Visual attention
Models, Performances and applications

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Outline

Outline

COMPLEX VISUAL SCENES

(a) Prey vs Predator

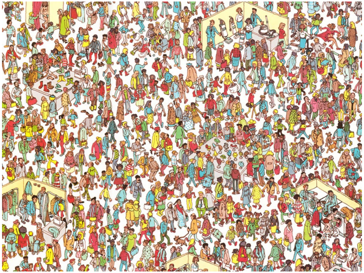
(b) King of the world?

(c) Salvador Dali

(d) René Magritte

Human Visual System

Natural visual scenes are cluttered and contain many different objects that cannot all be processed simultaneously.



Amount of information coming down the optic nerve $10^8 - 10^9$ bits per second

Far exceeds what the brain is capable of processing...

Human Visual System

- Example of change blindness.....

YouTube link: `www.youtube.com/watch?v=ubNF9QNEQLA`

Fundamental questions

WE DO NOT SEE EVERYTHING AROUND US!!!

Two majors conclusions come from the change blindness experiments:

- Observers never form a complete, detailed representation of their surroundings;
- Attention is required to perceive change.

It raises fundamental questions:

How do we select information from the scene?

Can we control where and what we attend to?

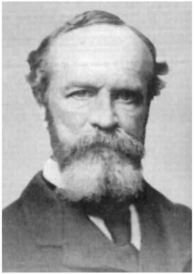
Do people look always at the same areas?

They are all connected to VISUAL ATTENTION.

Outline

William James, an early definition of attention...

Everyone knows what attention is. It is the taking possession by the mind in clear and vivid form, of one out of what seem several simultaneously possible objects or trains of thoughts... It implies withdrawal from some things in order to deal effectively with others. William James, 1890[James, 1890]



William James (1842-1910)
A pioneering American psychologist and philosopher.

Selective Attention is the natural strategy for dealing with this bottleneck.

Visual Attention definition

As Posner proposed [Posner, 1980], visual attention is used:

- to select important areas of our visual field (alerting);
- to search a target in cluttered scenes (searching).

There are two kinds of visual attention:

- Overt visual attention: involving eye movements;

  Often compared to a window on the brain...[Henderson et al., 2007]

- Covert visual attention: without eye movements (Covert fixations are not observable). Attention can be voluntarily focussed on a peripheral part of the visual field (as when looking out of the corner of one's eyes).

  Covert attention is the act of mentally focusing on one of several possible sensory stimuli.

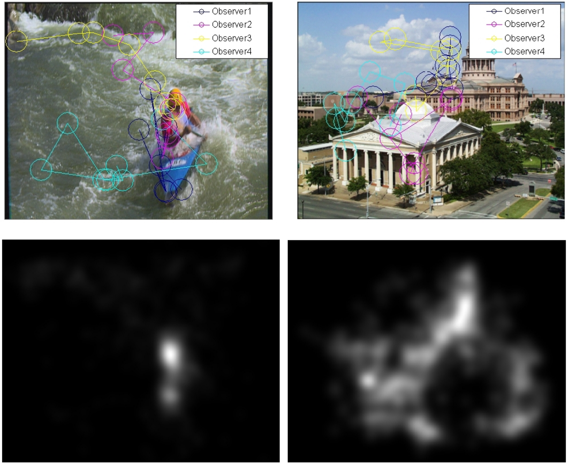
Overt attention - Eye Movements

There exists different kinds of eye movements:

- **Saccade**: quick eye movements from one fixation location to another. The length of the saccade is between 4 to 12 degrees of visual angle;
- **Fixation**: phase during which eyes is almost stationnary. The typical duration is about 200 / 300 ms [Findlay & Gilchrist, 2003]. But it depends on a number of factors (depth of processing [Velichkovsky et al., 2002]; ease or difficulty to perceive something [Mannan et al., 1995]);
- **Smooth pursuit**: voluntary tracking of moving stimulus;
- **Vergence**: coordinated movement of both eyes, converging for objects moving towards and diverging for objects moving away from the eyes.

A scanpath is a sequence of eye movements (fixations - smooth pursuit - saccades...).

Overt attention - Eye Movements



From [Le Meur & Chevet, 2010].

