

TOP-DOWN CONTROL OF VISUAL ATTENTION IN OBJECT DETECTION

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ABSTRACT

Current computational models of visual attention focus on bottom-up information and ignore scene context. However, studies in visual cognition show that humans use context to facilitate object detection in natural scenes by directing their attention or eyes to diagnostic regions. Here we propose a model of attention guidance based on global scene configuration. We show that the statistics of low-level features across the scene image determine where a specific object (e.g. a person) should be located. Human eye movements show that regions chosen by the top-down model agree with regions scrutinized by human observers performing a people search task. The results validate the proposition that top-down information from visual context modulates the saliency of image regions during the task of object detection. Contextual information provides a shortcut for object detection, enabling efficient object detection systems.

1. INTRODUCTION

The features that define an object are not limited to the ones present in the region that the object occupies. This is illustrated in Fig. 1. Both images contain the same blob. However the meaning attached to the blob changes when changing the context (a dish on the table or a car in the street). Despite the importance of including contextual information in object descriptions, the use of context is not very popular in computer vision for object detection.

In this paper, we describe a computational model of attention guidance that takes into account visual context [8, 9]. We show that the statistics of low-level features across natural scenes are strongly correlated with the location of a specific object. In the current study, the scheme is tested with the task of localizing the probable location of people in scenes, and the selected regions are compared to human eye movement scan patterns.

Models that integrate attention mechanisms are relevant for computer vision as they can suggest strategies for finding shortcuts for object detection and recognition. These shortcuts can be used to select a set of possible candidate



(a) a dish?



(b) a car?

Fig. 1. Locating an object in a scene is context dependent.

locations of target objects within an image. Then, computationally more expensive object recognition procedures can be applied in those regions [4]. In this paper, we propose a simple attentional mechanism that does not use specific information about the appearance of the target. Instead we use a simple model of image saliency based on the distribution of local features in the image and a model of contextual priors (that learn the relationship between context features and the location of the target during past experience) in order to select interesting regions of the image. The paper shows that there could exist pre-attentive heuristics based on the context within which an object is embedded, that would provide a low-cost object detection shortcut by pre-selecting relevant image regions.

2. SALIENCY AND OBJECT DETECTION

For bottom-up schemas of attention allocation, regions with different properties from their neighboring regions are considered more informative and, therefore, are supposed to attract attention. Those models provide a measure of the 'saliency' of each location in the image across various low-level feature (contrast, color, orientation, texture, motion, [2, 10]). Saliency measures are interesting in the framework of object detection because, when looking for a target in an image, frequent features in the image are more likely to belong to the background and, therefore, are poor predictors

