Computational models of attention
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1 Abstract

This chapter reviews recent computational models of visual attention. We begin with models for the bottom-up or stimulus-driven guidance of attention to salient visual items, which we examine in seven different broad categories. We then examine more complex models which address the top-down or goal-oriented guidance of attention towards items that are more relevant to the task at hand.

2 Introduction

A large body of psychophysical evidence on attention can be summarized by postulating two forms of visual attention (James, 1890/1981). The first is driven by the visual input; this so-called exogenous, bottom-up, stimulus-driven, or saliency-based form of attention is rapid, operates in parallel throughout the entire visual field, and helps mediate pop-out, the phenomenon by which some visual items tend to stand out from their surroundings and to instinctively grab our attention (Treisman & Gelade, 1980; Koch & Ullman, 1985; Itti & Koch, 2001). The second, endogenous, top-down, or task-driven form of attention, depends on the exact task at hand and on subjective visual experience, takes longer to deploy, and is volitionally controlled. Normal vision employs both processes simultaneously, to control both overt and covert shifts of visual attention (Itti & Koch, 2001). Covert focal attention has been described as a rapidly shiftable “spotlight” (Crick, 1984), which serves the double function of selecting particular locations and objects of interest, and of enhancing visual processing at those locations and for specific attributes of those objects. Thus, attention acts as a shiftable information processing bottleneck, allowing only objects within a circumscribed visual region to reach higher levels of processing and visual awareness (Crick & Koch, 1998).

Most computational models of attention to date have focused on bottom-up guidance of attention towards salient visual items. Many, but not all, of these models have embraced the concept of a topographic saliency map (Koch & Ullman, 1985) that highlights scene locations according to their relative conspicuity or salience. This has allowed for validation of saliency models against eye movement recordings, by measuring the extent to which human or monkey observers fixate locations that have higher predicted salience than expected by chance (Parkhurst et al., 2002; Tatler et al., 2005). However, recent behavioral studies have shown that the majority of eye fixations during execution of many tasks are directed to task-relevant locations that may or may not also be salient, and fixations are coupled in a tight temporal relationship with other task-related behaviors such as reaching and grasping (Hayhoe et al., 2003). Several of these studies have used naturalistic interactive or immersive environments to give high-level accounts of gaze behavior in terms of objects, agents, “gist of the scene” (Potter & Levy, 1969; Torralba, 2003), and short-term memory, to describe, for example, how task-relevant information guides eye movements while subjects make a sandwich (Land & Hayhoe, 2001; Hayhoe et al., 2003), or how distractions such as setting the radio or answering a phone affect eye movements while driving (Sodhi et al., 2002). While these more complex attentional behaviors have been more difficult to capture in computational models, we review below several recent efforts that have successfully modeled attention guidance during complex tasks, such as driving a car or running a hot-dog stand that serves many hungry customers.

While we focus on purely computational models (which autonomously process visual data without the requirement of a human operator, or of manual parsing of the data into conceptual entities), we also point the reader to several relevant previous reviews on attention theories and models more generally (Itti & Koch, 2001; Paletta et al., 2005; Frintrop et al., 2010; Gottlieb & Balan, 2010; Toet, 2011; Tsotsos & Rothenstein, 2011).
3 Computational models of bottom-up attention

Development of computational models of attention started with the Feature Integration Theory of Treisman & Gelade (1980), which proposed that only simple visual features are computed in a massively parallel manner over the entire visual field. Attention is then necessary to bind those early features into a united object representation, and the selected bound representation is the only part of the visual world that passes through the attentional bottleneck (Figure 1a). Koch and Ullman (1985) extended the theory by proposing the idea of a single topographic saliency map, receiving inputs from the feature maps, as a computationally efficient representation upon which to operate the selection of where to attend next: A simple maximum-detector or winner-take-all neural network was proposed to simply pick the next most salient location as the next attended one, while an active inhibition-of-return mechanism would later inhibit that location and thereby allow attention to shift to the next most salient location (Figure 1b). From these ideas, a number of fully computational models started to be developed (e.g., Figure 1c,d).

