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Saliency Maps

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Abstract

Visual attention modelling is a key to understanding how the human brain is able to focus on the important things to see. Such a model can be used in a wide field of technology, for instance in robotic systems, computer graphics or computer visition. In this paper I will explain the principles of the pre-attentive visual system, that is the part of the visual system that controls the focus of attention, and compare different modelling approaches with their neuro-biological counterparts inside the visual system. I will show that early models, such as the one by Itti and Koch from the year 2001, closely follow insights from neurobiological studies trying to imitate the brain as closely as possible, while the later ones, for example Perazzi from 2012, are only inspired by the visual system and divert from true modelling to achieve various effects. I will explain both models in detail, as well as the the effects achieved, and the real world applications they can be used for.

Contents

1 Introduction

1.1 Motivation

Visual attention describes the mechanisms in the human brain that mainly control what we look at – the steps and stages in the visual system that help control eye movement, thus finding important features in a visual scene. It furthermore filters the peripheral field of view for intense stimuli, thus reducing the amount of visual data to be processed. Visual attention is crucial to recognise our surroundings and an ongoing task. It even has evolutionary relevance since fast and good visual detection are great advantages for both predator and prey.

Part of the fascination about the way the human brain perceives visual scenes and finds objects of interest is in the speed and robustness it achieves doing so. By understanding the inner neuro-biological workings, we hope to achieve similar results in artificial recognition technologies, which can be used in a wide field of applications, especially robotics, surveillance or navigational aid.

However, visual attention approaches can be used in other contexts as well, being adjusted to the needs of the context. In computer graphics, object recognition and object boundary detection are frequent tasks that can be achieved by similar means. In these cases, the neuro-biological findings are often used as a starting point in developing new methods.

There are many different approaches to explain and simulate the processes that make up visual attention. Most explanations however first divide it up into bottom-up and top-down parts. The bottom-up approach deals solely with image-based processing, not interpreting the objects in the visual scene but rather working mainly with localized contrast and center-surround mechanisms, combining them into different maps that represent visual saliency. The top-down approach is guided by the task at hand and much more complex, taking into account knowledge and intention of the perceiving person.

In this paper I will compare different approaches explaining the neuro-biological visual attention system with some algorithms for different related use-cases. I will focus on bottom-up approaches, always keeping in mind how they interact with the top-down parts in the visual system.

1.2 Examples

Figure 1 displays some examples for saliency maps generated from an input image (a). The grayscale images (b) through (g) are saliency maps, in which white depicts high values of saliency, dark colors depict less salient regions. It is very clear that there are many possible and different saliency maps that can be generated. The first three (b), (c) and (d) are rather blurry, but their highest saliency values are distributed around the object of interest. Algorithm (e) yields high saliency values on object boundaries, similar to an edge detection algorithm. The last two (f) and (g) then highlight whole objects thay may be of interest, in these maps it is still possible to find details.

All these algorithms may be useful for a specific task. While the latter ones are more useful in object boundary detection, the former are usually easier to compute and find points of interest for further analysis.

