Efficient Visual Attention with Deep Learning

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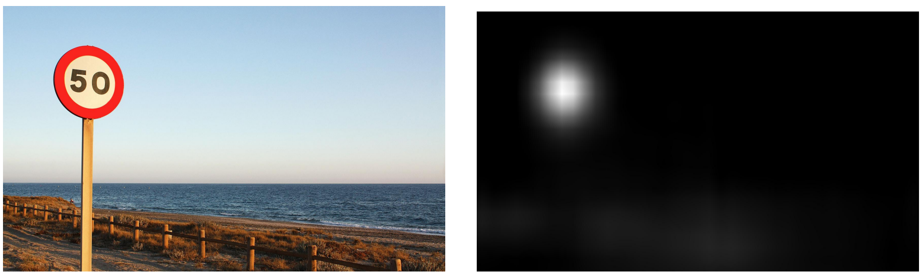
Abstract. *The high volume of visual data contains information that is mostly irrelevant for intelligent agents. Humans realize sensorial filtering by what we call attention. We propose a new fully convolutional neural network architecture designed for detecting visual salience similarly to humans, yielding a performance level close to state-of-the-art in MIT300 benchmark with around three times less parameters than similar models.*

Resumo. *A alta quantidade de dados visuais contém informação que é em sua maior parte irrelevante para agentes inteligentes. Nos seres humanos, há um filtro sensorial realizado pela atenção. Propomos uma nova arquitetura de rede neural totalmente convolucional para detecção de saliência visual similarmente a humanos, provendo um desempenho próximo ao estado-da-arte no MIT300 benchmark com cerca de três vezes menos parâmetros que modelos similares.*

1. Introduction

One of the most challenging unsolved problems in Artificial Intelligence is vision. It is fundamental for the conception of systems that interact with the real, physical world. Such systems would be useful for applications that involve robotics and tasks in domestic houses, industry and agriculture, so there is great potential for the benefit of society.

Vision is remarkably data and computationally intensive: In humans, approximately half the brain is involved in vision-related tasks [Fixott 1957]. Even our minds can't handle all the sheer amount of sensorial information received every second: We have attention, a fundamental mechanism that, among other functionalities, filters out irrelevant information – either visual or from other senses– and helps us focus our cognitive processes on what is important at a given moment. These facts are a strong evidence that, in order to solve vision, we need to have attention.



(a) (b)

Figure 1. Example of visual saliency. b) is the salience map where brighter pixels represent regions more salient to humans on the original image a).

Visual attention can be defined as the delimitation of a certain spatial region on an image for further cognitive processing [Treisman and Gelade 1980]. The phenomenon emerges from two fundamentally different processes: There is *top-down* attention, an internal stimuli (e.g. find a red apple in a tree because of hunger, which will make red be more reconizable on the scene), and *bottom-up* attention [Colombini 2014], an external process that captures the agent's attention from conspicuous stimuli. In this work, we focus on the latter, also named visual saliency.

Visually salient regions on images are usually represented by *saliency maps* (figure 1), images generated such that areas with high-valued pixels express high saliency on the original image, whereas regions with low-valued pixels represent low saliency. Datasets with such maps are obtained by colleting eye-fixation data from humans.

1.1. Related work

Early computational models of visual saliency were generally built based on filtering of images for extraction of a pre-selected set of features considered important for *bottom-up* attention. *Vocus* [Frintrop 2005] is a computational model that extracts features shown to be naturally salient to humans such as color/luminance contrast and orientation from different scales of the image.

A rapid change of paradigm ocurred around 2015 when *Deep Learning* techniques showed to be very effective in the generation of saliency maps. Models such as *Salicon* [Jiang et al. 2015] showed that applying convolutional neural networks with weights initialized from image classification networks, e.g. *VGG-16* [Simonyan and Zisserman 2014] could yield maps very similar to those generated from humans. *ML-Net* [Cornia et al. 2016] uses the output from different layers of *VGG-16* to use information from various dimensions and levels of abstraction. *DeepFix* [Kruthiventi et al. 2015] extends a pre-trained model with new layers that account for global features and center bias. *Salnet* [Pan et al. 2016] is a work that explores two models that are simple yet provide good results. Models are usually evaluated and ranked on *MIT saliency benchmark* [Bylinskii et al. 2016a], which uses a variety of metrics to express how close generated saliency maps are to those created from human data. As of today, at least nine out of the ten best models in the ranking use Deep Learning.

1.2. Motivation

Current state of the art models are in general quite expensive computationally, partly because most of them are based on very big pre-trained networks. The convolutional layers of *VGG-16* are composed of around 14.7 million parameters. While pre-trained weights from classification tasks showed to be effective for saliency prediction, it is reasonable to question whether creating a proper network from scratch could yield a smaller amount of parameters that are more efficient for the sole task of salience prediction. Also, there are some ideas from previous work on psychology that weren't found to be used in current models but are considered worthwhile to be explored.

