Modelli computazionali di attenzione visiva

Corso di Interazione uomo-macchina II

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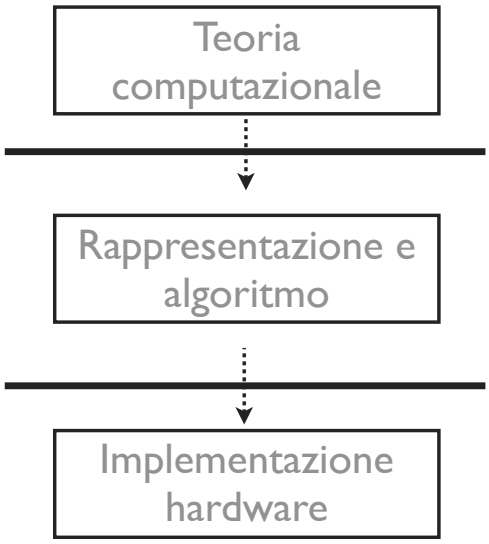
Interazione fra organismi //tecnologie

	Example Social Behaviours							Tech.		
Social Cues	emotion	personality	status	dominance	persuasion	regulation	rapport	speech anlysis	computer vision	biometry
Physical appearance										
height			√	√					√	√
attractiveness		√	√	√	√		√		√	√
body shape		√		√					√	√
Gesture and posture										
hand gestures	√	√			√	√	√		√	√
posture	√	√	√	√	√	√	√		√	√
walking		√	√	√					√	√
Face and eyes behaviour										
facial expressions	√	√	√	√	√	√	√		√	√
gaze behaviour	√	√	√	√	√	√	√		√	
focus of attention	√	√	√	√	√	√	√		√	
Vocal behaviour										
prosody	√	√		√	√		√	√		
turn taking	√	√	√	√		√	√	√		
vocal outbursts	√	√		√	√	√	√	√		
silence	√		√				√	√		
Space and Environment										
distance	√	√	√		√		√		√	
seating arrangement				√	√		√		√	

A. Vinciarelli, M. Pantic, H. Bourlard, *Social Signal Processing: Survey of an Emerging Domain*, Image and Vision Computing (2008)

Modelli nelle scienze cognitive e nella percezione //livelli di spiegazione

Livelli di spiegazione secondo Marr



Modelli nelle scienze cognitive e nella percezione //livelli di spiegazione

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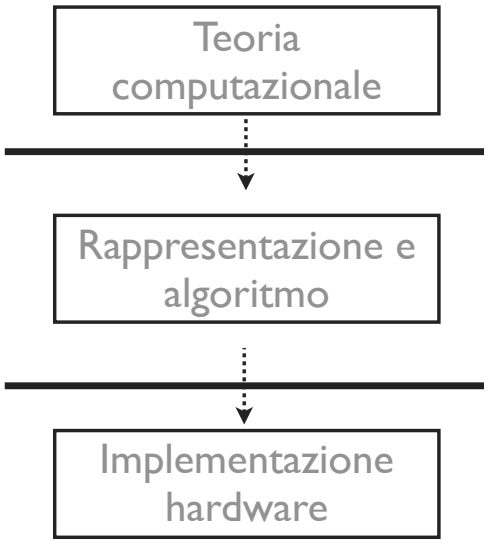
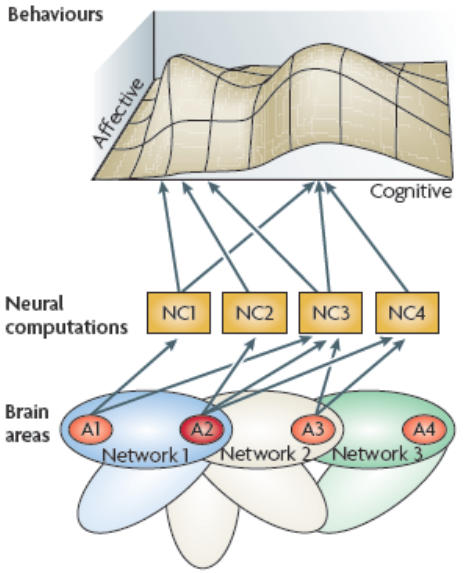
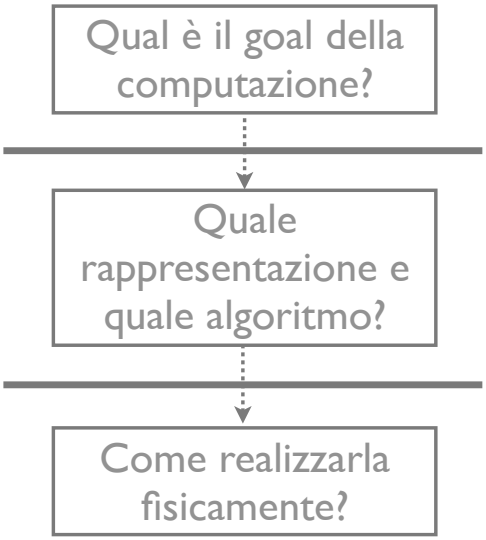




Modelli nelle scienze cognitive e nella percezione //livelli di spiegazione

Modello teorico

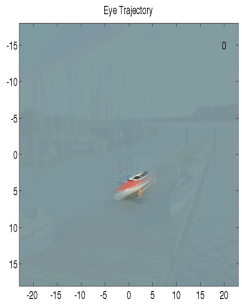
Livelli di spiegazione secondo Marr



Livello psicologico / comportamentale

Livello neurofisiologico

Modelli di attenzione visiva //livelli di spiegazione



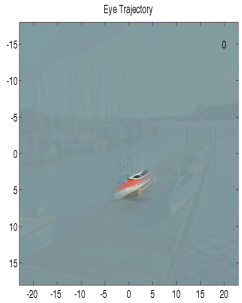
Qual è il goal della computazione?

Quale rappresentazione e quale algoritmo?

Come realizzarla fisicamente?

$$\mathbf{I} \underset{\mathbf{T}}{\mapsto} \{\mathbf{r}_F(1), \mathbf{r}_F(2), \cdots\}$$

Modelli di attenzione visiva //livelli di spiegazione



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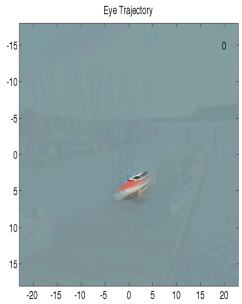

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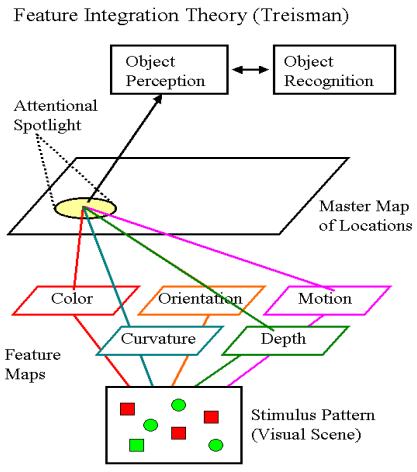
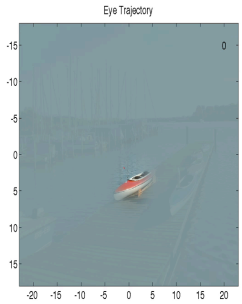
Come realizzarla fisicamente?