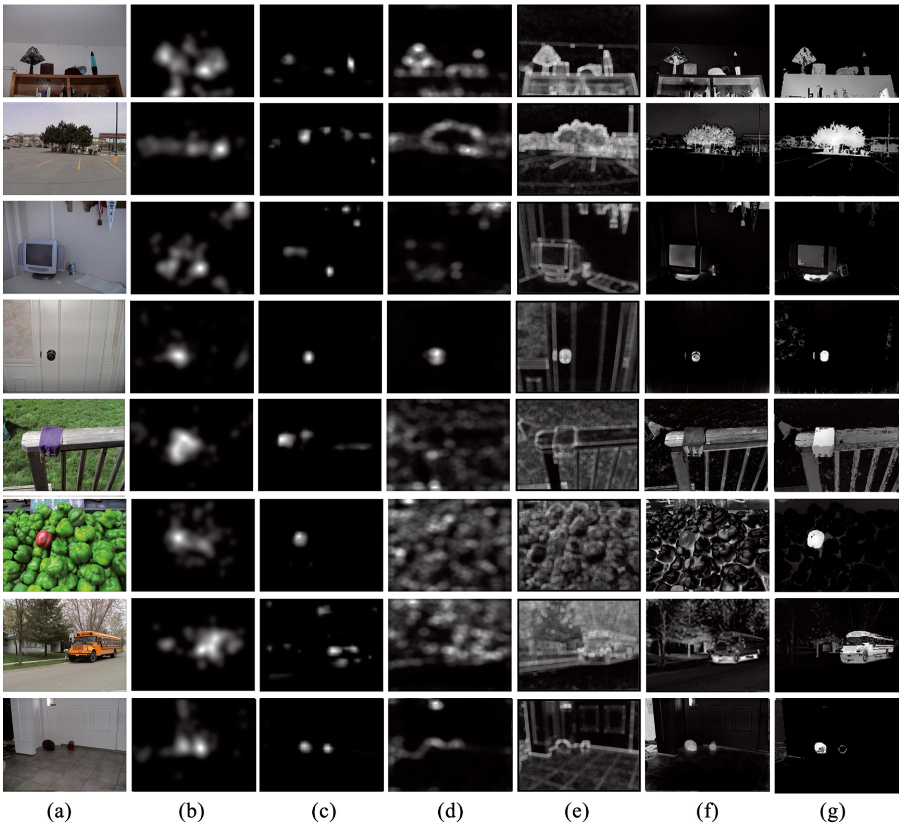


Figure 1: Different algorithms yield different maps – for different applications. For reference, the columns corresponding to the subsequently presented algorithms are: Koch/Itti (b), Hou (c), Perazzi (g).

2 Methods

In this section I will describe a few terms and methods that are used by almost any approach and where these methods can be found inside the visual system, neuro-biologically modelled.

2.1 A word about Contrast

The concept of *contrast* is being used quite often in the context of saliency detection. However, the definition may vary between publications on this topic, depending on the data it is applied to and the effect to achieve. *Color intensity* contrast is a measure to describe the difference in color perception, either based solely on brightness (in cases with grayscale pictures) or the perceived color variance. To technically measure this color variance, an appropriate color representation has to be used. The Lab color space describes a representation based on human perception. It uses three components, the **L**ightness and two dimensions of complementary color (**a**, **b**) and is designed to model the perceived color as realistically as possible. Calculating the Euclidean distance between two colors in this space yields a reasonable contrast measure.

The reference value for the contrast calculation however can be obtained in different ways. Mainly, there is a difference between global and local contrast. Some simple algorithms calculate the contrast-based saliency value based on the color difference to the mean color of the whole scene. While this is an easy and simple approach, it is to argue how accurate this models the human brain, which rather works mainly with center-surround cell linking, yielding a local contrast measure. Either way, most algorithms normalize local contrast based on the image mean brightness, as the eye does by adjusting the iris.

Furthermore, the contrast measure can be based not only on spatial color distribution, but also temporal change. While the inner receptive fields of the retina, the fovea, have high spatial resolution, allowing us to perceive every detail, the outer parts are instead connected to parts of the visual system with higher temporal resolution. In these outer parts, contrast can also be determined in the temporal domain, so movements "in the corner of the eye" are more likely to catch our attention and cause a saccade to detect the object.

2.2 Blurring

Blur filters are often used in saliency map algorithms. Their main goal is to calculate a mean color for a local patch in order to remove detail from an image by taking neighboured pixels into account. The filter adds the colors with a weighted function based on their relative position. This is very easy to implement in a neural network, as it can be done with a simple topographical perceptron layer and only local connections. This process can also be applied on other (multidimensional) data for various effects.

An often used weight function for blurs is the Gaussian distribution, which yields a smoothed texture and can be decomposited into multiple passes, one for each dimensions, resulting in a linear instead of polynomial runtime. This is especially important for high-dimensional spaces, such as the usually threedimensional color space.

2.3 Winner-take-all and Inhibition of return

When intentionally searching a visual scene for some target, the eyes saccade from one point of interest to another. The first target is selected by the highest saliency value determined from the scene. This is called *winner- take- all*[3], as only one point can be looked at, and the others are ignored. However, when the point of interest is discarded as not being the target, the next highest saliency value is determined. To prevent the focus of attention going back to the first point, it is then marked as seen and not interesting by inhibitory synapses, hence the name *inhibition of return*. The effect was first described in 1984 and thoroughly investigated since[4].

For a search pattern like this to work, top-down stimuli need to influence the saliency map. For example, when searching for a specific face in a group of people, the faces are already of higher saliency, allowing us to scan them one by one for the person we're looking for. The task, searching for a specific face, is here enhancing saliency at the location of the faces, which is not stimuli-driven but requires a higher level of processing. This kind of processing, object identification, is done in the *ventral stream* (also called "Object recognition pathway"), a part of the visual system that processes the visual input in parallel to the *dorsal stream*, which detects and refines object locations ("Space/Action pathway") [6]. At some point, the ventral stream feeds into the dorsal stream, so object identities can be included in the saliency map, and thus in the visual search.

2.4 Frequency analysis

Frequency analysis is a complex procedure that can be applied to single- or multidimensional data, such as images. It is computed by Fourier transform and produces a mapping from frequency to intensity, i.e. how much a certain frequency occurs in the data.