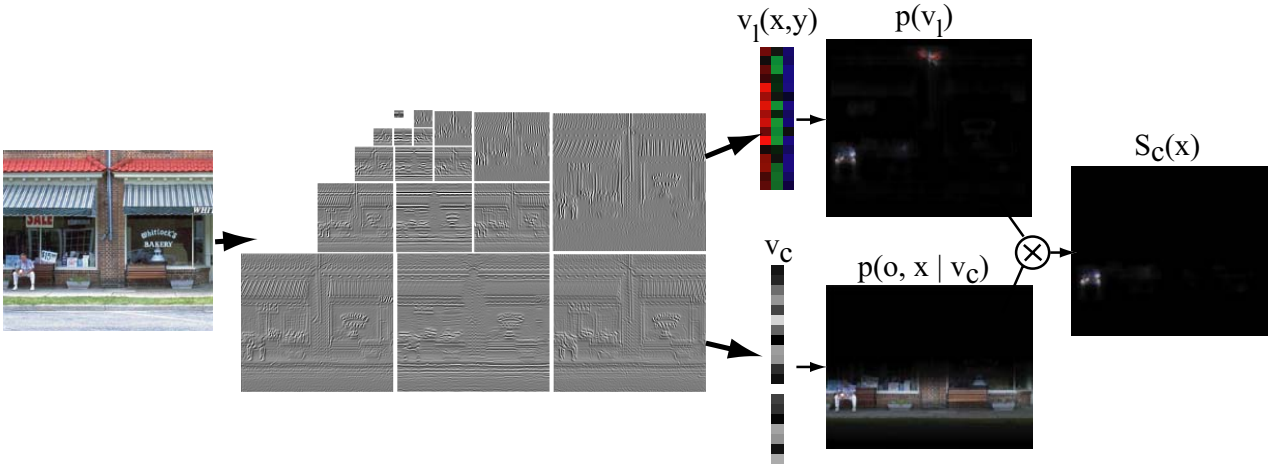


Fig. 2. Attentional system for object detection integrating local saliency and contextual priors about target location.

of the presence of the target.

In the saliency map models, a saliency map is computed using a hardwire schema (e.g., [2]): the local image features are processed by center-surround inhibition and then a winner take all strategy is used to select the most salient regions. The image features most commonly used for describing local image structure (orientation, scale and texture) are the outputs of multiscale oriented band-pass filters. Here, we decompose each color subband using a steerable pyramid [7] with 4 scales and 4 orientations (fig. 2). Each location has a features vector $\mathbf{v}_l(\mathbf{x}) = \{v_l(\mathbf{x}, k)\}_{k=1,48}$ with 48 dimensions (fig. 2).

Here, we define the saliency in terms of how likely is to find a set of local features in the image. We use a probabilistic definition of saliency that fits more naturally with object detection and recognition formulations as we show later:

$$S(\mathbf{x}) = p(\mathbf{v}_l)^{-1} \quad (1)$$

In this definition, the saliency of a location is large when the image features at that location are more unexpected in the image. We approximate this probability by fitting a gaussian to the distribution of local features in the image ([6]):

$$p(\mathbf{v}_l) = \frac{e^{-1/2(\mathbf{v}_l - \mu)^T X^{-1}(\mathbf{v}_l - \mu)}}{(2\pi)^{N/2} |X|^{1/2}} \quad (2)$$

Although a mixture of gaussians produces a better fit of the distribution, it did not significantly change the selected salient points. As discussed later (fig. 3), the accuracy of this model in predicting the fixated points by human subjects did not differ with the performance of a more complex model of saliency maps [2].

3. CONTEXTUAL OBJECT PRIMING

However, when looking for an object, the use of saliency $S(\mathbf{x})$ as defined in eq. (1) is insufficient for explaining human performance or for building interesting object detection procedures. During the first glance at a scene (or 200 msec), the attention of the observer is driven towards a region in the image and the first saccade is programmed. This process is task-dependent. When subjects are asked to search for a specific target object, that object is fixated (and so located) faster when it is consistent with the scene context than when it is inconsistent [1]. Human observers are clearly using a top-down mechanism to find regions of interest where an object should be located, independent of the presence of the physical features of the object [1].

3.1. Contextual modulation of saliency

The role of the visual context is to provide information about past search experiences in similar environments and strategies that were successful in finding the target. When using a statistical framework, object detection is formulated as the evaluation of the probability function $p(o | \mathbf{v}_l)$. This is the probability of the presence of the object o given a set of local measurements. As suggested in [9] a more robust approach should include contextual information. We can write the probability of presence of object o at the location \mathbf{x} as:

$$p(o, \mathbf{x} | \mathbf{v}_l, \mathbf{v}_c) = \frac{p(\mathbf{v}_l | o, \mathbf{x}, \mathbf{v}_c)}{p(\mathbf{v}_l | \mathbf{v}_c)} p(o, \mathbf{x} | \mathbf{v}_c) \quad (3)$$

where \mathbf{v}_c is the vector of contextual features (see next section). Using Bayes rule, the probability can be decomposed into three factors[9]: the target appearance (object likelihood, $p(\mathbf{v}_l | o, \mathbf{x}, \mathbf{v}_c)$), the local saliency $p(\mathbf{v}_l | \mathbf{v}_c)$ and the contextual priors $p(o, \mathbf{x} | \mathbf{v}_c)$. We are interested in the terms

that do not require knowledge of the appearance of the target:

$$S_c(\mathbf{x}) = \frac{p(o, \mathbf{x} | \mathbf{v}_c)}{p(\mathbf{v}_l | \mathbf{v}_c)} = S(\mathbf{x})p(o, \mathbf{x} | \mathbf{v}_c) \quad (4)$$