Un semplice modello computazionale //Itti e Koch

- Nella sua formulazione originale è un modello bottom-up:
  - ha alla base il concetto di salienza degli stimoli fisici
- Basato sul modello psicologico della Treisman (FIT)



Modelli di attenzione visiva //livelli di spiegazione



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guardo i punti salienti

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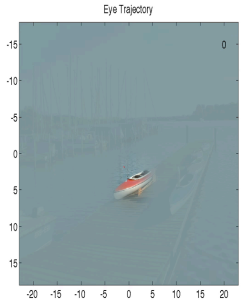
$\arg\max \mathcal{R}$

scelgo il più saliente

Modelli di attenzione visiva //livelli di spiegazione



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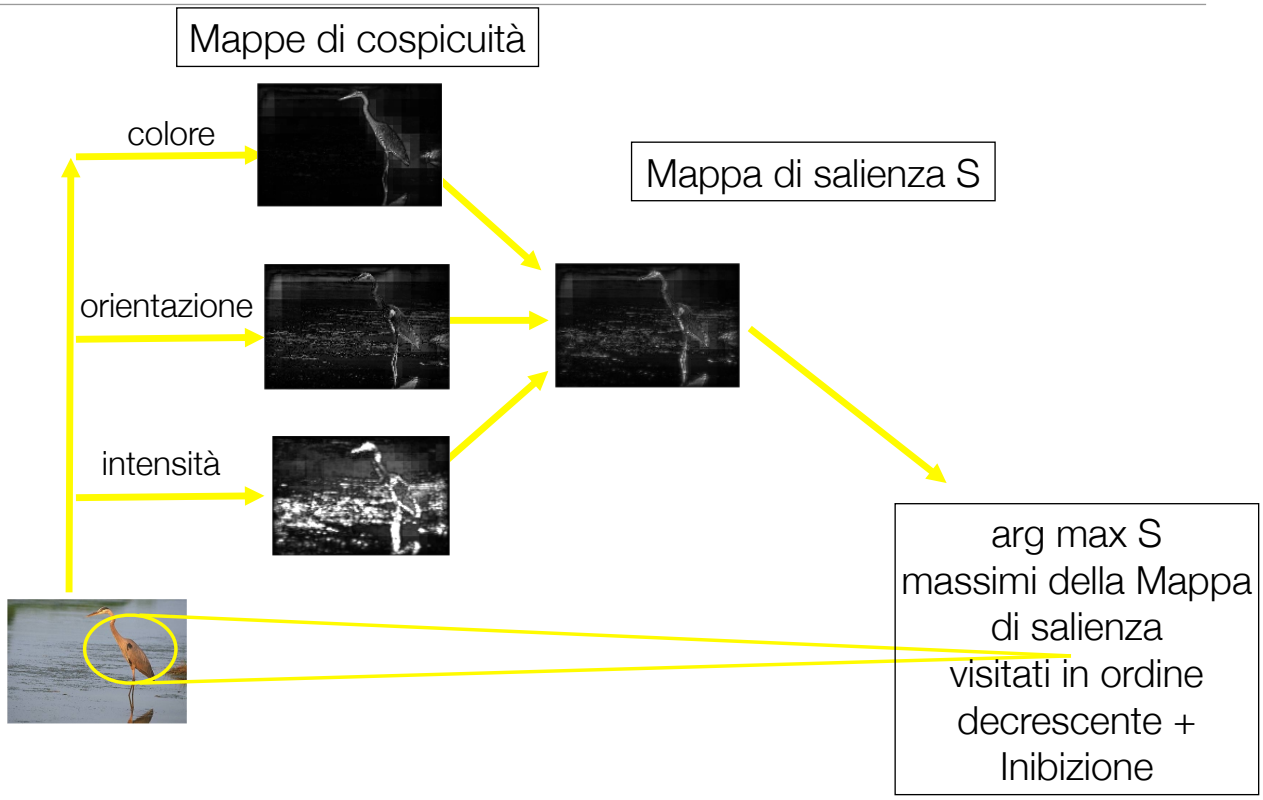
Un semplice modello computazionale //Itti e Koch: algoritmo



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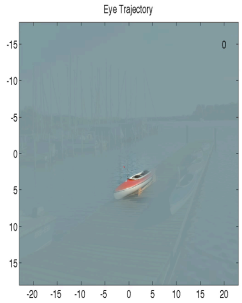

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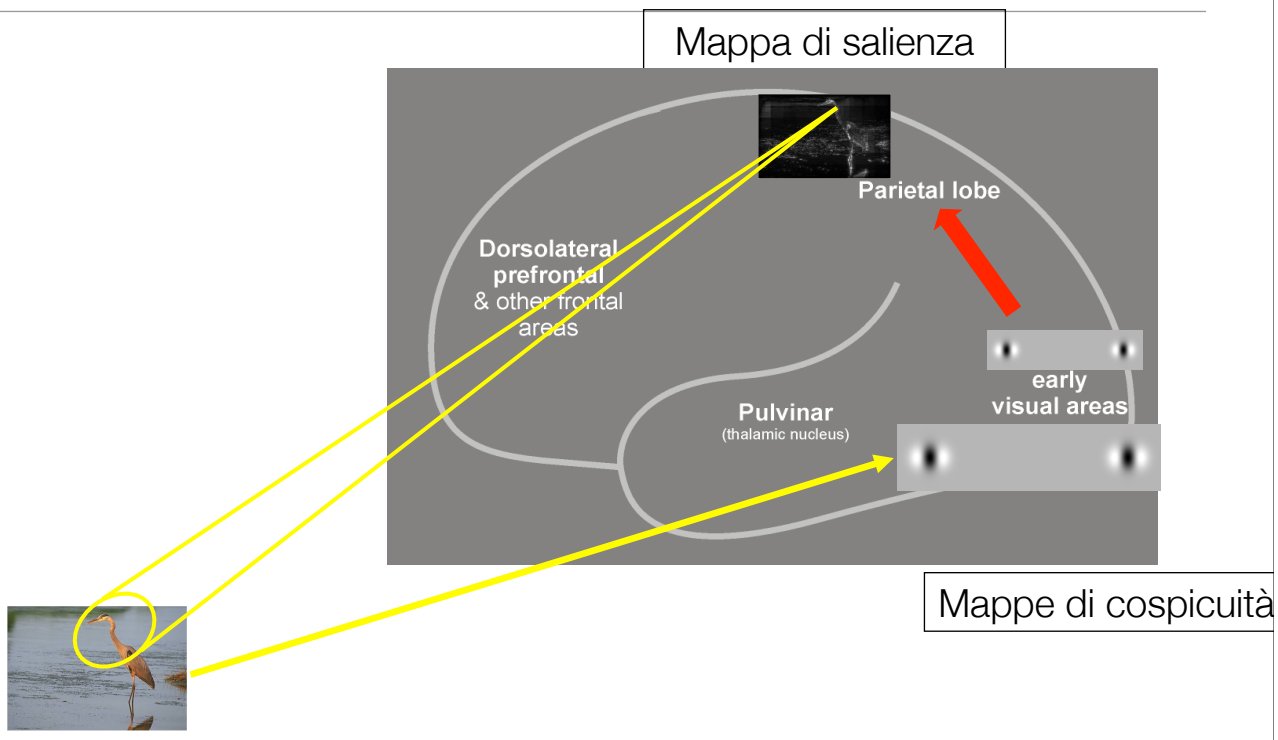
Un semplice modello computazionale //Itti e Koch: implementazione neurale



