Saccade Mechanisms for Image Classification, Object Detection and Tracking

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Abstract

We examine how the saccade mechanism from biological vision can be used to make deep neural networks more efficient for classification and object detection problems. Our proposed approach is based on the ideas of attention-driven visual processing and saccades, miniature eye movements influenced by attention. We conduct experiments by analyzing: i) the robustness of different deep neural network (DNN) feature extractors to partially-sensed images for image classification and object detection, and ii) the utility of saccades in masking image patches for image classification and object tracking. Experiments with convolutional nets (ResNet-18) and transformer-based models (ViT, DETR, TransTrack) are conducted on several datasets (CIFAR-10, DAVSOD, MSCOCO, and MOT17). Our experiments show intelligent data reduction via learning to mimic human saccades when used in conjunction with state-of-the-art DNNs for classification, detection, and tracking tasks. We observed minimal drop in performance for the classification and detection tasks while only using about 30% of the original sensor data. We discuss how the saccade mechanism can inform hardware design via “in-pixel” processing.

1. Introduction

Over the last decade, advances in Deep Neural Networks (DNN) have led to tremendous progress towards solving many computer vision tasks such as video-based scene understanding. In this paper, we consider the high resource use caused by the high-bandwidth data transmitted from sensor to DNN. The high data requirement puts increasingly powerful DNNs at odds with increasingly powerful sensors (e.g., increasing resolution in megapixels) in applications with cloud-based and edge device-based endpoints. We examine how mechanisms from biological vision can mitigate and reduce the data requirement to improve the practicability and efficiency of DNN-based end-to-end systems for image and video processing applications. Our approach is based on the ideas of attention-driven visual processing and saccades [11], miniature eye movements influenced by attention. The focus of this paper is on understanding the effect of intelligent image patch selection as a pre-processing step for DNN-based image classification, object detection, and multi-object tracking. First, we examine the robustness of state-of-the-art (SOTA) DNNs to random masking of image patches. We compare two broad types of DNNs: convolutional (ResNet-18) and self-attention-based transformers (ViT, DETR, TransTrack). Subsequently, we explore the benefits of intelligently filtering “non-salient” patches via saccades for classification and tracking. Experiments are conducted on several datasets: CIFAR-10, DAVSOD, MSCOCO, and MOT17. We observed minimal decreases in standard metrics while only using \sim 30\% of the original sensor data, and unlike recent work [16], our approach requires no fine-tuning of the SOTA DNN on partial images.

2. Saccades as a Data-Reduction Mechanism

Recently, there has been great interest in using attention mechanisms in computer vision models to improve model accuracy, improve model robustness to novel data, and reduce computation [14]. These attention mechanisms are often inspired by human vision [9]: the human visual system has the capability of selecting important sensory information before passing the selected information to higher-level cortical areas where the brain performs further processing [6]. In contrast to prior work, we examine the use of saccades, which reduce data bandwidth by sending partially-sensed images (in our work by selecting subsets of image patches) to the DNN for processing. This is orthogonal to other methods for improving efficiency of DNNs such as network weight quantization.

Saccades are quick and simultaneous eye movements between two or more phases of fixations influenced by attention. Saccadic movement of human eyes directs the fovea, the central part of the retina, by small increments (about 1-2 degrees) quickly to the point of interest. By moving the eye, small parts of a scene can be sensed with greater resolution [25]. Saccades are jerky motions that are discontinuous in directions and in magnitudes. However, the disconnected, fragmented scanning of the scene does not disrupt the feature integration [26]. Studies have shown that saccadic motions can be compensated, and features are not mixed or mis-
placed. Furthermore, attention always shifts to the intended location before the eyes begin to move [24].

There is considerable evidence that ties attention to saccadic eye movements [17]. Taking inspiration from the human visual system, we explore the effect of intelligent image patch selection as a means to reduce the amount of data that must be processed by DNNs, enabling the use of deep learning for real-time applications. This work can then lead to the design of new in-pixel or near-pixel computing sensors that only digitize and process minimal data as predicted from previous frames.

**Connection to Existing Work in Computer Vision** Other work has attempted to efficiently explore portions of a scene and thus limit processing by some downstream model (e.g., active vision [1, 4, 5]). Recently, there has been interest in incorporating active dynamic perception with deep learning-based models, e.g., Deep Anticipatory Networks [27], Glance and Focus Networks [18], shift-aware models for visual saliency object detection [13], and other deep reinforcement learning-based approaches for learning how to pan and zoom [7, 29, 30]. Furthermore, the use of attention and saliency are well-studied problems in the computer vision community [23]. Similar to our findings, recent work [3, 16] has shown that if properly trained, transformers (DNNs based on self-attention) can successfully capture the image context even with extreme masking. There have also been past approaches that leverage saccades as a means of improving DNNs, e.g., Recurrent Attention Models, which first sense a coarse/blurry image is sensed completely, and then saccades refine certain image locations [2, 22]. Our approach differs from others because (a) we aim to understand whether mimicking human saccades is effective data reduction mechanism, and (b) whether the performance of SOTA DNNs be maintained without finetuning to partially sensed images.