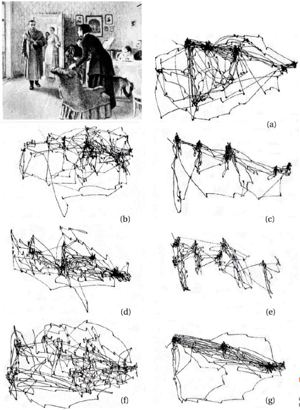
Yarbus [Yarbus, 1967]

(1914-1986)

A. Yarbus [Yarbus, 1967] demonstrated how eye movements changed depending on the question asked of the subject.

1. No question asked
2. Judge economic status
3. What were they doing before the visitor arrived?
4. What clothes are they wearing?
5. Where are they?
6. How long is it since the visitor has seen the family?
7. Estimate how long the unexpected visitor had been away from the family.

Each recording lasted 3 minutes.



Yarbus [Yarbus, 1967]

A. Yarbus showed that our attention depends on bottom-up features and on top-down information:

- Bottom-up attention (also called exogenous): some things draw attention reflexively, in a task-independent way...
  - → Involuntary;
  - → Very quick;
  - → Unconscious.

- Top-down attention (also called endogenous): some things draw volitional attention, in a task-dependent way...
  - → Voluntary (for instance to perform a task, find the red target);
  - → Very slow;
  - → Conscious.

In this talk, we are interested in bottom-up saliency which is a signal-based factor that dictates where attention is to be focussed.

Outline

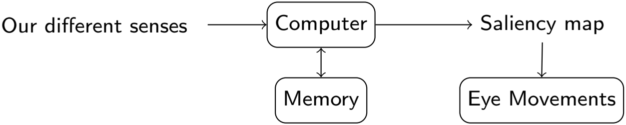
Computational models: two schools of thought

- One based on the assumption that there is an unique saliency map [Koch et al., 1985, Li, 2002]:

Definition (saliency map)

A topographic representation that combines the information from the individual feature maps into one global measure of conspicuity. This map can be modulated by a higher-level feedback.

A comfortable view for the computational modelling...



- There exist multiple saliency maps (distributed throughout the visual areas) [Tsotsos et al., 1995].

  Many candidate locations for a saliency map:
  - → Primary visual cortex[Li, 2002]
  - → Lateral IntraParietal area (LIP) [Kusunoki et al., 2000]
  - → Medial Temporal cortex [Treue et al., 2006]

The brain is not a computer [Varela, 1998].

Computational models

The following taxonomy classifies computational models into 3 classes:

Biologically inspired

- [Itti et al., 1998]
- [Le Meur et al., 2006, Le Meur et al., 2007]
- [Bur et al., 2007]
- [Marat et al., 2009]

Probabilistic models

- [Oliva et al., 2003]
- [Bruce, 2004, Bruce & Tsotsos, 2009]
- [Mancas et al., 2006]
- [Itti & Baldi, 2006]
- [Zhang et al., 2008]

Beyond bottom-up models

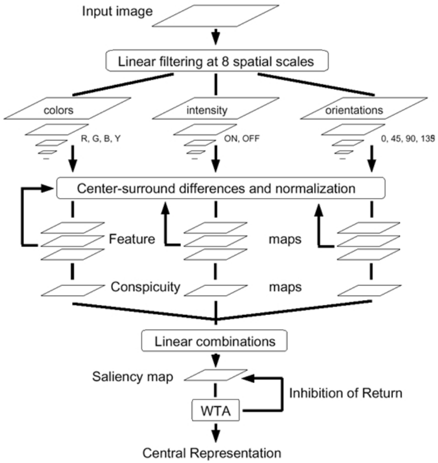
- Goal-directed models: [Navalpakkam & Itti, 2005]
- Machine learning-based models: [Judd et al., 2009]

A recent review presents a taxonomy of nearly 65 models [Borji & Itti, 2012].

Biologically inspired models

Itti's model [Itti et al., 1998], probably the most known...

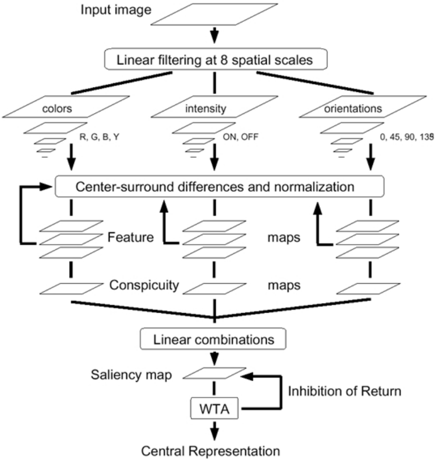
- Based on the Koch and Ullman's scheme;
- Hierarchical decomposition (Gaussian);
- Early visual features extraction in a massively parallel manner;
- Center-surround operations;
- Pooling of the feature maps to form the saliency map.