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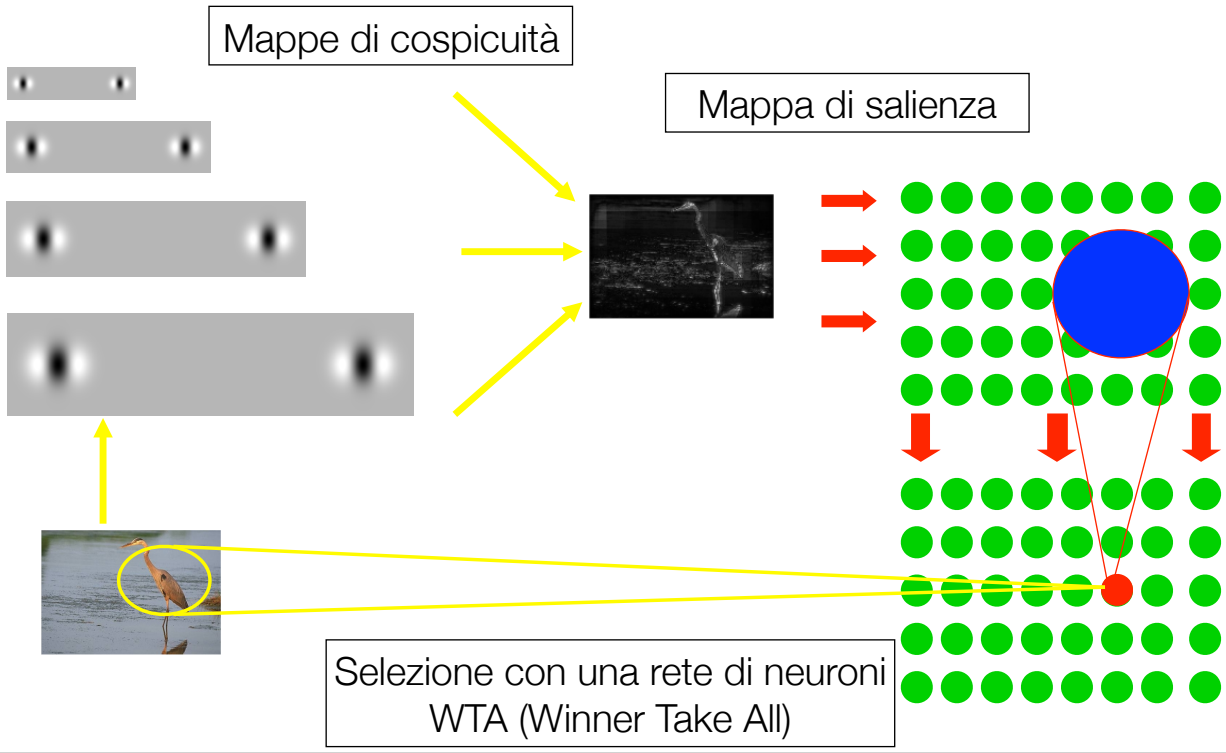
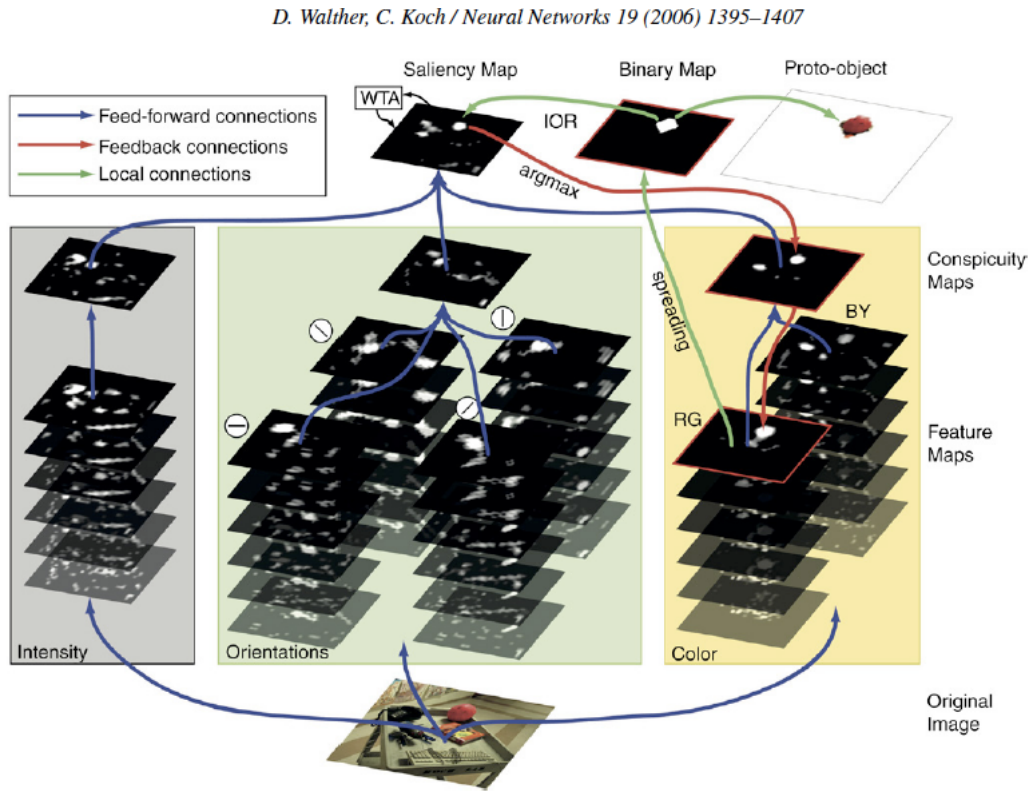
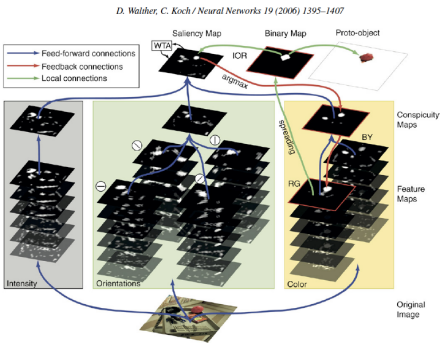


Un semplice modello computazionale //Itti e Koch



Un semplice modello computazionale //Itti e Koch

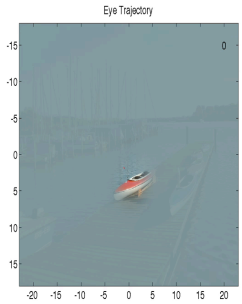


Free Matlab Code:

toolbox ufficiale: http://www.saliencytoolbox.net

diverse versioni: http://www.klab.caltech.edu/~harel/share/gbvs.php

Modelli di attenzione visiva //livelli di spiegazione



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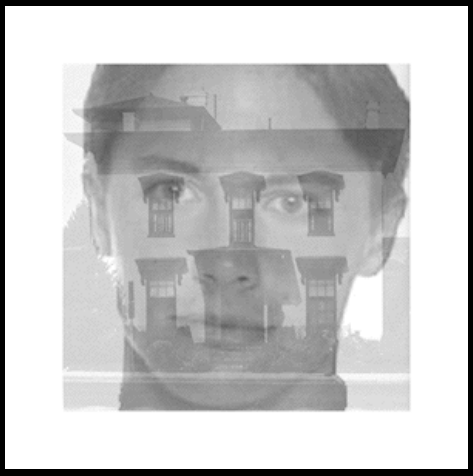
What gets selected? Object Based Attention



- O'Craven et al. (1999)

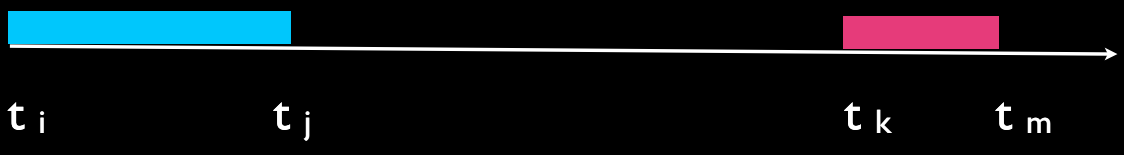
What gets selected? Object Based Attention

- Summing up:
  - Importance of 'object-based' processes in dynamic tasks
  - Center-of-mass capture of attention
  - Physical constraints: objects vs. substances
  - Dynamic tuning of the Focus of Attention (FOA)

