researchers have used OpenCV to try to solve this problem [20]. Children with ASD have been found to complete search tasks such as this more quickly than non-ASD children [21].

I. Introduction

Autism spectrum disorder (ASD) is a developmental condition that leads to social and communication difficulties and restricted/repetitive behavior [1]. It is thought that these symptoms have biological origins, because the critical period for developing ASD occurs before birth. Findings have shown that behaviors shown by patients with ASD have a neurological basis. These neurological underpinnings can manifest themselves as sensory processing abnormalities, including auditory processing and visual processing [4].

These auditory processing abnormalities lead to both disabilities and extraordinary abilities [18]. Those with autism may have difficulty in following instructions that stems not from their non-compliant nature but rather in their difficulties in paying attention to and comprehending spoken instructions. On the other hand, there is a high prevalence of absolute pitch (otherwise known as perfect pitch) in those with ASD [14].

Just as the way evolutionary biologists, notably Darwin, have remarked admiringly at the intricately designed structure of the human eye [2], which is part of the human visual pathway, the authors of this paper focus on the remarkable features present in the abnormal visual processing of those with ASD [5] [6].

There has been extensive research on the visual abnormalities of patients with ASD [7]. Specifically, patients with ASD have been found to have acute visual ability and extraordinary performance on many visual tasks, for example in the "Where's Waldo?" task shown in Figure 1. There are many different explanations for this. For example, this difference in visual acuity could be the product of a unique mode of conscious attention, or it could be the unconscious byproduct of biologically-determined organization and properties of the visual pathway [13].

We aim to contribute to the general understanding of the latter phenomenon. In an effort to contribute to such an understanding, researchers from diverse fields have posed the following question: what could be different about the visual pathway of these patients? To answer this question, bioinformatics researchers have examined and found sparse global neuronal connectivity, but dense local neuronal connectivity in patients with ASD [8].

The perceptual layer of the visual pathway is composed of the retina that senses visual information from the outside world. We aim to explore sparse and dense neural connectivity at the sensing layer using a computational approach, building upon prior work on neural networks of autism [9] [10].

Therefore, we turn to computer science research. Modern machine learning algorithms such as artificial neural networks have a biologically-plausible basis [11]. Techniques such as drop-out were inspired by evolution through natural selection. These biological underpinnings come not only from inspiration by evolution, but also by the brain. These include the reward function that simulates the dopaminergic reward pathway in the brain [15], the perceptron that is a mathematical model of a single biological neuron [16], the layers of neurons that simulate biological neurons, and the connection weights between the layers that represent the strengths of synaptic connections between neurons or the myelination along the axon of a neuron [17].

Sparse connectivity between neurons serves to lower the amount of information that gets sent from neuron to neuron. This information nevertheless retains its core properties, and thus can be seen as data compression. Indeed, computer scientists have explored compression in attempts to solve modern challenges of efficiency that arise from big data and machine learning. The data being collected for training of machine learning algorithms in the world today is immense.

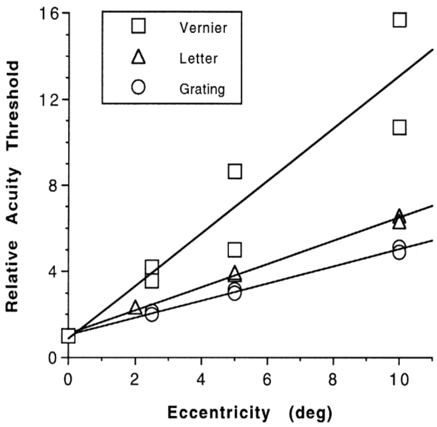


Figure 2: This graph shows a negative correlation between acuity and eccentricity (measure of distance in degrees from the fovea), for three different acuity tasks. The threshold of acuity increases as eccentricity increases. [22]

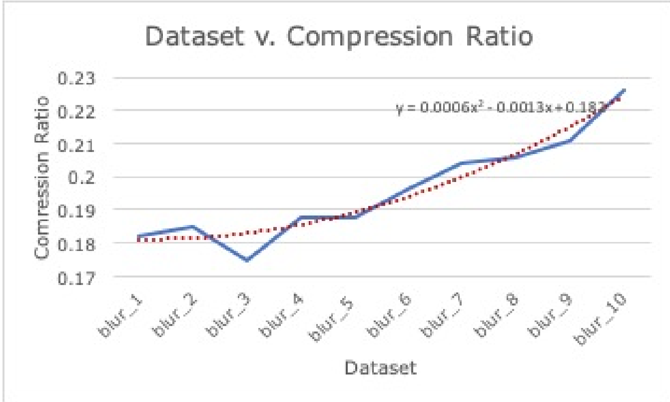


Figure 3: This graph shows that as blur decreases from reverse_1 to reverse_10, the compression generally increases, i.e. the file size of the image decreases. We included a quadratic fit line to illustrate this general trend. The equation of this trendline is $y = 0.0006x^2 - 0.0013x + 0.182$.