Biologically inspired models

Itti's model [Itti et al., 1998], probably the most known...

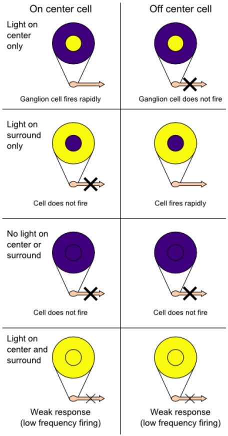
- Hierarchical decomposition (Gaussian):



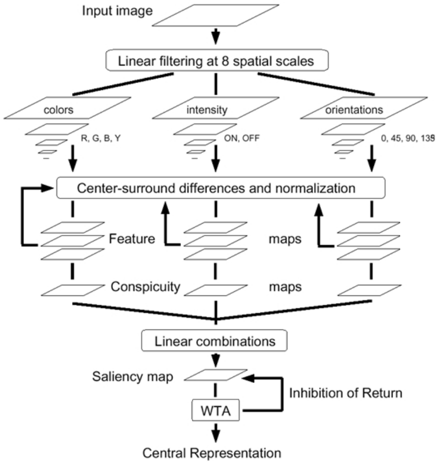
Biologically inspired models

Itti's model [Itti et al., 1998], probably the most known...

- Center-surround operations:



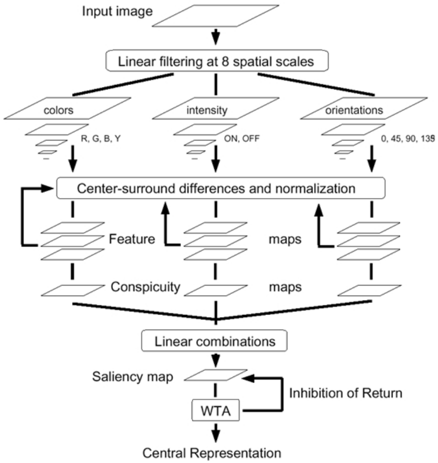
From Wikipedia.



Biologically inspired models

Itti's model [Itti et al., 1998], probably the most known...

- Normalization and combination:
  - → **Naive summation**: all maps are normalized to the same dynamic and averaged;
  - → **Learning linear combination**: depending on the target, each feature map is globally multiplied by a weighting factor. A simple summation is then performed.
  - → **Content-based global non-linear amplification**:
    1. Normalize all the feature maps to the same dynamic range;
    2. For each map, find its global maximum M and the average $\overline{m}$ of all the other local maxima;
    3. Globally multiply the map by $(M - \overline{m})^2$.



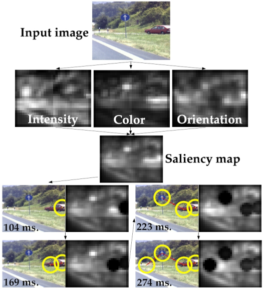
Biologically inspired models

Itti's model [Itti et al., 1998], probably the most known...

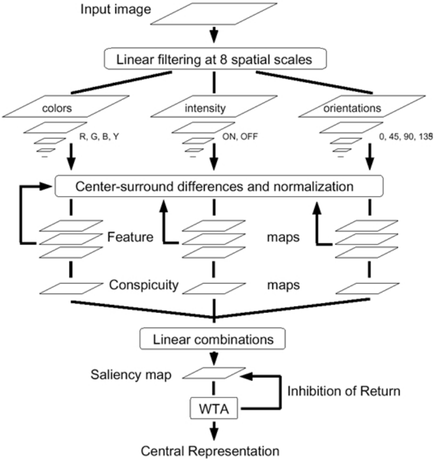
- Winner-Take-All:

  The maximum of the saliency map ⇒ the most salient stimulus ⇒ focus of attention

  Inhibitory feedback from WTA [Koch et al., 1985]



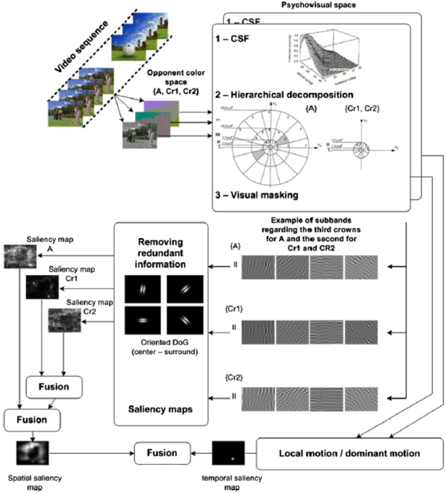
From Itti's Thesis.