Towards event-based attention

People walking together

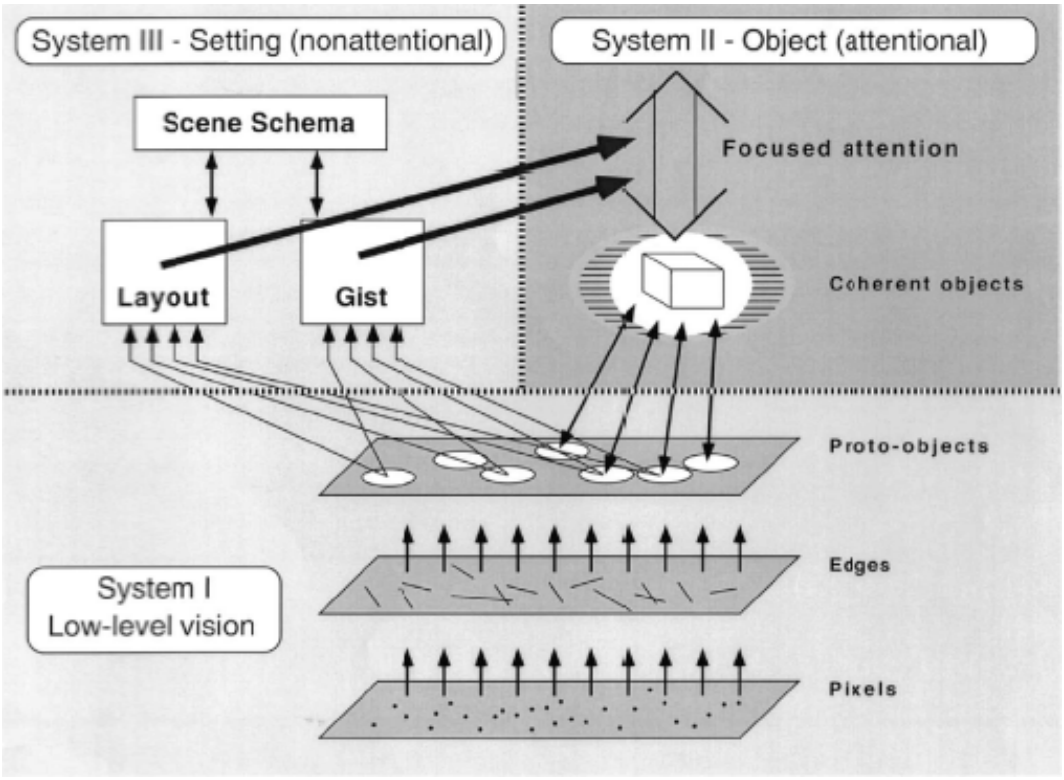
People fighting



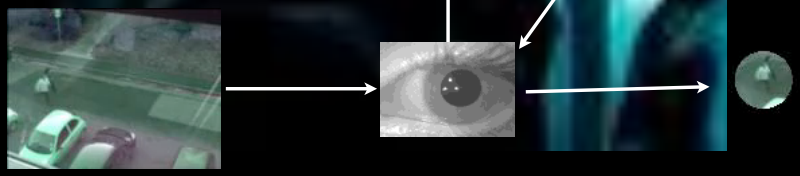
Towards event-based attention

- Nearly all of the work on attention concerns static objects, or moving objects
- Attention may also interact directly with information which is inherently dynamic, e.g. stereotypical motions

Livello di spiegazione psicologico
//rappresentazione dinamica di scene (Rensink)



Modelling visual attention



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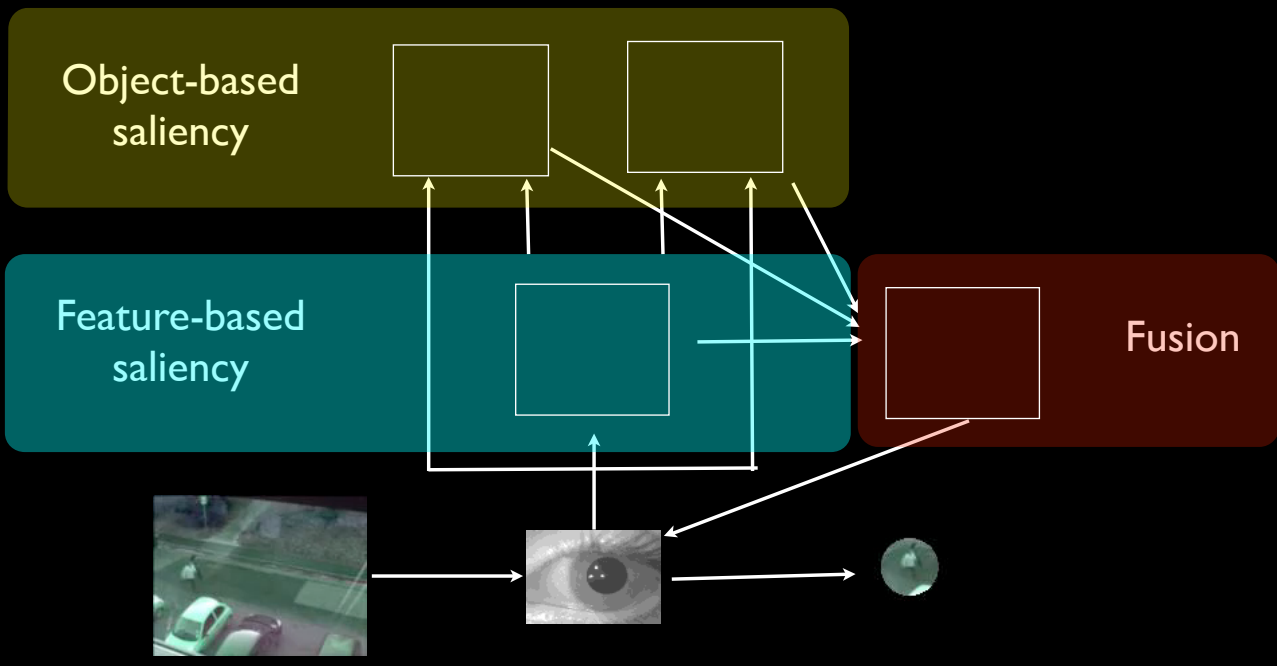
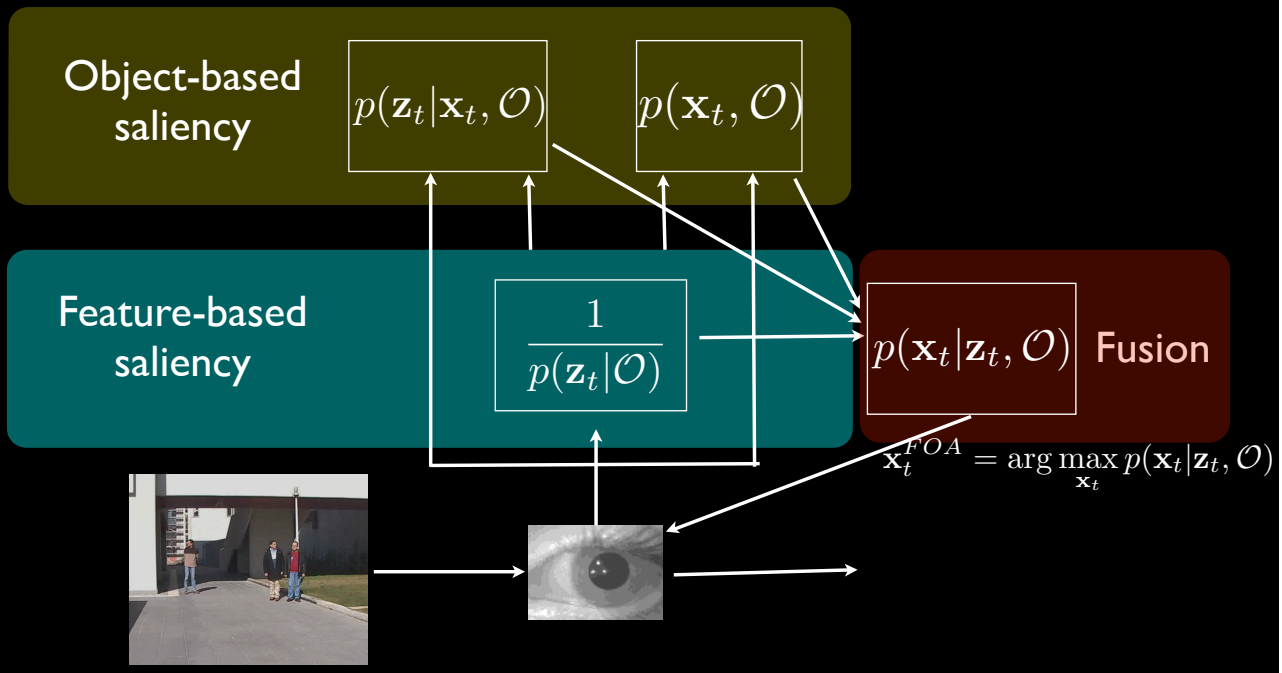