### 3. Saccades for Image Classification, Object Detection and Tracking

In this section, we show the effect of partially obscuring images before passing through a DNN image classifier. We aim to validate the following hypotheses: i) Self-attention-based transformers [12] are robust to partially-sensed patch-based inputs, and ii) Mimicking saccadic motions captured via human eye-fixation data reduces the amount of information that must be processed by deep learning models while sacrificing minimal amounts of classification accuracy.

#### 3.1. Transformer-Based Models are Robust to Partially-Sensed Patch-Based Inputs

We look at the effect of random patch selection on two classes of DNN architectures for image classification: convolutional neural networks (CNNs) viz. ResNet-18 [15] and a transformer-based model viz. “Vision Transformer (ViT)” [12]. We hypothesize that the vision transformer, which breaks images into patches and processes the rasterized sequence of patches using self-attention, will be more robust to random masking of patches in the input image (see Fig. 1 (left) for examples). This is inline with recent work [3, 16], which shows that transformers fine-tuned with heavy input masking are capable of reconstruction of the missing patches. Transformers are ideal for input patch masking because they naturally reduce processing of masked patches and are compatible with new hardware designs (Section 4). We conduct our first experiment on the CIFAR-10 dataset [19] where we vary the percentage of masked patches and see the effect on various architectures in Figure 1.

The transformer (ViT) is significantly more robust to random masking of patches when using a pre-trained model. Fine-tuning ViT improves further, maintaining above 80% accuracy even with only 40% of the image sensed. In comparison, the pretrained CNN is significantly less robust with a faster drop in accuracy. Fine-tuning improves accuracy for both models; however, it could be a result of overfitting.

Next, we examine the effect of random patch selection for object detection. We subsample the MSCOCO object detection benchmark [20] for manageable experimentation. The subsampled set contains 18,403 training and 800 validation images taken from the MSCOCO training and test sets, respectively. We use DETR [8] as the transformer-based object detector. We measure the mean average precision (mAP) and mean average recall (mAR) at different levels of masking and consider (i) random selection of patches and, (ii) foreground patches selected from instance segmentation ground truth. Qualitative results appear in Figure 2 where we observe that objects are correctly detected despite missing one or more patches in the interior of the bounding box (when selecting patches intelligently). Quantitative re-
Figure 2. Example DETR detections at various masking levels.

Figure 3. Robustness of the DETR detector to masked images from COCO: random vs oracle patch selection; mAP (left) and mAR (right) metrics at different levels of masking.

Figure 4. Example from the DA VSOD dataset [13] where the human focuses on different objects as time progresses.

Figure 5. Training schema to mimic attention shift using an RNN.

3.2. Learning Saccades

Next, we consider video data (unlike previous experiments). We train a recurrent DNN (an RNN) to anticipate human attention, thus mimicking saccades. The DA VSOD dataset [13] contains videos annotated with human eye fixation data. This dataset provides saliency shift ground truth where humans rapidly attend to different objects in a dynamically-changing scene (see Figure 4). We look at the effect of selecting patches that contain salient foreground objects based on the human eye fixations at time $t$. We compared three methods: i) select random patches, ii) select patches that overlap with salient objects (objects that contain at least one fixation), and iii) select patches predicted by a trained recurrent neural network (RNN) [10]. The RNN is trained to predict the sequence of human attention at future time steps based on partially sensed inputs at earlier time steps. Figure 5 shows the training method for the RNN to predict human attention at times $t+1$, $t+2$, $t+3$. During training, every fourth video frame is fully-sensed after the RNN state is reset to $h_0$. During testing, only the first frame of the test video is fully-sensed, and the RNN state only resets between videos. The evaluation is per-frame image classification accuracy on four classes (human, animal, artifact, and vehicle) from the DAVSOD dataset. The training optimizes binary cross-entropy with ground truth attention masks. At each time step, the RNN outputs a heatmap from which the top-$k$ patches are selected ($k$ is varied in the experiment).

Our experiments suggest that reducing data via mimicking human saccades is noticeably more effective (higher accuracy) than random selection of patches. In Figure 6 (top), accuracy is not degraded when at least 30% patches are selected using the oracle (gray line). Our RNN is able to reasonably predict where humans will look (AUROC of 0.78 when trained to select 30% of patches). In Figure 6 (top, blue line), the RNN-based patch selection noticeably outperforms random patch selection (orange line) and only slightly under-performs true human attention (gray line).