1.3. Objectives

This work aims at building a visual saliency model that is a) effective, yielding results similar to other state of the art models, and b) relatively simple and computationally efficient. It is important that both criteria are matched because we aim at extending the model in the future for video and real time applications such as navigating robots.

2. Proposed model

Figure 2 illustrates the overall architecture of our fully convolutional neural network. It extracts features from increasingly smaller dimensions of the input image.

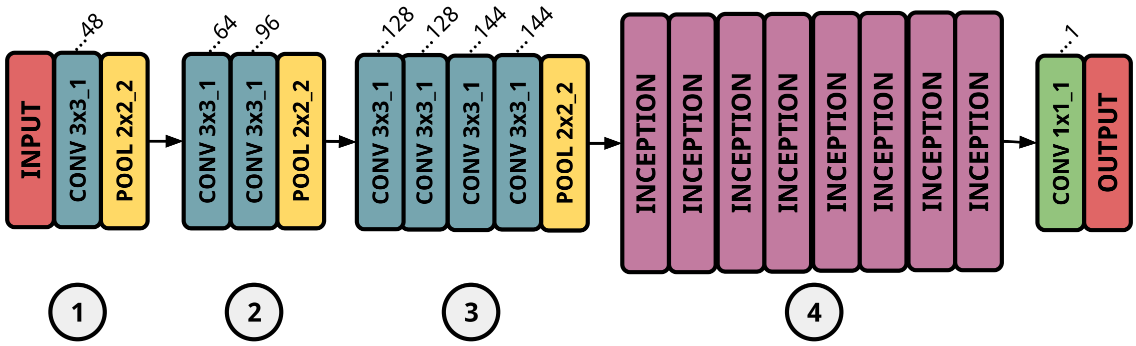


Figure 2. Overview of the network. Filters sizes are in format width×height_stride.

The network is composed of four main blocks:

1. First level extracts low level features from the input image, of dimensions $W \times H \times 3$ (width, height, depth), using a single layer with 48 convolution filters with ReLu activation followed by max-pooling that reduces image by a factor of two. It was found that further decreasing the number of filters in this layer considerably hurts performance, which makes sense because it is important to capture high spatial frequency and high contrast information in the context of visual saliency.
2. Second level extracts low-medium level features from the input of dimensions $W/2 \times H/2 \times 48$ using two layers with 64 and 96 convolution filters, respectively, followed by ReLU activation and max-pooling.
3. Third level extracts medium-high level features from input with dimensions $W/4 \times H/4 \times 96$ using four convolution layers. The first two have 128 filters each, the last two have 144 filters each. Every convolution layer is followed by ReLu. Max-pooling is realized at the end. A considerable depth in this level was found to be important for the networks performance.
4. Fourth and last level is composed of eight inception blocks that extract high level features from the input with dimensions $W/8 \times H/8 \times 144$. Great level of depth and Inception blocks were found to be very important at this level. A 1×1 convolution makes a linear combination of the output maps at the end of the 8 inception blocks, followed by ReLu, producing the final saliency map of dimensions $W/8 \times H/8 \times 1$.

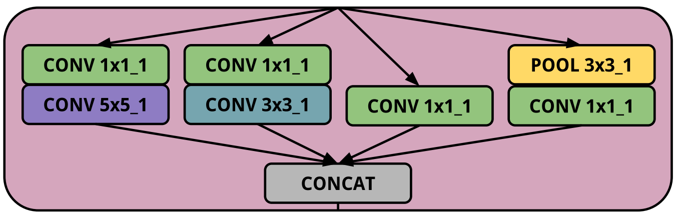


Figure 3. Inception block layout.

Figure 2 illustrates the inception architecture [Szegedy et al. 2014] used in each block: We use filters of size 5×5, 3×3 (both preceeded by 1×1 convolutions in order to reduce number of input filters), 1×1, and a max-pooling of size 3×3. Each of these operations is realized in parallel from the same input and the outputs are concatenated at the output. Inception allows the network to use information from different spatial dimensions as well as previous layers (lower level saliency information) in the final map computation, which is considered to be important for visual saliency. The network has a total of 3717841 parameters, a very low number compared to other models.

Table 1. Number of filters used in each inception block.

Block	pool	conv 1×1	3×3 reduce	conv 3×3	5×5 reduce	conv 5×5
1	96	128	96	192	58	96
2	64	128	80	160	24	48
3	64	128	80	160	24	48
4	64	128	96	192	28	56
5	64	128	96	192	28	56
6	64	128	112	224	32	64
7	64	128	112	224	32	64
8	112	160	128	256	40	80

2.1. Implementation

We used *Theano* `0.9.0.dev` along with *Lasagne* `0.2.dev1` on a machine with *Ubuntu 16.04 LTS* and kernel *Linux* `4.8.0-54-generic`. Training was conducted on a GPU *NVIDIA GTX 1080*. Code is available at `https://goo.gl/WzpyYJ`.