3 Approaches

In this section I aim to present some different approaches and the ideas they introduced in the field of visual attention research.

3.1 Koch 1987 – Shifts in selective visual attention: towards the underlying neural circuitry

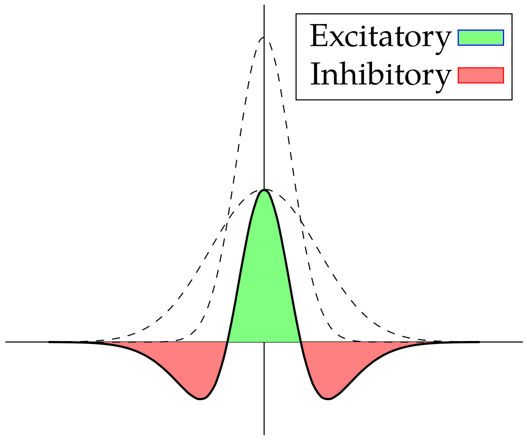
The paper Koch et al. (1987) describes extensively how the visual system is able to cope with the large amount of stimuli received from the sensory cells by only processing parts of them. Koch labels this *selective attention* and thus coins a term for a lot of future research. The Koch model is very basic. It proposes the decomposition of the filtering process into an early representation, in which only basic features of the scene are analysed in simple steps and projected onto retinotopical (that is, topographically equivalent to the retina) maps. It then introduces the "saliency map", in which these basic features are combined.

> "A 'saliency map', that is, an explicit two-dimensional topographical map that encodes stimulus conspicuity, or saliency, at every location in the visual scene."[2]

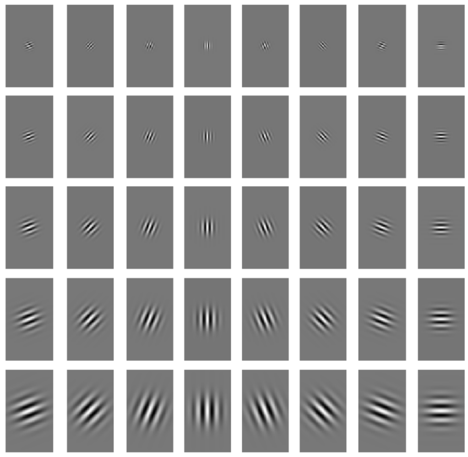
According to the Koch model, there exists a mapping from the representations of all the basic features in topographical maps into a "more central one", containing only information of the most conspicious location. A large part of his research goes into developing a model for the winner-take-all method, and how it is possible to implement this using neural networks.

3.2 Itti 2001 – Computational Modelling of visual Attention

Itti et al. (2001) refines Koch's findings and describes the early stages more in detail. It explains different strategies for detection of features, mostly using center-



(a) Typical center-sourround filter, the Difference of Gaussians (Gaussians are dashed), also called "Mexican hat".



(b) The real part of a Gabor function for five different scales and eight different orientations.

Figure 2: Detailed feature filters

sourround filters (see Figure 2a) on any kind of contrast-based feature, derived from color. More interesting are edge detection filters, implemented by Gabor kernels. These kernels are the product of a center-sourround filter (difference of Gaussians) and a sinusoidal function. They exists for different sizes and all orientations (Figure 2b).

Furthermore, the model explains the mechanism for merging the feature maps into a general saliency map. Important in this process is the weighting of the different features, i.e. how important having a special[1] color is in comparison to having a special orientation. Itti finds that there are two main factors that impact this weighting – one being top-down, cognitive decision, the other being training. However, there seem to be no strong interactions between the different feature maps, such as especially high saliency for a combination of a specific color with a specific orientation. The ability to detect these combinations can also not be learned, which leads to the conclusion that the feature weighting is the first stage in the visual system influenced by learning.

[1] read: different from the others, high contrast

3.3 Perazzi 2012 – Contrast Based Filtering for Salient Region Detection

Perazzi et al. try to provide a fast and reliable application-oriented algorithm for salient region detection. This is different in detecting saliency points in that it tries to retain object features in the saliency map, especially boundaries of the salient objects. Special about this method is that it is possible to implement with only using Gaussian blur functions. This is a huge convenience for achieving great performance due to the ability to decompose multidimensional blurs into multiple passes.

The Perazzi model first decomposes the input image into segments, using an edge-preserving algorithm. It uses a variation of SLIC, a simple K-means clustering algorithm using geodesic image distance in Lab color space. The yielded segments, called *elements*, are then analysed for uniqueness and distribution.

Uniqueness denotes the rarity of the element color, compared to all other segments, weighted by the distance between them. By choosing a constant weight function independent of the distance, the global uniqueness is determined, while a local weight function may overemphasize object boundaries. Perazzi et al. therefor choose a Gaussian function for the weight and show that this gives good, not-too- localized results and is decomposable by axis.