Our final experiment is on multi-object tracking where saccades can be useful for capturing object motion. We applied our learned RNN-based saccade to a pre-trained transformer-based tracker viz. TransTrack [28]. We compared our RNN to random patch selection on the MOT17 pedestrian tracking benchmark\(^2\) [21]. This dataset does not provide human attention, so we used foreground object location maps as a proxy for training the RNN. We evaluated

\(^2\)Training and validation videos were redistributed so training and validation videos were disjoint, see here for data and example outputs.
Saccades are compatible with this paradigm and the sensor edge. Hardware Benefit: By reducing non-salient data, potentially reducing the data bandwidth and feature dimensionality by an order of magnitude before the captured data is sent to the processing unit behind the imager. A patch that is not sensed does not need to be read out from the analog pixel (ROIC) and digitized (ADC) leading to savings in power.

**Future Work:** There is still work to be done in this area. We assumed we had access to human eye fixations or proxy ground truth information to guide the saccade mechanism. In many cases, we discarded background patches, which can provide useful information for processing novel scenes. We expect the model could be improved by directly learning from interaction which patches are and are not informative. Such saccades could account for the confidence of predictions of individual objects, and explicitly tackle the tradeoff between exploitation to increase confidence with exploration to find new objects using Reinforcement Learning.

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**References**

1. J. Aloimonos et al. Active vision. *IJCV*, 1988.
2. J. Ba et al. Multiple object recognition with visual attention. *arXiv*, 2014.
3. R. Bachmann et al. Multimae: Multi-modal multi-task masked autoencoders. *arXiv*, 2022.
4. R. Bajcsy. Active perception. *Proceedings of IEEE*, 1988.
5. D. Ballard. Animate vision. *Artificial intelligence*, 1991.
6. A. Borji et al. What stands out in a scene? A study of human explicit saliency judgment. *Vision research*, 2013.
7. J. C. Caicedo et al. Active object localization with deep reinforcement learning. In *ECCV*, 2015.
8. N. Carion et al. End-to-end object detection with transformers. In *ECCV*, 2020.
9. M. Carrasco. Visual attention: The past 25 years. *Vision research*, 2011.
10. K. Cho et al. On the properties of neural machine translation: Encoder-decoder approaches. *arXiv*, 2014.
11. H. de Barjac et al. Essai de classification biochimique et sérologique de 24 souches d’abacillus du typeb thuringiensis. *Entomophaga*, 1962.
12. A. Dosovitskiy et al. An image is worth 16x16 words: Transformers for image recognition at scale. *arXiv*, 2020.
13. D.-P. Fan et al. Shifting more attention to video salient object detection. In *CVPR*, 2019.
14. M.-H. Guo et al. Attention mechanisms in computer vision: A survey. *Computational Visual Media*, 2022.
15. K. He et al. Deep residual learning for image recognition. In *CVPR*, 2016.
16. K. He et al. Masked autoencoders are scalable vision learners. *arXiv*, 2021.
17. J. E. Hoffman et al. The role of visual attention in saccadic eye movements. *Perception & psychophysics*, 1995.
18. G. Huang et al. Glimpse and focus networks for dynamic visual recognition. *arXiv*, 2022.
19. A. Kratkyevsky et al. Learning multiple layers of features from tiny images, 2009.
20. T.-Y. Lin et al. Microsoft coco: Common objects in context. In *ECCV*, 2014.
21. A. Milan, I. Leal-Taixe, I. Reid, S. Roth, and K. Schindler. Mot16: A benchmark for multi-object tracking. *arXiv preprint arXiv:1603.00831*, 2016.
22. V. Mnih et al. Recurrent models of visual attention. *NeurIPS*, 2014.
23. T. Nguyen et al. Attentive systems: A survey. *IJCV*, 2018.
24. M. Peterson et al. Covert shifts of attention precede involuntary eye movements. *Perception & psychophysics*, 1995.
25. J. M. Provis et al. Adaptation of the central retina for high acuity vision: cones, the lutea and the avascular zone. *Progress in retinal and eye research*, 2013.
26. J. Reuther et al. The eye that binds: Feature integration is not disrupted by saccadic eye movements. *Attention, Perception, & Psychophysics*, 2020.
27. Y. Satung et al. Maximizing information gain in partially observable environments via prediction rewards. In *AAMAS*, 2020.
28. P. Sun et al. Transtrack: Multiple object tracking with transformer. *arXiv*, 2020.
29. B. Uzkent et al. Efficient object detection in large images using deep reinforcement learning. In *WACV*, 2020.
30. B. Uzkent et al. Learning when and where to zoom with deep reinforcement learning. In *CVPR*, 2020.