Modelling visual attention:

Vision as an inference process



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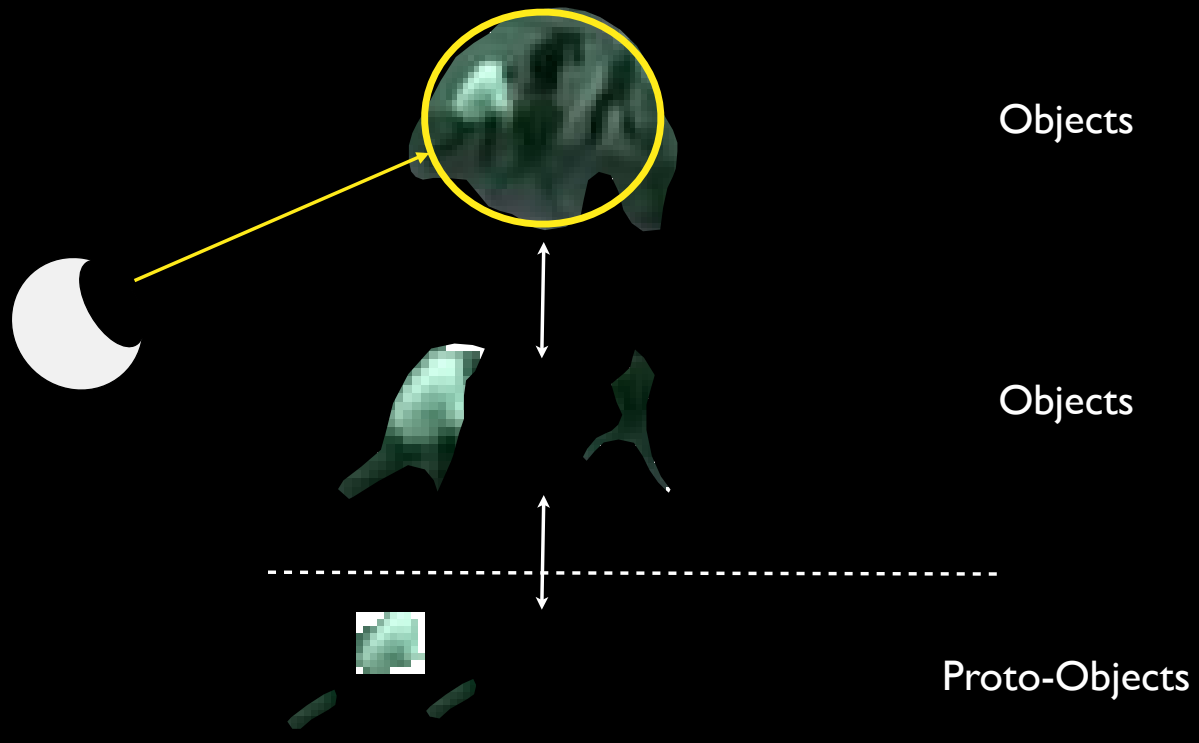

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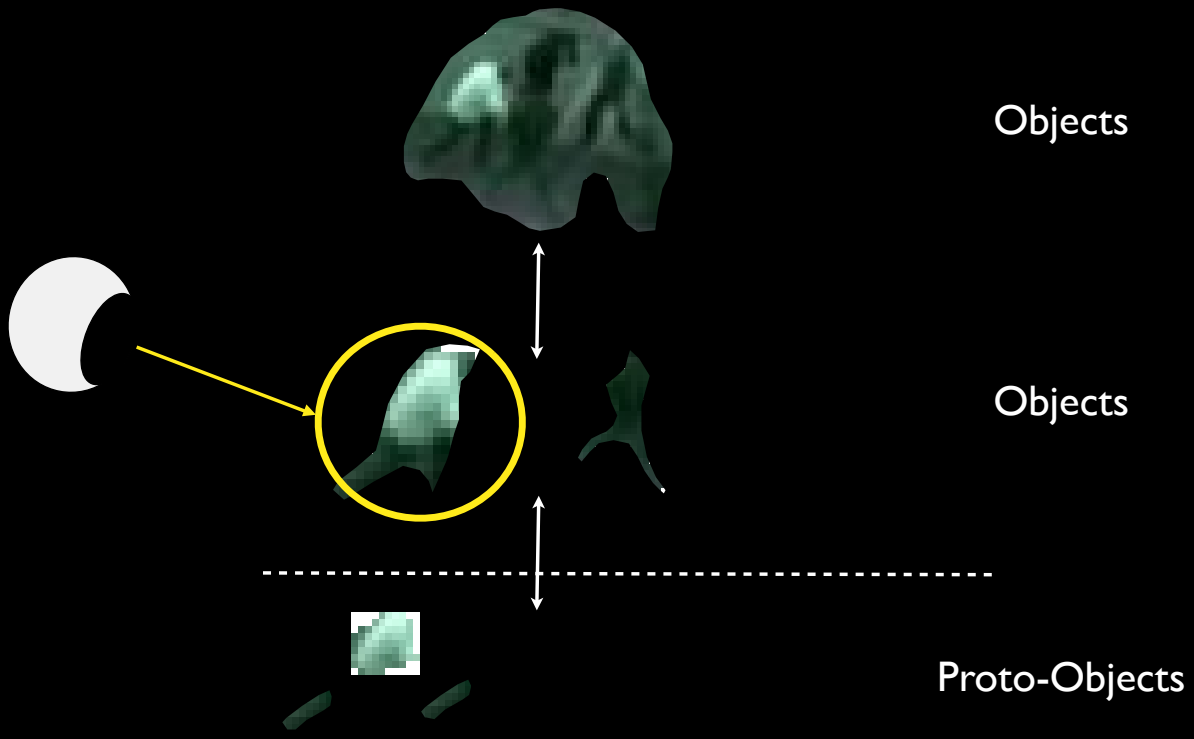

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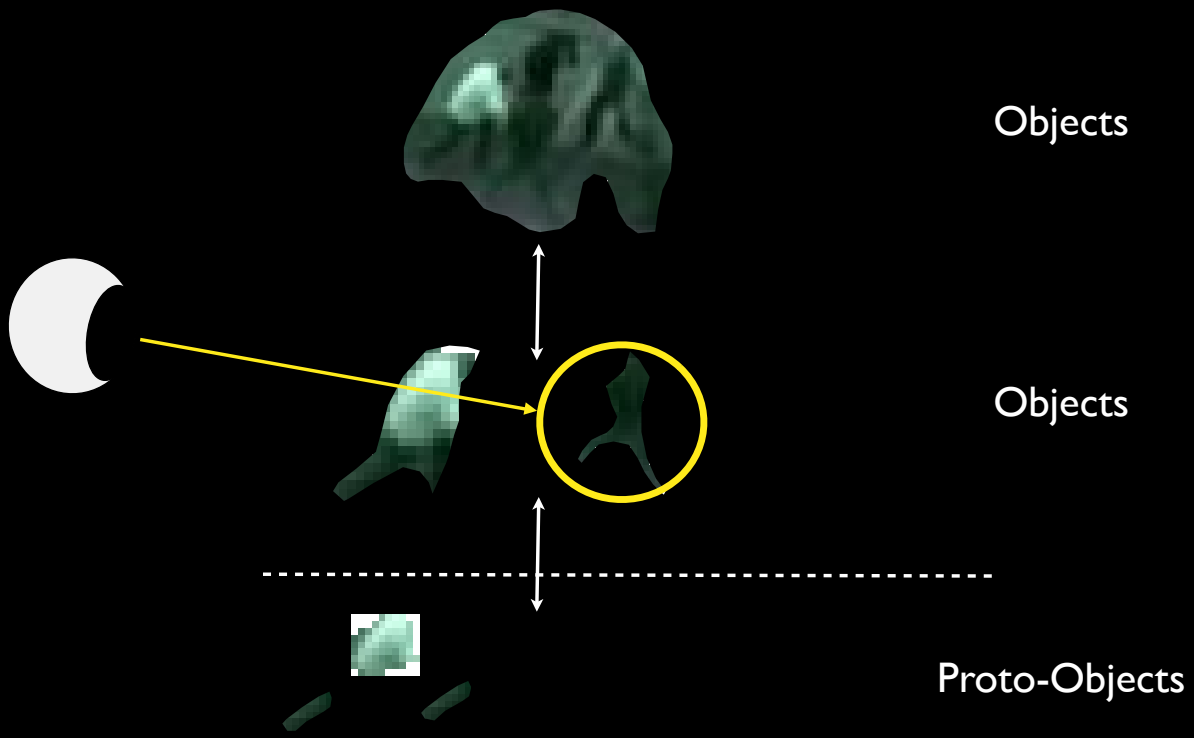