The second feature, distribution, measures the occurence of a color elsewhere in the image. A low variance indicates a compact object, which in the Perazzi model is considered more salient. A very similar Gaussian weight function is used, such that the position needs to be blurred in color space, again being decomposable by color component axis. After calculating both features for each element, the elements are assigned a saliency from the features, which are then applied to the original image pixels by an up-sampling algorithm.

3.4 Hou 2007 – Saliency Detection: A Spectral Residual Approach

Hou found that in natural scene images, frequency analysis yields a typical average pattern. The difference between the frequency analysis of a specific image to this average pattern returns what spatial frequencies in the image are *special*, that is, are not just average image data but some kind of interesting object. From these frequencies, the original places in the image can be looked up in reverse, producing a saliency map.

This model is independent of low-level features, but rather works by detecting what parts of the image are not "background noise". The great advantage of this is the generality of the system. There are however no findings that similar processes are going on in the human brain, so this model is – similar to the Perazzi model – just a technical solution for the visual attention tasks performed by the brain.

4 Discussion

4.1 Algorithm Requirements

In this section I will compare the algorithms and methods and explain in detail which features may be relevant for specific kinds of task, and how they are introduced.

When comparing saliency maps produced by different state-of-the-art methods, one immediately finds a huge difference in the *blurriness* of the object. This is usually a result of center-sourround filters, as they work by taking neighboured pixels (stimuli) into account. In practical examples, more blurriness is often introduced when the image is downsampled, since many local contrast functions have complexity $\mathcal{O}(n^2)$, and downsampling greatly reduces the number of pixels.

While blurriness is not a problem in finding single points of interest (winner-take-all), it does remove detail from the map. This particularly impedes object detection, as the boundaries cannot be retrieved from the saliency map. This task is performed in the ventral pathway, and does not require the saliency map. In technical solutions however, it may be desirable to reduce the amount of work and generalize both pathways into one algorithms.

A second feature desired from an algorithm is the ability to sort the salient points by intensity, to *determine an order* for the attention flow. This is quite the opposite to boundary detection, which is a binary decision ("part of the object or not?"). Some algorithms not presented in this paper completely lack this feature by only calculating local saliency measures, not taking into account the whole scene ("is there any object even more interesting?").

Further features of interest are the ability for *iterative saliency analysis*, giving approximate results quickly and refining the exact saliency over time, which can be quite useful in the field of robotics, where quick decisions have to be made, but slower corrections may be desireable.

Also, many algorithms only consider static visual scenes, while spatio-temporal data cannot always be processed. This is essential for *movement detection* and quite obviously an important task for the human brain.

4.2 Comparison

It is easily possible to separate any method into two categories – neural models and computational models. The approaches by Itti/Koch and Perazzi are exceedingly good examples for both categories, respectively. While neural models try to explain the visual system, they mostly try to emulate the pre-attentive stage. This stage is highly parallel[2] and only yields the location of salient points. Thus, these models cannot be used selfcontained and are rather theoretical than practical. Moreover, parallel computations as in neural networks are hard to evaluate with artificial computational devices, rendering these approaches useless for real-time applications.

The computational models go further, using basic features like the neural models to compute some kind of saliency map that may already contain sequential-type computations as found in the higher levels of the visual system. While these are generally easier to compute, they are often specialized for specific tasks and do not provide the great reliability of the visual system.

Table 1 compares the categories according to above-mentioned desired features using the exemplary approaches by Itti/Koch, Perazzi and Hou.

Approach	**Itti/Koch**	**Perazzi**	**Hou**
Model type	neural	computational	computational
Figure 1 column	(b)	(g)	(c)
Object detection	impossible	great (with contours)	good
Order of interest	good / inhibition of return	fair	fair
Iterative analysis	simple	not possible	n/a
Movement detection	use 3-dim. input space	possible	difficult

Table 1: Comparison between approaches and their features and capabilities

5 Conclusion

I have found that there exists a great variety of saliency detection methods for a wide area of applications. However, each method is specialized for different features, with only very few focusing on being a general model.

The most referenced and most neuro-biologically plausible model was defined by Itti/Koch. This model explains the workings of the human brain and can easily be implemented using neural structures. However, it returns very blurred saliency maps that are not useful in every context.

More computationally oriented approaches like Perazzi and Hou were derived from the works of Koch and Itti in recent years, however, while being easier to implement using computer hardware, these approaches are often more task specific and less biologically founded.

Overall, saliency detection is a field of research in neuroinformatics that did receive and still receives lots of attention. I has great potential for it has many possible use cases throughout science and industry.

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