Biologically inspired models

Le Meur's model [Le Meur et al., 2006], an extension of Itti's model...

- Based on the Koch and Ullman's scheme
- Light adaptation and Contrast Sensitivity Function
- Hierarchical and oriented decomposition (Fourier spectrum)
- Early visual features extraction in a massively parallel manner
- Center-surround operations on each oriented subband
- Enhanced pooling [Le Meur et al., 2007] of the feature maps to form the saliency map



Other models in the same vein: [Marat et al., 2009], [Bur et al., 2007]...

Probabilistic models

Such models are based on a probabilistic framework taken their origin in the information theory.

Definition (Self-information)

Self-information is a measure of the amount information provided by an event. For a discrete X r.v defined by $\mathcal{A} = \{x_1, ..., x_N\}$ and by a pdf, the amount of information of the event $X = x_i$ is given by:

$$I(X = x_i) = -log_2 p(X = x_i), \text{ bit/symbol}$$

Properties:

- if $p(X = x_i) < p(X = x_j)$ then $I(X = x_i) > I(X = x_j)$
- $p(X = x_i) \rightarrow 0$, $I(X = x_i) \rightarrow +\infty$

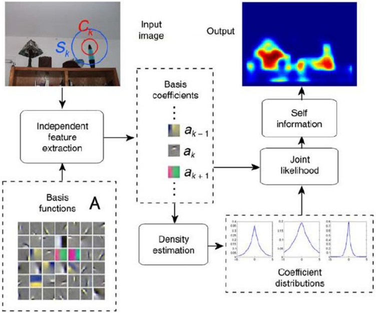
The saliency of visual content could be deduced from the self-information measure.

Self-information $\equiv$ rareness, surprise, contrast...

Probabilistic models

- First model resting on this approach has been proposed in 2003 [Oliva et al., 2003]: $S(\mathbf{x}) = \frac{1}{p(\mathbf{v}_l(\mathbf{x}))}$, where $\mathbf{v}_l$ is a feature vector (48 dimensions), the probability density function is computed over the whole image.

- Bruce in 2004 [Bruce, 2004] and 2009 [Bruce & Tsotsos, 2009] modified the previous approach by using the self-information locally on independent coefficients (projection on a given basis).



From [Bruce & Tsotsos, 2009]

Other models in the same vein: [Mancas et al., 2006], [Zhang et al., 2008]

Probabilistic models

The support regions used to calculate the pdf are not the same:

- Local spatial surround [Gao et al., 2008, Bruce & Tsotsos, 2009]. Note also that Gao et al. [Gao et al., 2008] uses the mutual information to quantify the saliency;
- Whole image [Oliva et al., 2003, Bruce & Tsotsos, 2006];
- Natural image statistics [Zhang et al., 2008] (self-information);
- Temporal history, theory of surprise [Itti & Baldi, 2006].

Machine learning-based models

Judd's model [Judd et al., 2009] combines bottom-up and top-down information:

- Low-level features:
  - → Local energy of the steerable pyramid filters (4 orientations, 3 scales);
  - → Three additional channels (Intensity, orientation and color) coming from Itti's model;
- Mid-level features: Horizon line coming from the gist;
- High-level features:
  - → Viola and Jones face detector;
  - → Felzenszwalb person and car detectors;
  - → Center prior.

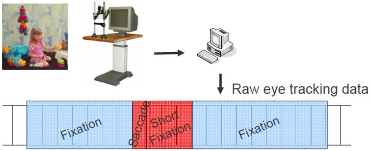
The liblinear support vector machine is used to train a model on the 9030 positive and 9030 negative training samples.