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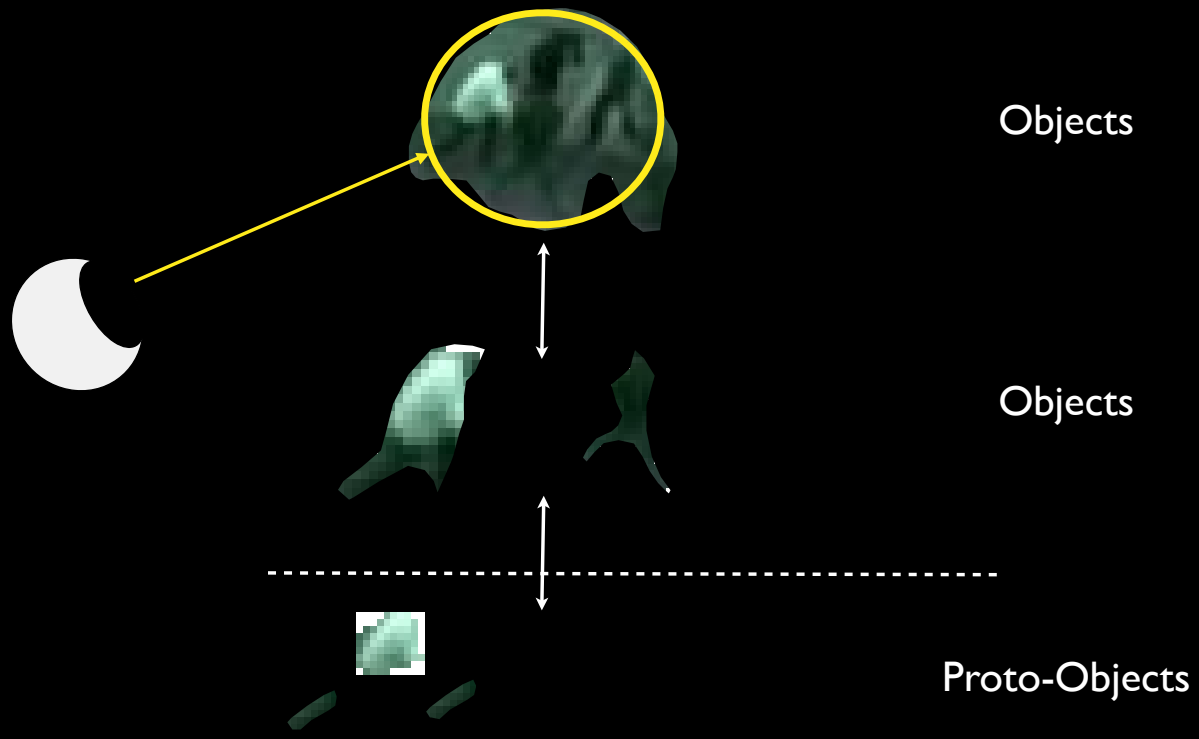
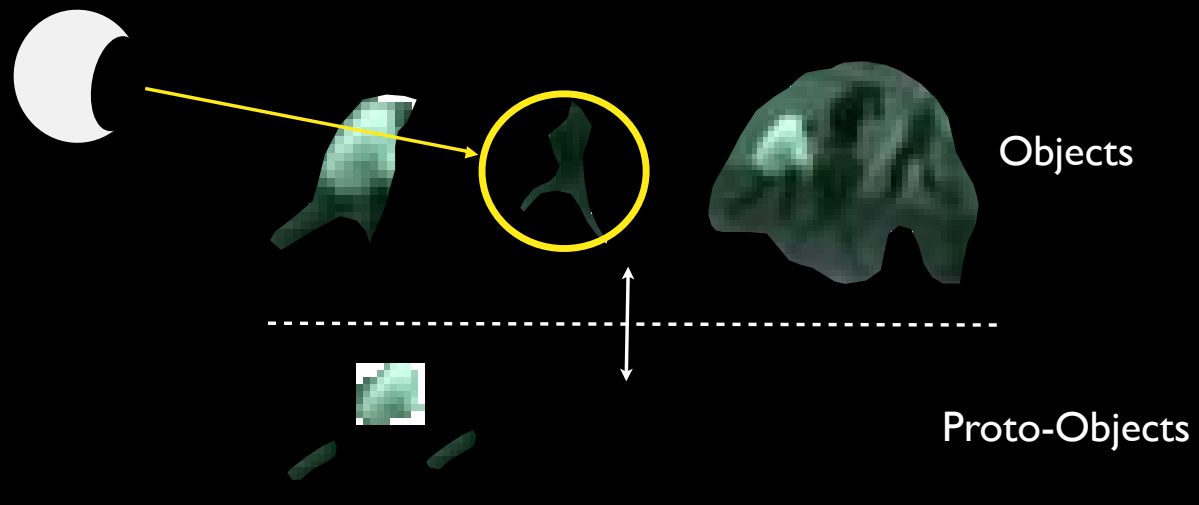


Towards event-based attention: may not be hierarchical



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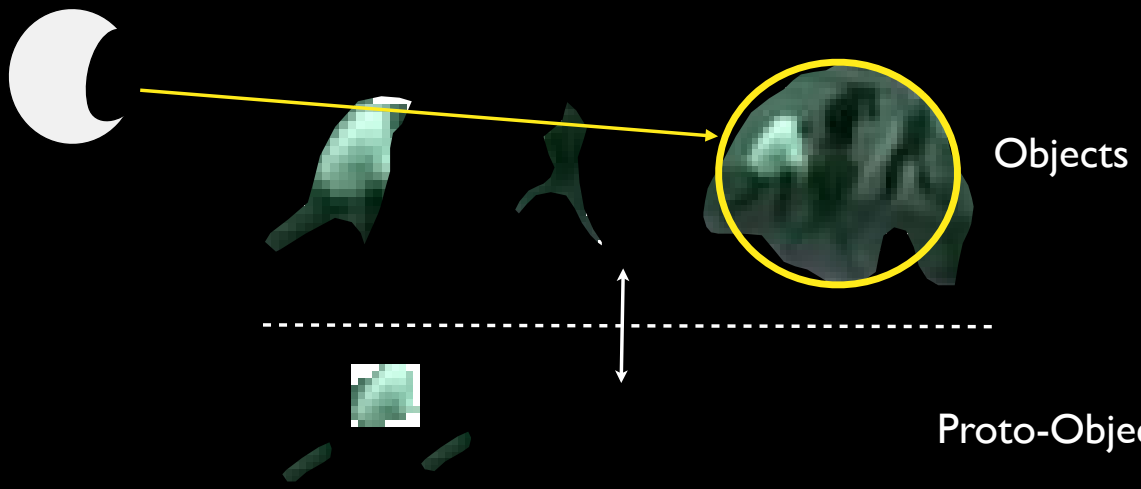