Many research groups have more recently developed new models of bottom-up attention. Fifty three bottom-up models are classified along 13 different factors in Figure 2. Most of these models fall into one of the seven general categories described below, with some models spanning several categories (also see Tsotsos & Rothenstein, 2011 for another taxonomy). Additional details and benchmarking of these models was recently proposed by Borji et al. (2013; 2012a).

Cognitive models. Development of saliency-based models escalated after Itti et al.’s (1998) implementation of Koch and Ullman’s (1985) computational architecture. Cognitive models were the first to approach algorithms for saliency computation that could apply to any digital image. In these models, the input image is decomposed into feature maps selective for elementary visual attributes (e.g., luminance or color contrast, motion energy), at multiple spatial scales. The feature maps are combined across features and scales to form a master saliency map. An important element of this theory is the idea of center-surround operators, which define saliency as distinctiveness of an image region compared to its surroundings. Almost all saliency models are directly or indirectly inspired by cognitive concepts of visual attention (e.g., Le Meur et al., 2006; Marat et al., 2009).

Information-theoretic models. Stepping back from biologically-plausible implementations, models in this category are based on the premise that localized saliency computations serve to guide attention to the most informative image regions first. These models thus assign higher saliency to scene regions with rare (low probability) features. Information of visual feature \( F \) is \( I(F) = -\log p(F) \), inversely proportional to the likelihood of observing \( F \). By fitting a distribution \( P(F) \) to features, rare features can be immediately found by computing \( P(F)^{-1} \) at every location in an image. While, in theory, using any feature space is feasible, often these models (inspired by efficient coding in visual cortex) utilize a sparse set of basis functions learned from natural scenes. Example models in this category are AIM (Bruce & Tsotsos, 2005), Rarity (Mancas, 2007), LG (Local + Global image patch rarity) (Borji & Itti, 2012), and incremental coding length models (Hou & Zhang, 2008).

Graphical models. Graphical models are generalized Bayesian models, which have been employed for modeling complex attention mechanisms over space and time. Torralba (2003) proposed a Bayesian approach for modeling contextual effects on visual search which was later adopted in the SUN model (Zhang et al., 2008) for fixation prediction in free viewing. Itti & Baldi (2005) defined surprising stimuli as those which significantly change beliefs of an observer. Harel et al. (2007) propagated similarity of features in a fully connected graph to build a saliency map. Avraham & Lindenbaum (2010), Jia Li et al., (2010), and Tavakoli et al. (2011), have also exploited Bayesian concepts for saliency modeling.

Decision theoretic models. This interpretation proposes that attention is driven optimally with respect to the task. Gao & Vasconcelos (2004) argued that, for recognition of objects, salient features are those that best distinguish a class of objects of interest from all other classes. Given some set of features \( X = \{X_1, \ldots, X_d\} \), at locations \( l \), where each location is assigned a class label \( Y \) \( (Y_l = 0 \) for background, \( Y_l = 1 \) for objects of interest), saliency is then a measure of mutual information (usually the Kullback-Leibler divergence), computed as \( I(X, Y) = \sum_{i=1}^{d} I(X_i, Y) \). Besides having good accuracy in predicting eye fixations, these models have been very successful in computer vision applications (e.g., anomaly detection and object tracking).

Spectral analysis models. Instead of processing an image in the spatial domain, these models compute saliency in the frequency domain. Hou & Zhang (2007) derive saliency for an image by computing its Fourier
transform, preserving the phase information while discarding most of the amplitude spectrum (to focus on image discontinuities), and taking the inverse Fourier transform to obtain the final saliency map. Bian & Zhang (2009) and Guo & Zhang (2010) further proposed spatio-temporal models in the spectral domain.

**Pattern classification models.** Models in this category use machine learning techniques to learn stimulus-to-saliency mappings, from image features to eye fixations. They estimate saliency \( s \) by computing \( p(s|f) \), where \( f \) is a feature vector which could be the contrast of a location compared to its surrounding neighborhood. Kienzle et al. (2007), Peters & Itti (2007), and Judd et al. (2009) used image patches, scene gist, and a vector of several features at each pixel, respectively, and used pattern classifiers to then learn saliency from the features. Tavakoli et al. (2011) used sparse sampling and kernel density estimation to estimate the above probability in a Bayesian framework. Note that some of these models may not be purely bottom-up since they use features that guide top-down attention, for example faces or text (Judd et al., 2009; Cerf et al., 2008).