This overwhelming amount of data can lead to inefficiencies. Fortunately, it has been found that eliminating particular data and compressing data is a viable solution to optimize the sample complexity of machine learning algorithms and make them learn more efficiently, while retaining algorithm performance. Compressed sensing is a mechanism through which machine learning algorithms selectively retain essential portions of data, in order to more efficiently learn and perform specific tasks [12].

Specifically, methods of signal denoising and the least absolute shrinkage and selection operator (LASSO) have been used to perform compressed sensing [8]. We aim to study compression in the form of blurring. We view blurring as a compression mechanism that can model the sparse neuronal connectivity of the brain, knowing that the sparse layout of the rods and cones at the periphery of the retina leads to lower acuity in peripheral vision [3], as seen in Figure 2. Is there a specific level of blurring that can lead to enhanced vision? In regular human life, one does not need to understand and attend to every little detail. Therefore, we ask: to what extent can compression lead to neural networks that model the visual pathway and perform well?

II. Methods

The goal of our project is to determine the relative performance of our model of the visual pathway as input images undergo different levels of blur.

We pre-processed our 600,000 input images from the extended CIFAR-10 dataset with a form of radial blurring similar to the way the eye actually allows humans to view their surroundings. We did this at varying levels of blur, with the intent of finding the relationship between blur intensity and classification performance.

To simulate the sensing itself, we constructed a neural network that is meant to recognize and label visual inputs. However, due to limitations on our storage space and data usage, we decided to decrease the number of images to 60,000 for the rest of the experiment and used the regular CIFAR-10 dataset and labeling information as our input. We then trained our neural network on the images each at discretely increased levels of radial blur.

We kept track of the accuracy at which the neural network was able to label the input and the compression level of each inputted image. Our data, then, allows us to determine the relationship between the compression level of the visual input and its corresponding recognition performance.

The table below shows the datasets, their compression ratio, an image of the mask of the blur applied to the images, and an example of an image with that blur. In the mask images, the white space corresponds to the blurred portion of the image. Compression ratio was calculated by dividing the size in MB of the dataset by the size in MB of the original dataset (170MB). Each dataset consists of a different level of blurring applied to the same original dataset, and the compression ratio generally increases as the blur decreases. We found this to be counter-intuitive, as we were expecting the blurred images to be smaller, compressed versions of the originals [3].

We plotted a graph to visualize the relationship between blur and compression. As displayed in the graph in Figure 3, there is an inverse relationship between compression and blur.

III. Data Exploration & Results

The human eye is well known to focus on the central part of input images, while crocodiles and reptiles are known to have cylindrical activated vision masks, which allow them to have clear vision in the central cylindrical slit of inputs. This idea led us to explore if the human eye has leveraged the trade-off between bandwidth and accuracy. It may be noted that multiple ways of digital blurring processes exist. This is a direct offshoot of the way reptiles and humans have different activation functions for acuity. We started out with the activation functions in Figure 4.

As a follow-up on the ramifications of eye's properties, stereo images were explored for binocular and parallax effects.