2.2. Training

We resize images to dimensions $320 \times 240 \times 3$ during training. Each image is normalized channel-wise subtracting the channel mean and dividing by the standard deviation. We consider normalizing per image, rather than per dataset, to be more reasonable because visual saliency is highly connected to the context of the image. We also convert the images to the LAB colorspace. *Vocus* [Frintrop 2005] cites that the LAB colorspace is more closely related to human vision by encopassing red-green, yellow-blue and luminance maps. We conjecture that this colorspace facilitate extraction of important luminance and color contrasts by the learned convolution filters. Our prior tests showed better performance using image-wise normalization and LAB instead of the commonly used RGB.

We aimed at maximizing (or minimizing the negative) of the *Correlation Coefficient* of the ground-truth saliency map G and the predicted map P: $CC(P, G) = cov(P, G)/(\sigma(P)\sigma(G))$. There is a variety of metrics for evaluating saliency predictions [Bylinskii et al. 2016b], but we consider CC to be the most appropriate because it simmetrically penalizes both false positives and false negatives.

We considered two datasets for training: *SALICON* [Jiang et al. 2015], with 15000 images, and *Judd* [Judd 2016], with 1003 images. The network was trained using Stochastic Gradient Descent with Nesterov Momentum of 0.9. We first used SALICON with data augmentation by flipping images horizontally and vertically and the target normalized by mean-std (Last conv layer had ReLu removed in this step). We first used mean-std normalization of targets because it was noted that it allowed for a faster convergence. Training iterated for 5 epochs with learning rate of 0.009 and then for 3 epochs with learning rate of 0.001. We then switched to using unit normalization on targets. The network was trained for 1 epoch with learning rate of 3×10^{-5} and L2 regularization of 10^{-4}. Finally, we used Judd with data augmentation by flipping images horizontally and the target normalized by unit normalization. Training iterated for 2 epochs with learning rate of 5×10^{-5} and L2 regularization of 3×10^{-5}. Batch sizes were 10 for SALICON and 2 for Judd. The whole training process took around two and a half hours.

3. Results

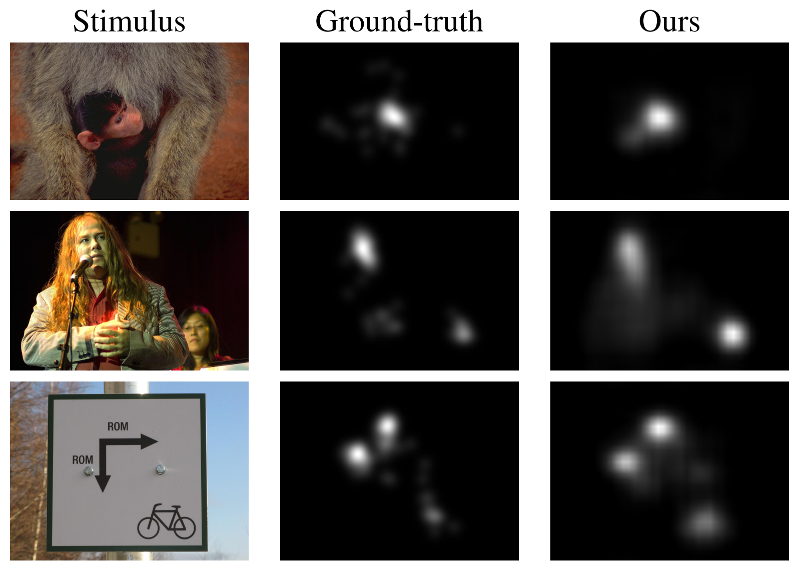


Figure 4. Examples of predictions made by our model.

Table 2. State of the art models and metric scores on *MIT300 benchmark*.

Model	Num. parameters	AUC-Judd ↑	CC ↑	NSS ↑	Sim ↑	EMD ↓
Infinite humans	-	0.92	1.0	3.29	1.0	0
DeepFix	≈16.7 million	0.87	0.78	2.26	0.67	2.04
Salicon	≈14.7 million	0.87	0.74	2.12	0.60	2.62
Ours	**3.72 million**	**0.85**	**0.71**	**1.98**	**0.62**	**2.37**
ML-Net	≈15.4 million	0.85	0.69	2.07	0.60	2.53
SalNet	25.8 million	0.83	0.57	1.51	0.52	3.31

Predition took an average time of 8 milliseconds. Figure 4 show some maps generated by our model. They are generally considerably similar to the ground truth. We tested our model on the 300 images of the *MIT300 benchmark*. Table 3 shows the results, metrics in bold show our values. Our model achieves results comparable to the state of the art models, while having at least one fourth of the number of parameters.

4. Conclusion

In this paper, we proposed a novel fully convolutional neural network for the prediction of visual saliency on images. Our model architecture and data preprocessing were designed specifically for the task of salience prediction. Our methods showed to be effective, yielding a network with performance on *MIT300 benchmark* consistently among the ten best results on various metrics while having around three times less parameters than other state of the art models.

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