The interest of this term is that it avoids using a specific model of the appearance of the target. The term $S_c(\mathbf{x})$ does not incorporate any information about the distribution of features that belong to the target. Therefore, it can be computed efficiently, and does not depend on the featural complexity of the target. The term $S(\mathbf{x}) = p(\mathbf{v}_l | \mathbf{v}_c)^{-1}$ (local saliency) provides a measure of how unlikely it is to find a set of local measurements within the context \mathbf{v}_c . It can be approximated by the distribution of local features within the image as in eq. (2). A term of saliency, eq. (1), appears naturally in a statistical framework for object detection.

Here, we are ignoring the term $p(\mathbf{v}_l | o, \mathbf{x}, \mathbf{v}_c)$. However, experimental work [10] has shown that simple features of the target are also used for guiding attention (for instance when looking for a red spot, attention can be directed to red regions in the image).

3.2. Computing contextual image features

Contextual features have to describe the structure of the whole image [5]. The representation has to be low dimensional so that the PDF $p(o, \mathbf{x} | \mathbf{v}_c)$ can be learnt efficiently and has to keep relevant information about the scene so that the PDF can provide strong priors about the location of the target. There are many possible representations of contextual information such as, collecting global image statistics, as color histograms, wavelet histograms, etc. Following [5], here we represent the context by reducing the dimensionality of the local features $v_l(\mathbf{x}, k)$. First we take the absolute value to remove variability due to contrast. Then we subsample each subband by a factor M :

$$v(\mathbf{x}, k) = \{|v_l(\mathbf{x}, k)|^2 \downarrow M\} \quad (5)$$

We further reduce the dimensionality by decomposing the image features $v(\mathbf{x}, k)$ into the basis functions provided by the principal component analysis:

$$a_n = \sum_{\mathbf{x}} \sum_k |v(\mathbf{x}, k)| \psi_n(\mathbf{x}, k) \quad (6)$$

We propose to use the decomposition coefficients $\mathbf{v}_C = \{a_n\}_{n=1,L}$, with $L = 60$, as context features. The functions ψ_n are the eigenfunctions of the covariance matrix defined by the image features $v(\mathbf{x}, k)$. The resolution reduction of eq. (5) allows for the PCA to be computed more efficiently. We perform the PCA on a database of more than 3000 natural images.

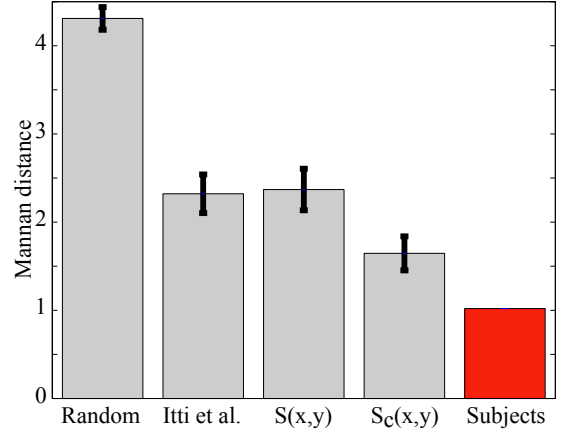


Fig. 3. Mean distance values of scan pattern similarity between human subjects and each of the different conditions.

3.3. Learning the location of people

The role of the visual context factor in modulating attention is to provide information about past search experience in similar environments and the strategies that were successful in finding the target. The learning is performed by training the PDF $p(o, \mathbf{x} | \mathbf{v}_c)$ using a database of images for which the location of the target is known. For the results shown in this paper we train the PDF to predict the location of people. For each image, the features \mathbf{v}_c and the location \mathbf{x} of the target ($o = people$) are known. We model the PDF using a mixture of gaussians and the learning is performed using the EM algorithm (see [9] for details). Fig. 2 shows an example of PDF $p(o, \mathbf{x} | \mathbf{v}_c)$.