Table I: Compression

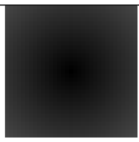
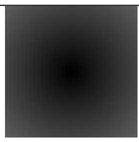
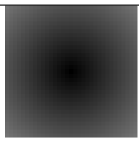
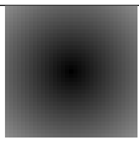
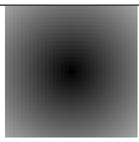
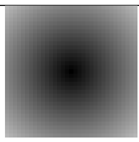
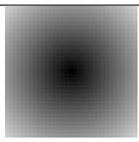
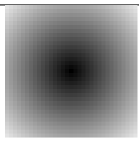
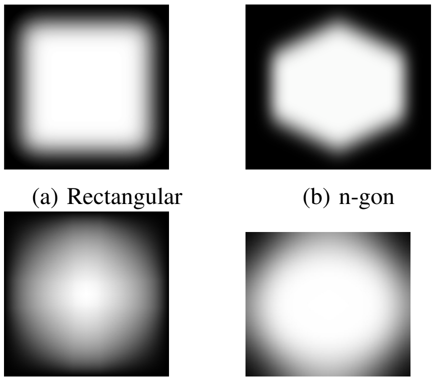
Dataset	Compression Ratio	Mask Image	Example Image
blur_1	.182		
blur_2	.185		
blur_3	.175		
blur_4	.188		
blur_5	.188		
blur_6	.196		
blur_7	.204		
blur_8	.206		
blur_9	.211		
blur_10	.226		

Figure 3 is an illustration of our approach in treating stereo based images. Depth graymaps were inferred using left and right angled images in order to produce *lens-blurred* images [19]. While chromatic aberrations and similar modes were being explored, all the experiments were carried out on masked images with radial parts of images being the most clear simulating acuity in human retina.

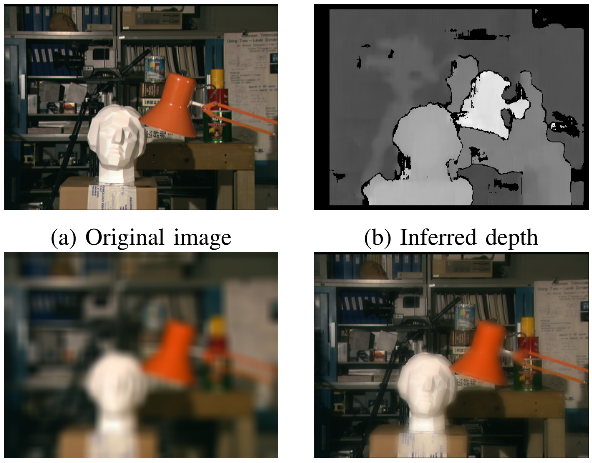
The codes are available at this Github repository: https://github.com/vishalanand/Computation-And-Brain [23]. We utilized K-80 GPU servers on Google Cloud with datasets ranging on the order of 40GB - 60GB.



(a) Rectangular (b) n-gon

(c) Circular (d) Ovoid

Figure 4: Further activations for blur vs. precision inflections



(a) Original image (b) Inferred depth

(c) Blurred image (d) Lens Blur vision

Figure 5: Binocular depth for bandwidth vs precision trade-off

The Table 1 explores the compression ratio and the bandwidth has been shown to go down by factor of 4. The accompanying plots suggest the accuracy to shift in favor of low compressed images, however the inflection point could not be evaluated since the CIFAR dataset was too grainy to have been relevant - *blurring a blurred image* could be better handled by usage of higher intensity images. It may be noted that CIFAR-10's extended version takes enormous time for pre-processing over our activation masks, while CIFAR-10's usual images took 2 hours on each of the individual 20 masks that were being explored in this project.

These explorations are meant to better understand why the eyes would have went the route of acuity activation on images, which would enable better understanding in figuring out the current state-of-the-art in 10^{12} time-steps.

As a sanity check, we wanted to make sure that we would find a strong positive relationship between the number of epochs on which the neural networks have been trained and the precision of the neural networks on classification of images. Therefore, we plotted a graph of precision vs. epoch for the baseline neural network model, i.e. the one without blur. As

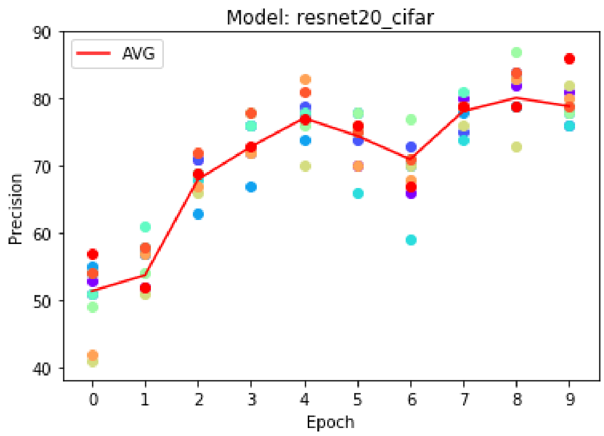


Figure 6: This graph shows that as the epochs increase, the precision increases for the neural network model with input images that have not undergone any blur procedure.