**Other models.** Other models exist that do not easily fit into our categorization. For example, Seo & Milanfar (2009) proposed self-resemblance of local image structure for saliency detection. The idea of decorrelation of neural response was used for a normalization scheme in the Adaptive Whitening Saliency (AWS) model (Garcia-Diaz et al., 2009). Kootstra et al. (2008) developed symmetry operators for measuring saliency and Goferman et al. (2010) proposed a context-aware saliency detection model with successful applications in re-targeting and summarization.

In summary, modeling bottom-up visual attention is an active research field in computational neuroscience and machine vision. New theories and models are constantly proposed which keep advancing the state of the art.

### 4 Top-down attention models

Models that address top-down, task-dependent influences on attention are more complex, as some representations of goal and of task become necessary. In addition, top-down models typically involve some degree of cognitive reasoning, not only attending to but also recognizing objects and their context, to incrementally update the model's understanding of the scene and to plan the next most task-relevant shift of attention (Navalpakkam & Itti, 2005; Yu et al., 2008; Beuter et al., 2009; Yu et al., 2012). For example, one may consider the following information flow, aimed at rapidly extracting a task-dependent compact representation of the scene, that can be used for further reasoning and planning of top-down shifts of attention, and of action (Navalpakkam & Itti, 2005; Itti & Arbib, 2006):

- **Interpret task definition:** by evaluating the relevance of known entities (in long-term symbolic memory) to the task at hand, and storing the few most relevant entities into symbolic working memory. For example, if the task is to drive, be alert to traffic signs, pedestrians, and other vehicles.

- **Prime visual analysis:** by priming spatial locations that have been learned to usually be relevant, given a set of desired entities and a rapid analysis of the “gist” and rough layout of the environment (Rensink, 2000; Torralba, 2003), and by priming the visual features (e.g., color, size) of the most relevant entities being looked for (Wolfe, 1994).

- **Attend and recognize:** the most salient location given the priming and biasing done at the previous step. Evaluate how the recognized entity relates to the relevant entities in working memory, using long-term knowledge of inter-relationships among entities.

- **Update:** Based on the relevance of the recognized entity, decide whether it should be dropped as uninteresting or retained in working memory (possibly creating an associated summary “object file” (Kahneman et al., 1992) in working memory) as a potential object and location of interest for action planning.

- **Iterate:** the process until sufficient information has been gathered to allow a confident decision for action.

- **Act:** based on the current understanding of the visual environment and the high-level goals.
An example top-down model that includes the above elements, although not in a very detailed implementation, was proposed by Navalpakkam & Itti (2005). Given a task definition as keywords, the model first determines and stores the task-relevant entities in symbolic working memory, using prior knowledge from symbolic long-term memory. The model then biases its saliency-based attention system to emphasize the learned visual features of the most relevant entity. Next, it attends to the most salient location in the scene, and attempts to recognize the attended object through hierarchical matching against stored representations in visual long-term memory. The task-relevance of the recognized entity is computed and used to update the symbolic working memory. In addition, a visual working memory in the form of a topographic task-relevance map (TRM) is updated with the location and relevance of the recognized entity. The implemented prototype of this model has emphasized four aspects of biological vision: determining task-relevance of an entity, biasing attention for the low-level visual features of desired targets, recognizing these targets using the same low-level features, and incrementally building a visual map of task-relevance. The model was tested on three types of tasks: single-target detection in 343 natural and synthetic images, where biasing for the target accelerated its detection over two-fold on average; sequential multiple-target detection in 28 natural images, where biasing, recognition and working memory contributed to rapidly finding all targets; and learning a map of likely locations of cars from a video clip filmed while driving on a highway (Navalpakkam & Itti, 2005).