4. HUMAN EYE MOVEMENTS

In this section we study how the system explores a set of 36 real-world scenes for which eye movements have been recorded for 8 subjects. In order to model the human eye scan paths, we compare human fixation patterns to patterns derived from a purely bottom-up approach (saliency) and patterns that included top-down information (contextual priming). None of the images used in the experiments were used during the training. First we describe the procedure for recording eye movements.

4.1. Apparatus and Procedure

The right eye was tracked using a Generation 5.5 SRI Dual Purkinje Image Eyetracker. Digitized full-color photographs of 36 real-world scenes, taken from various sources, were displayed on a NEC Multisync P750 monitor (refresh rate = 143 Hz) at a viewing distance of 1.13 m, subtending 15.8 deg. x 11.9 deg. of visual angle. There were 14 scenes with no people and 22 scenes containing anywhere from 1 to 6

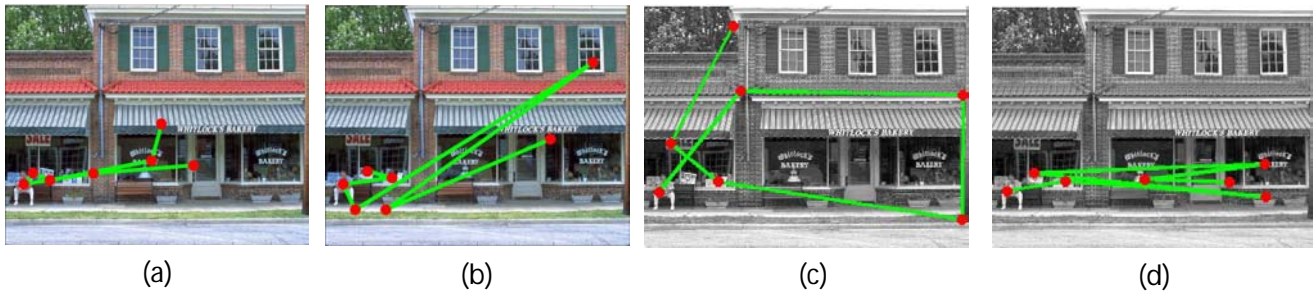


Fig. 4. Pattern of 7 first eye movements performed by (a) a human observer (b) Itti et al. saliency model, (c) $S(x)$ saliency model, (d) and saliency with inclusion of top down information, $S_c(x)$.

people. After the subject centered their fixation, a scene appeared and observers were instructed to count the number of people present. A scene was displayed until the subject's response or for a maximum of 10 s. The eyetracker was used to record the position and duration of eye movements during the search and the fixated number as the subjects response.

4.2. Eye Movement Data Analysis

In order to analyze the saccades data, we computed the squared difference between corresponding fixation points in two set of fixations (see [3]): the eye movements pattern made for each image and subject, was compared with the eye movements pattern made by Itti et al. [2] saliency model, $S(x)$ saliency model, and $S_c(x)$ context control model (cf. Figs. 3 and 4). In addition, we compared the distance between subjects and a random pattern of fixations. Like in [3], the study is restricted to the first seven fixations. Figure 3 summarizes the results. Distance between patterns of fixations was normalized so that average distance within subjects was 1 (each subject compared with other subjects on the same image, for all images). The graph shows that the pattern of fixations performed by the contextual model resembled human eye movements the closest. Pure saliency models performed worse but were still more similar to human data than a pure random process. There is no statistical difference between performances of Itti's model or the probabilistic definition of saliency (eq. 1).

5. SUMMARY AND CONCLUSIONS

In this paper, we presented a computational model of attention guidance that integrates context information with image saliency to determine regions of interest within a complex scene. By comparing scan patterns of different models to those of human observers, we validate the proposition that top-down information from visual context modulates the saliency of regions during the task of object detection. Contextual information provides an essential shortcut for object detection in order to build efficient object detection systems.

6. REFERENCES

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