Towards event-based attention: a Bayesian model

$$O_t = \{\mathbf{r}_t, \mathcal{A}_t, \mathcal{O}\}$$

Observed (spatio-temporal) features

$$\mathbf{x}_{n,t} = \{\mathbf{x}^{col}_{n,t}, \mathbf{x}^{vel}_{n,t}, \mathbf{x}^{space}_{n,t}\}$$

color velocity coordinates

Towards event-based attention: a Bayesian model

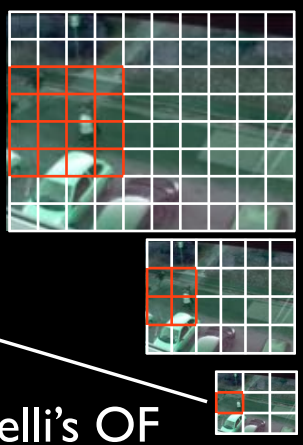
Observed (coarse) velocity features

$$\arg\max p(\mathbf{x}_t^{vel} | \frac{\partial x_t^L}{\partial \mathbf{r}}, \frac{\partial x_t^L}{\partial t}) \propto$$
$$\arg\max p(\frac{\partial x_t^L}{\partial t} | \mathbf{x}_t^{vel}, \frac{\partial x_t^L}{\partial \mathbf{r}}) p(\mathbf{x}_t^{vel})$$

Gaussian Gaussian

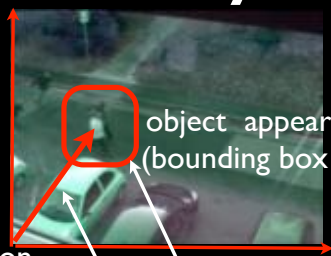
$$\mathbf{x}_{n,t} = \{\mathbf{x}_{n,t}^{col}, \mathbf{x}_{n,t}^{vel}, \mathbf{x}_{n,t}^{space}\}$$

velocity



Simoncelli's OF

Towards event-based attention: a Bayesian model



object appearance (bounding box dim)

object label

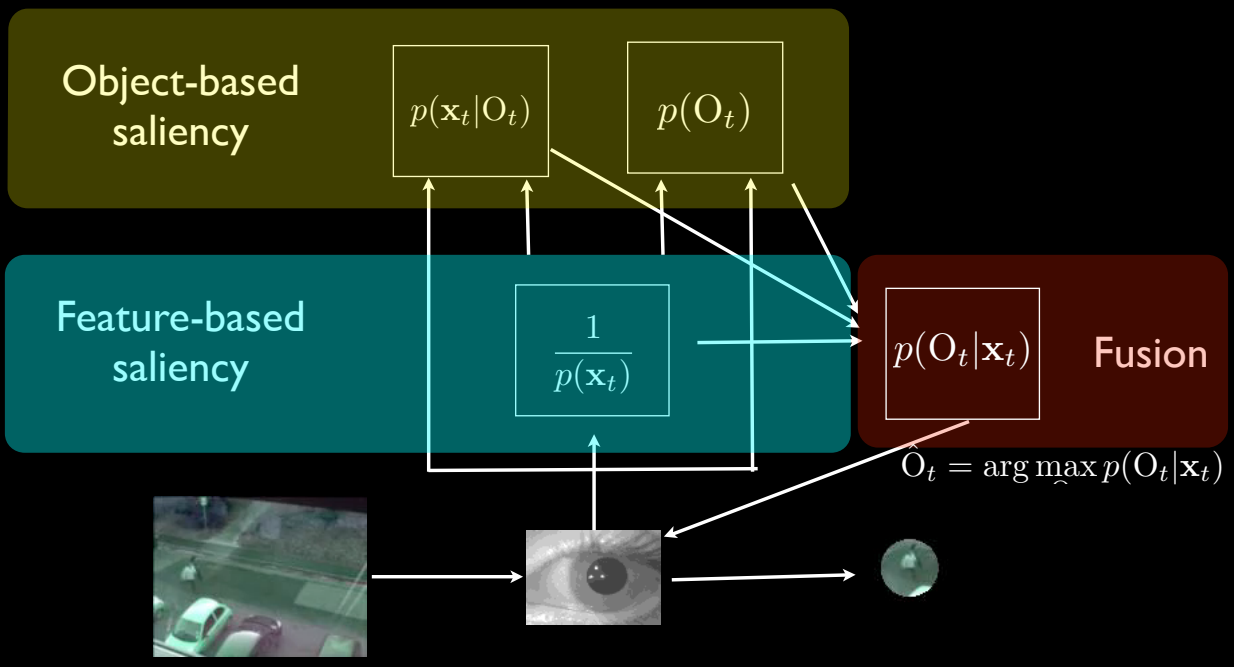
object location (center of mass)

$$O_t = \{\mathbf{r}_t, \mathcal{A}_t, \mathcal{O}\}$$

observations

$$\mathbf{x}_{n,t} = \{\mathbf{x}_{n,t}^{col}, \mathbf{x}_{n,t}^{vel}, \mathbf{x}_{n,t}^{space}\}$$

Eye-movements and visual attention



Towards event-based attention: a Bayesian model

Objects/Groups of Objects features (e.g., velocity)

Focus based on appearance & objects

$$p(\mathrm{O}_t|\mathbf{x}_t) \simeq \frac{p(\mathbf{x}_t|\mathbf{r}_t,\mathcal{A}_t,\mathcal{O})p(\mathbf{r}_t,|\mathcal{A}_t,\mathcal{O})}{p(\mathbf{x}_t)}$$

Low-level saliency & proto-object segmentation

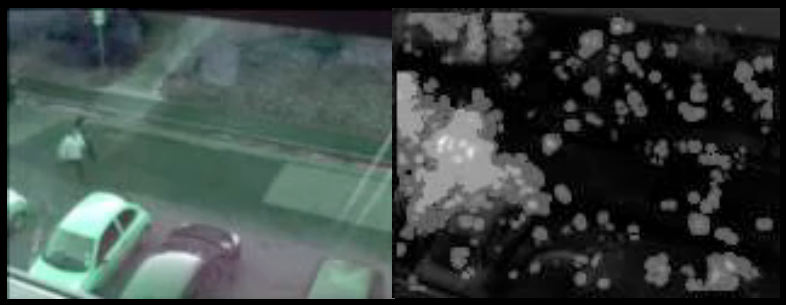
A Bayesian model: proto-objects & saliency

$$p(\mathrm{O}_t|\mathbf{x}_t) \simeq \frac{p(\mathbf{x}_t|\mathbf{r}_t,\mathcal{A}_t,\mathcal{O})p(\mathbf{r}_t,|\mathcal{A}_t,\mathcal{O})}{p(\mathbf{x}_t)}$$

Low-level saliency & proto-object segmentation

Expectation-Maximization

A Bayesian model: saliency



Feature-based saliency $\frac{1}{p(\mathbf{x}_t)}$

A Bayesian model: feature likelihood given proto-objects

Objects/Groups of Objects features (e.g., velocity)

$$p(\mathrm{O}_t|\mathbf{x}_t) \simeq \frac{p(\mathbf{x}_t|\mathbf{r}_t,\mathcal{A}_t,\mathcal{O})p(\mathbf{r}_t,|\mathcal{A}_t,\mathcal{O})}{p(\mathbf{x}_t)}$$

$$\mathrm{p}(\mathbf{x}_t|\mathbf{r}_t,\mathcal{A}_t,\mathcal{O}) = \frac{exp\{(\mathbf{x}_{n,t}^{vel}-\tilde{\mu}_k^{vel})^2\}}{\sum_n exp\{(\mathbf{x}_{n,t}^{vel}-\tilde{\mu}_k^{vel})^2}$$

1) significant mean velocity

2) large spatial support, with respect to spatiotemporal blobs that have non null velocity but tiny space/time support

A Bayesian model: feature likelihood given proto-objects

$$\mathrm{p}(\mathbf{x}_t|\mathbf{r}_t,\mathcal{A}_t,\mathcal{O}) = \frac{exp\{(\mathbf{x}_{n,t}^{vel}-\tilde{\mu}_k^{vel})^2\}}{\sum_n exp\{(\mathbf{x}_{n,t}^{vel}-\tilde{\mu}_k^{vel})^2}$$

A Bayesian model: fixation probability

Focus based on appearance & objects

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$$\mathrm{p}(\mathbf{r}_t|\mathcal{A}_t,\mathcal{O}) = w_i\mathcal{N}(\mathbf{r}_t;\mu_{R_i},\Sigma_{R_i}), \mathbf{r}_t \in R_i$$