Some examples

(a) Original (b) Itti (c) Le Meur (d) Bruce (e) Zhang (f) Judd

Outline

From a fixation map to a saliency map



- Discrete fixation map f^i for the i^{th} observer (M is the number of fixations):

$$f^i(\mathbf{x}) = \sum_{k=1}^{M} \delta(\mathbf{x} - \mathbf{x}_{f(\boldsymbol{k})}) \tag{1}$$

- Continuous saliency map S (N is the number of observers):

$$S(\mathbf{x}) = \left(\frac{1}{N} \sum_{i=1}^{N} f^i(\mathbf{x}) \right) * G_\sigma(\mathbf{x}) \tag{2}$$

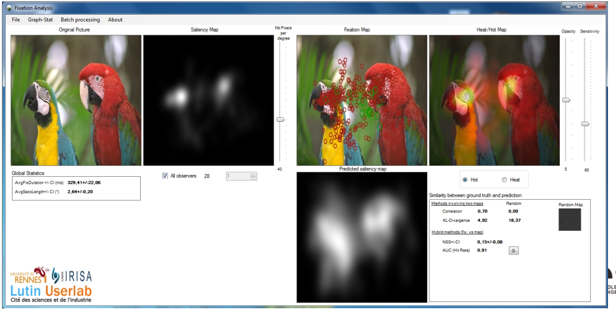
(g) Original (h) Fixation map (i) Saliency map (j) Heat map

Three principal methods

Three principal methods to compare two saliency maps:

- Correlation-based measure;
- Divergence of Kullback-Leibler;
- ROC analysis.

O. Le Meur and T. Baccino, Methods for comparing scanpaths and saliency maps: strengths and weaknesses, Behavior Research Method, 2012



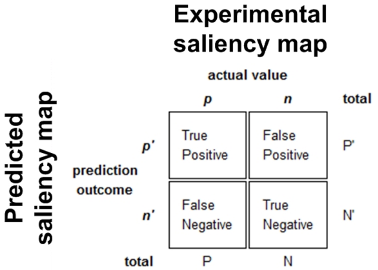
Three principal methods

ROC analysis (1/2)

Definition (ROC)

The Receiver Operating Characteristic (ROC) analysis provides a comprehensive and visually attractive framework to summarize the accuracy of predictions.

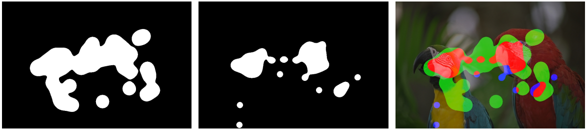
The problem is here limited to a two-class prediction (binary classification). Pixels of the ground truth as well as those of the prediction are labeled either as fixated or not fixated.



- Hit rate (TP)
- ROC curve
- AUC (Area Under Curve)
  - $\rightarrow$ AUC=1 $\Leftrightarrow$ perfect;
    AUC=0.5 $\Leftrightarrow$ random.

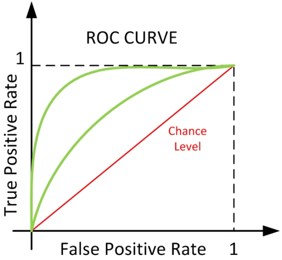
Three principal methods

ROC analysis (2/2)



(a) Reference (b) Predicted (c) Classification

A ROC curve plotting the false positive rate as a function of the true positive rate is usually used to present the classification result.



Advantages:

- + Invariant to monotonic transformation
- + Well defined upper bound

Drawbacks:

- − ...

Hybrid methods

Four methods involving scanpaths and saliency maps :

- Receiver Operating Analysis;
- Normalized Scanpath Saliency [Parkhurst et al.,2002, Peters et al., 2005];
- Percentile [Peters & Itti, 2008];
- The Kullback-Leibler divergence [Itti & Baldi, 2006].

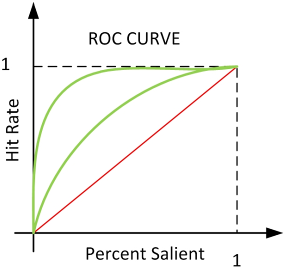
Hybrid methods

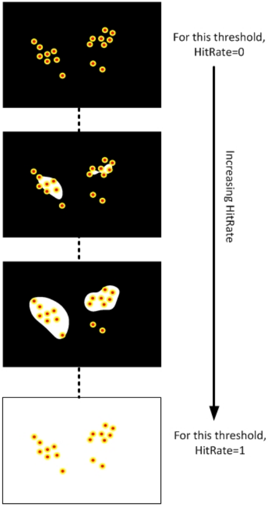
Receiver Operating Analysis

ROC analysis is performed between a continuous saliency map and a set of fixations.