While the previous example model uses explicit cognitive reasoning about world entities and their relationships, a complementary trend in top-down modeling uses fuzzy (as in fuzzy set theory (Zadeh, 1965)) or probabilistic reasoning to explore how several sources of bottom-up and top-down information may combine. For example, Ban et al. (2010) proposed a model where the bottom-up and top-down components interact through a fuzzy learning system (Figure 3.a). During training, a bottom-up saliency map selects locations, and their features are incrementally clustered and learned in a growing fuzzy topology adaptive reasoning theory model (GFTART), which is a neural network model that automatically learns to categorize many received pattern exemplars into a small (but possibly growing) set of categories. During testing, bottom-up interest in a given object activates its features stored in the GFTART model, and biases the bottom-up saliency model to become more sensitive to these features, thereby increasing the probability that the object of interest will stand out. In a related approach, Akamine et al. (2012) (also see Kimura et al., 2008) developed a dynamic Bayesian network that combines the following factors: First, input video frames give rise to deterministic saliency maps. These are converted into stochastic saliency maps via a random process that affects the shape of salient blobs over time (e.g., dynamic Markov random field (Kimura et al., 2008)). An eye focusing map is then created which highlights maxima in the stochastic saliency map, additionally integrating top-down influences from an eye movement pattern (a stochastic selection between passive and active state with a learned transition probability matrix). The authors use a particle filter with Markov chain Monte-Carlo (MCMC) sampling to estimate the parameters; this technique often used in machine learning allows for fast and efficient estimation of unknown probability density functions. Several additional recent related models using graphical models have been proposed (e.g., Chikkerur et al., 2010).

In a recent example, using probabilistic reasoning and inference tools, Borji et al. (Borji et al., 2012b, 2014) introduced a framework for top-down overt visual attention based on reasoning, in a task-dependent manner, about objects present in the scene and about previous eye movements. They designed a Dynamic Bayesian Network (DBN) that infers future probability distributions over attended objects and spatial locations from past observed data. Briefly, the Bayesian network is defined over object variables that matter for the task. For example, in a video game where one runs a hot-dog stand and has to serve multiple customers while managing the grill, those include raw sausages, cooked sausages, buns, ketchup, etc. Then, existing objects in the scene, as well as the previous attended object, provide evidence toward the next attended object (Figure 3.b). The model also allows to read out which spatial location will be attended, thus allowing one to verify its accuracy against the next actual fixation of the human player. The parameters of the network are learned from training data in the same form as the test data (human players playing the game). This object-based model was significantly more predictive of eye fixations, compared to simpler classifier-based models, several state-of-the-art bottom-up saliency models, and control algorithms such as mean eye position (Figure 3.c). This points toward the efficacy of this class of models to capture spatio-temporal visually-guided behavior in the presence of a task.

While fully-computational top-down models are more complex than their bottom-up counterparts, many recent examples thus exist that provide an inspiration for future efforts in developing models that more
accurately emulate the human cognitive processes that control top-down attention.

5 Outlook

Our review shows that tremendous progress has been made in modeling both bottom-up and top-down aspects of attention computationally. Tens of new models have been developed, each bringing new insights into the question of what makes some stimuli more important to visual observers than other stimuli.

While many models have approached the problem of modeling top-down attention, a fully implemented cognitive system that reasons about objects, their relationships, and their locations to guide the next shift of attention remains an elusive goal to date.

Several barriers exist in building even more sophisticated visual attention models, which, we argue, depend on progress in complementary aspects of machine vision, knowledge representation, and artificial intelligence, to support some of the components required to implement attention-driven scene understanding systems. Of prime importance is object recognition, which remains a hard problem in machine vision, but is necessary to enable reasoning about which object to look for next (using top-down strategies) given the set of objects that have been attended to and recognized so far. Also important is understanding the spatial and temporal structure of a scene, so that reasoning about objects and locations in space and time can be exploited to guide attention (e.g., understanding pointing gestures, or trajectories of objects in three dimensions). Additionally, building knowledge bases that can capture what an observer may know about different world entities and that allows reasoning over this knowledge is required to build more able top-down attention models. For example, when making tea [Land & Hayhoe, 2001], knowledge about different objects relevant to the task, where they usually are stored in a kitchen, and how to manipulate them is needed to decide where to look and what to do next.