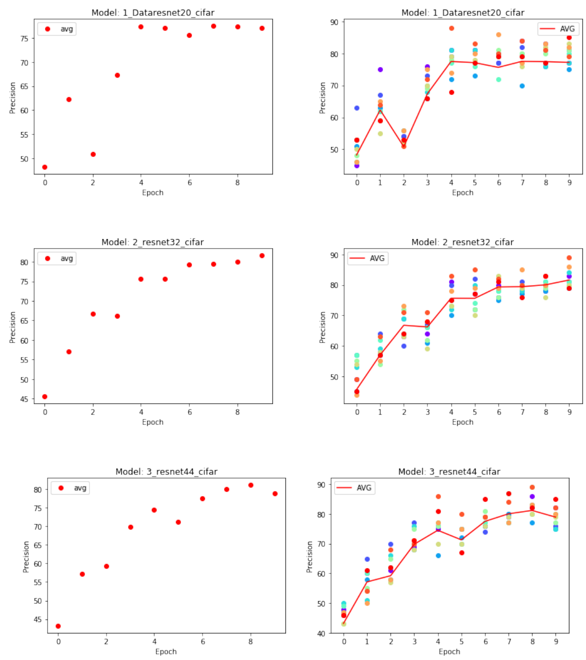


Figure 7: The left column contains scatter plots showing the average precision values of the models at each epoch. The right column contains plots of the range of precision values of the models for separate batches of images at each epoch. As expected, there is an overall positive correlation between epoch and precision.

plotted in the graph in Figure 6, there is a positive relationship between epoch number and precision.

As displayed in Figure 7, the same trend was seen in further model runs. We ran the dataset on three additional models and again charted the average precision per epoch. We then mapped every batch's individual precision per epoch and provided a line of best fit that illustrates the average precision against that data.

IV. Discussion

As shown by the results and by examining the ASD visual pathway, one can build ASD-inspired computer vision systems that take advantage of the visual enhancements of ASD patients. Although patients with ASD may lack ability in facial recognition, they excel in object recognition amid cluttered environments. This ability can be essential for many tasks in the real world.

Many real-world applications of this research exist in the domain of computer vision, such as in the development of self-driving cars, of which an essential ability is to detect pedestrians on the streets. With enhanced object recognition amid distracting traffic scenes, computer vision systems with autism-like visual capabilities could potentially be in a position to improve the safety of self-driving cars and future transportation. Moreover, security cameras with improved capacities to solve problems such as the "Where's Waldo?" puzzle could be made possible with increased research into the visual system of those with ASD.

Furthermore, there are clinical applications. Autism spectrum disorder can be understood as not only a disability, but also a condition that carries an asset for visual processing. A greater understanding of the strengths, as opposed to solely focusing on the widely-known disabilities of ASD, could improve the lives of those with ASD.

V. Future Directions

There was a huge limitation in our methods. The images we used were extremely pixelated even if we did not perform any blur, due to the fact that they already had dimensions of just 32 pixels by 32 pixels. Our most obvious next step would thus be to find a dataset with larger images, to more clearly show the effects of blur on performance.

Although we only performed radial blur as part of this research, there are different ways that blurring can be implemented. One could use an even more biologically-inspired blur layout based on the specific placement of rods and cones on the retina. In the future, we could also use stereo images (see box in methods section for more information). Currently there are stereo images available online, but they are not labeled.

A significant direction we did not get the chance to explore would be replicating this process on different kinds of neural networks and looking for similar, or even better, results. In particular, to bring this experiment even closer to simulating the human brain, we could conduct this experiment using more biologically-inspired neural networks than the one used here.

We could also evaluate the performance of neural networks on different visual tasks, such as on optical illusions, finding hidden objects within scenes, recognizing symmetry, etc., to which those on the autism spectrum have been found to be extraordinarily gifted.

In addition, we could begin to run experiments to see if memory and attention are used with visual tasks in an abnormal way that leads to visual abnormalities [13]. These tests can be performed on both humans and computational models, and we can see if the computational models perform like humans with and without autism spectrum disorder, in the case that the models have or do not have unique attentional and or memory mechanisms. In this way, the two fields of computer science and neuroscience can simultaneously and mutually advance.

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