- Hit rate is measured in function of the threshold used to binarize the saliency map [Torralba et al., 2006, Judd et al., 2009]:

ROC curve goes from 0 to 1!

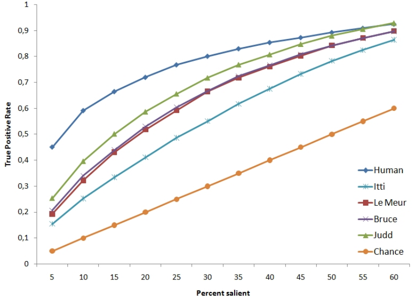




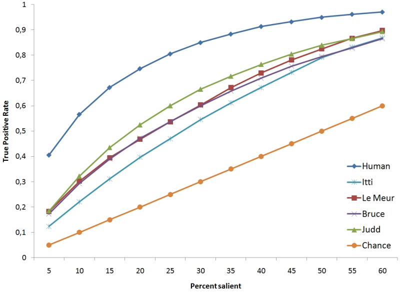
Performances

Comparison of four state-of-the-art models (Hit Rate) by using two dataset of eye movement:

N. Bruce's database:



O. Le Meur's database:



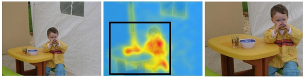
The inter-observer dispersion can be used as to the define the upper bound of a prediction

Outline

Attention-based applications

Understanding how we perceive the world is fundamental for many applications.

- Visual dispersion
- Memorability
- Quality assessment
- Advertising and web usability
- Robot active vision
- Non Photorealistic rendering
- Retargeting / image cropping:

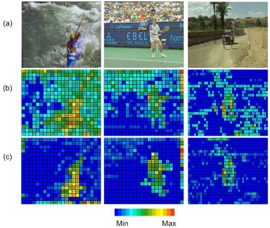


From [Le Meur & Le Callet, 2009]

- Region-of-interest extraction:

From [Liu et al., 2012]

- Image and video compression:



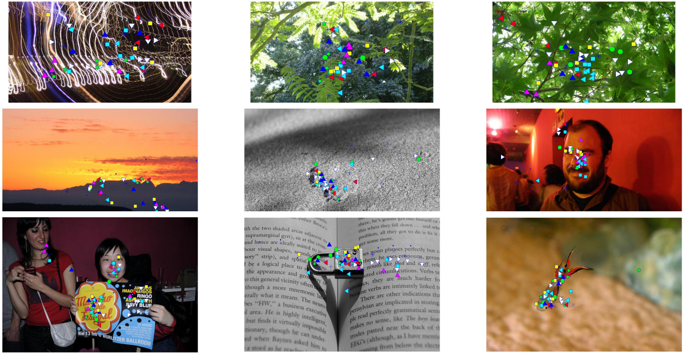
Distribution of the encoding cost for H.264 coding without and with saliency map.

Problematic and context

Definition (Inter-observer visual congruency)

Inter-observer visual congruency (IOVC) reflects the visual dispersion between observers or the consistency of overt attention (eye movement) while observers watch the same visual scene.

Do observers look at the scene similarly?

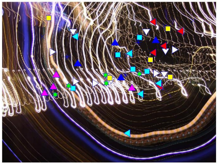


Problematic and context

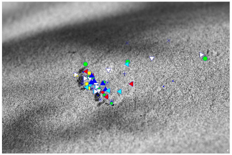
Two issues:

1. Measuring the IOVC by using eye data

LOW



HIGH



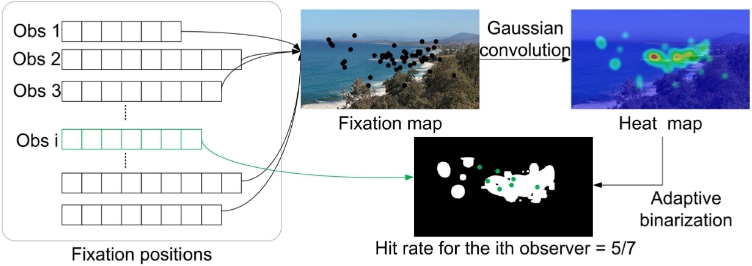
2. Predicting this value with a computational model

O. Le Meur et al., Prediction of the Inter-Observer Visual Congruency (IOVC) and application to image ranking, ACM Multimedia (long paper) 2011.