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Figure 1: Early bottom-up attention theories and models. (a) Feature integration theory of Treisman & Gelade (1980) posits several feature maps, and a focus of attention that scans a map of locations and collects and binds features at the currently attended location. (from Treisman & Souther (1985)). (b) Koch & Ullman (1985) introduced the concept of a saliency map receiving bottom-up inputs from all feature maps, where a winner-take-all (WTA) network selects the most salient location for further processing. (c) Milanese et al. (1994) provided one of the earliest computational models. They included many elements of the Koch & Ullman framework, and added new components, such as an alerting subsystem (motion-based saliency map) and a top-down subsystem (which could modulate the saliency map based on memories of previously recognized objects). (d) Itti et al. (1998) proposed a complete computational implementation of a purely bottom-up and task-independent model based on Koch & Ullman’s theory, including multiscale feature maps, saliency map, winner-take-all, and inhibition of return.
**Figure 2:** Survey of bottom-up and top-down computational models, classified according to 13 factors. Factors in order are: Bottom-up (f1), Top-down (f2), Spatial (−)/Spatio-temporal (++) (f3), Static (f4), Dynamic (f5), Synthetic (f6) and Natural (f7) stimuli, Task-type (f8), Space-based(+) / Object-based(−) (f9), Features (f10), Model type (f11), Measures (f12), and Used dataset (f13). In Task type (f8) column: free-viewing (f); target search (s); interactive (i). In Features (f10) column: CIO: color, intensity and orientation saliency; CIOFM: CIO plus flicker and motion saliency; M*: motion saliency, static saliency, camera motion, object (face) and aural saliency (Speech-music); LM*: contrast sensitivity, perceptual decomposition, visual masking and center-surround interactions; Liu* = center-plus histogram, multi-scale contrast and color spatial-distribution; R*: luminance, contrast, luminance-bandpass, contrast-bandpass; SM*: orientation and motion; J*: CIO, horizontal line, face, people detector, gist, etc; S*: color matching, depth and lines; = face. In Model type (f11) column, R means that a model is based on RL. In Measures (f12) column: K* = used Wilcoxon-Mann-Whitney test (T probability that a random chosen target patch receives higher saliency than a randomly chosen negative one); DR means that models have used a measure of detection/classification rate to determine how successful was a model. PR stands for Precision-Recall. In dataset (f13) column: Self data means that authors gathered their own data. For a detailed definition of these factors please refer to Borji & Itti (2012 PAMI).
Figure 3: Examples of recent top-down models. (a) Model of Ban et al. (2010) which integrates bottom-up and top-down components. r, g, b: red, green and blue color channels. I: intensity feature. E: edges. R, G: red-green color. B, Y: blue-yellow color. CSD&N: center surround differences and normalization. ICA: independent component analysis. GFT, ART: growing fuzzy topology adaptive resonance theory. SP: saliency point. (b) Graphical representation of the Dynamic Bayesian Network (DBN) approach of Borji et al. (2012) unrolled over two time-slices. $X_t$ is the current saccade position, $Y_t$ is the currently attended object, and $F_i$ is the function that describe object $i$ at the current scene. All variables are discrete. It also shows a time series plot of probability of objects being attended and a sample frame with tagged objects and eye fixation overlaid. (c) Sample predicted saccade maps of the DBN model (shown in b) on three video games and tasks: running a hot-dog stand (HDB; top three rows), driving (3DDS; middle two rows), and flight combat (TG, bottom two rows). Each red circle indicates the observers eye position superimposed with each maps peak location (blue squares). Smaller distance indicates better prediction. Models compared are as follows. MEP: mean eye position over all frames during the game play (control model). G: trivial Gaussian map at the image center. BU: bottom-up saliency map of the Itti model. Mean BU: average saliency maps over all video frames. REG(1): regression model which maps the previous attended object to the current attended object and fixation location. REG(2): similar to REG(1) but the input vector consists of the available objects at the scene augmented with the previously attended object. SVM(1) and SVM(2) correspond to REG(1) and REG(2) but using an SVM classifier. Similarly, DB(5) and DB(3) correspond to REG(1) and REG(2) meaning that in DB(5) the network considers just one previously attended object, while in DB(3) each network slice consists of the previously attended object as well information of the previous objects in the scene. REG(Gist): regression based only on the gist of the scene. kNN: k-nearest-neighbors classifier. Rand: white noise random map (control). Overall, DB(3) performed best at predicting where the player would look next (Borji et al., 2012).
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