Measuring the IOVC

To measure the visual dispersion, we use the method proposed by [Torralba et al., 2006]:

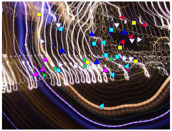
one-against-all approach



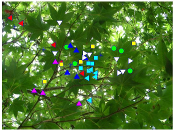
- $IOVC = 1$, strong congruency between observers.
- $IOVC = 0$, lowest congruency between observers.

Measuring the IOVC

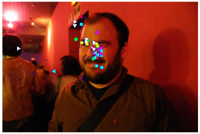
Examples based on MIT eye tracking database



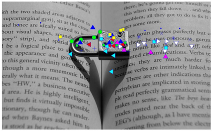
(a) 0.29



(b) 0.23

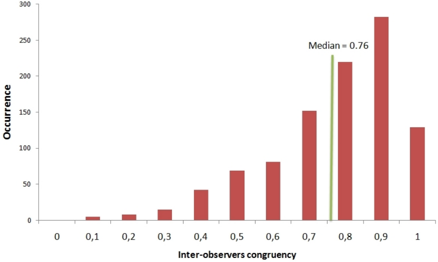


(c) 0.72



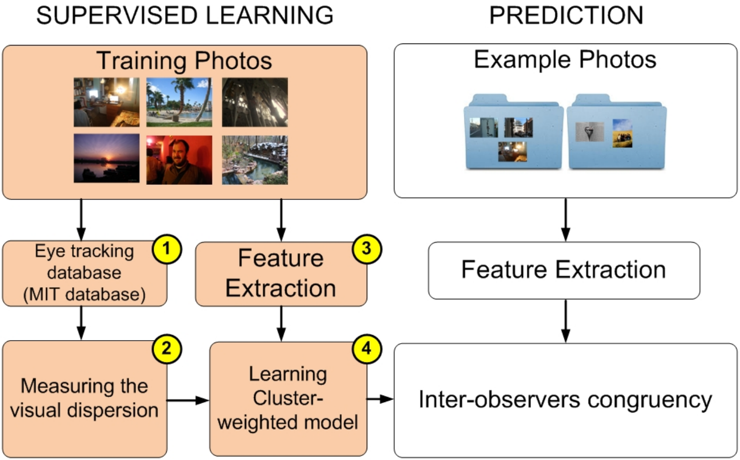
(d) 0.85

For the whole database:



IOVC computational model

Global architecture of the proposed approach:



Feature extraction

6 visual features are extracted from the visual scene:

Mixture between low and high-level visual features

- Color harmony [Cohen et al., 2006]
- Scene complexity:
  - → Entropy E [Rosenholtz et al., 2007]
  - → Number of regions (Color mean shift)
  - → Amount of contours (Sobel detector)
- Faces [Lienhart & Maydt, 2002] (*Open CV*)
- **Depth of Field**

$E = 14.67 dit/pel, \; NbReg = 103$

$E = 14.72 dit/pel, \; NbReg = 72$

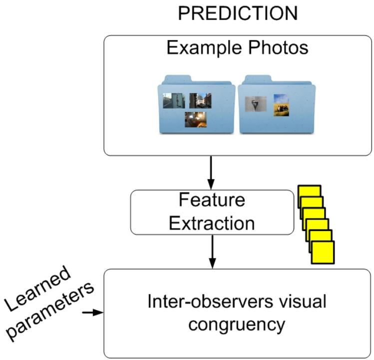
Feature extraction

Depth of Field computation inspired by [Luo et al., 2008]:

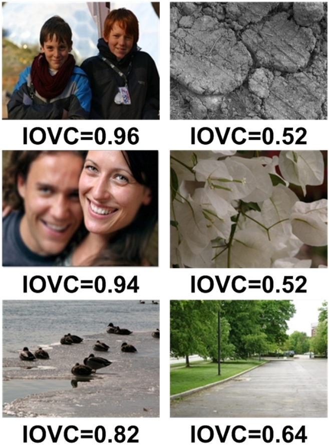
(a) Original (b) DoF=0.12 (c) Original (d) DoF=0.75

Feature extraction

After the learning, we can now predict:



Predicted IOVC:



Performance

Two tracking databases are used to evaluate the performance:

- MIT's dabase (1003 pictures, 15 observers)
- Le Meur's database (27 pictures, up to 40 observers)

(a) 0.94,0.96

We compute the Pearson correlation coefficient between predicted IOVC and 'true' IOVC:

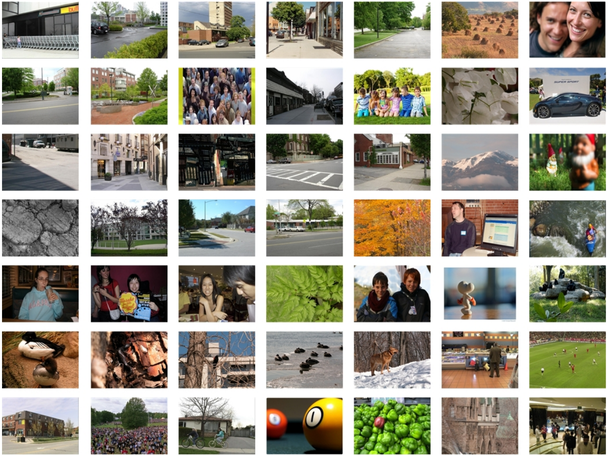
- MIT's dabase:
  $r(2004) = 0.34,\ p < 0.001$
- Le Meur's database:
  $r(54) = 0.24,\ p < 0.17$

(b) 0.89,0.94

(c) 0.91,0.91

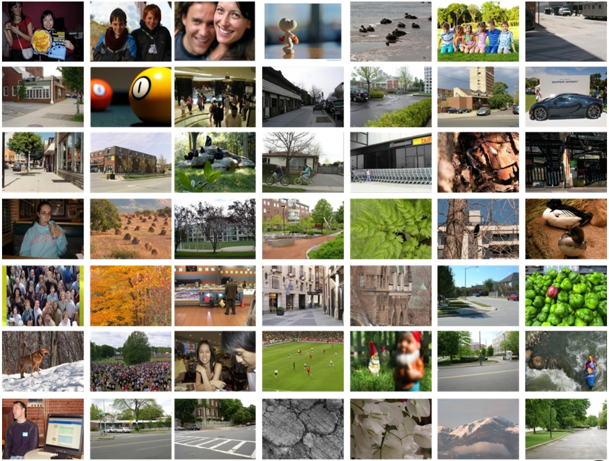
Application to image ranking

Goal: to sort out a collection of pictures in function of IOVC scores.



Application to image ranking

Goal: to sort out a collection of pictures in function of IOVC scores.



Application to image ranking

Goal: to sort out a collection of pictures in function of IOVC scores.

Top five pictures:

IOVC=0.98 IOVC=0.96 IOVC=0.94 IOVC=0.85 IOVC=0.82

Last five pictures:

IOVC=0.46 IOVC=0.52 IOVC=0.52 IOVC=0.64 IOVC=0.64

- can be combined with other factors to evaluate the interestingness or attractivness of visual scenes.

Conclusion

We do not perceive everything at once...

- Visual attention:

Overt	vs	Covert
Bottom-up	vs	Top-Down

- Computational models of visual attention:

  Biologically plausible Probabilistic beyond Bottom-up

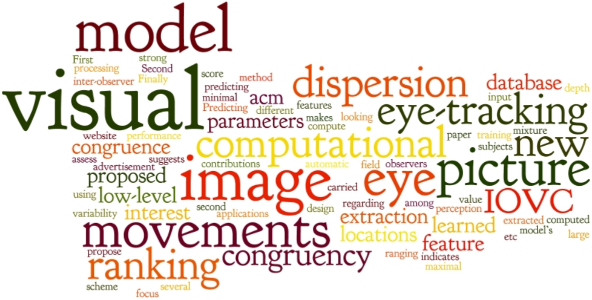
- Performances:

  between a set of fixations and a saliency map
  between two saliency maps

- Saliency-based applications.

Conclusion

Thanks for your attention



A special session has been accepted to WIAMIS'2013 (Paris):

O. Le Meur and Z. Liu, Visual attention, a multidisciplinary topic: from behavioral studies to computer vision applications

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