(width, height) of region R

importance weight of region Ri

$$w_i = |R_i|/M_R$$

A Bayesian model: fixation probability

$$\mathrm{p}(\mathbf{r}_t|\mathcal{A}_t,\mathcal{O}) = w_i\mathcal{N}(\mathbf{r}_t;\mu_{R_i},\Sigma_{R_i}), \mathbf{r}_t \in R_i$$

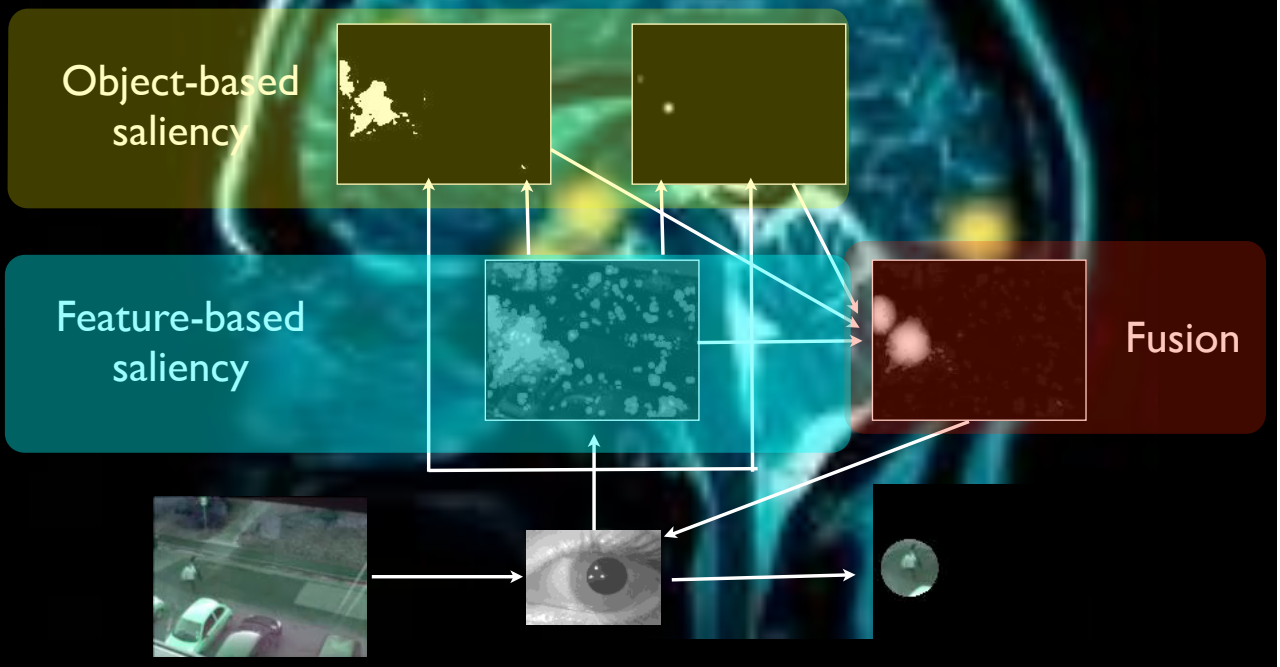
A Bayesian model: inference

$$p(\mathrm{O}_t|\mathbf{x}_t) \simeq \frac{p(\mathbf{x}_t|\mathbf{r}_t,\mathcal{A}_t,\mathcal{O})p(\mathbf{r}_t,|\mathcal{A}_t,\mathcal{O})}{p(\mathbf{x}_t)}$$

A Bayesian model: gaze selection

$$\hat{\mathrm{O}}_t = \arg\max_{\mathrm{O}_t} p(\mathrm{O}_t|\mathbf{x}_t)$$

The final picture



More examples

from: BEHAVE Interactions Test Case Scenarios
http://groups.inf.ed.ac.uk/vision/BEHAVEDATA/

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Example 1 (unconstrained)

Average eye-tracked (36 observers)

Bayesian Model

Example 2

Example 2 (unconstrained)

Average eye-tracked (36 observers)

Bayesian Model

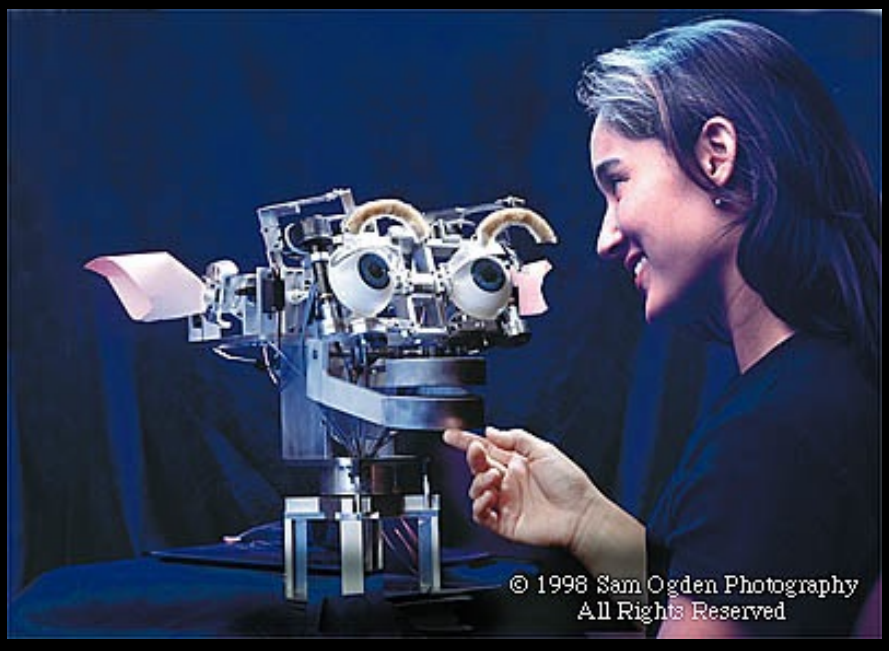
Example 2 (constrained)

Average eye-tracked (36 observers)

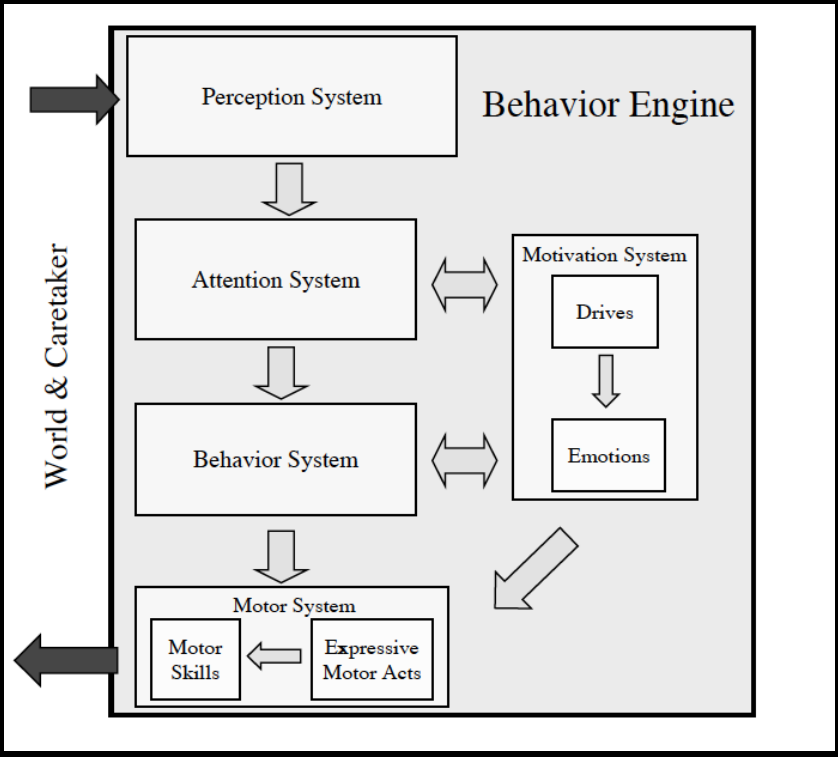
Bayesian Model

Situating vision in the world

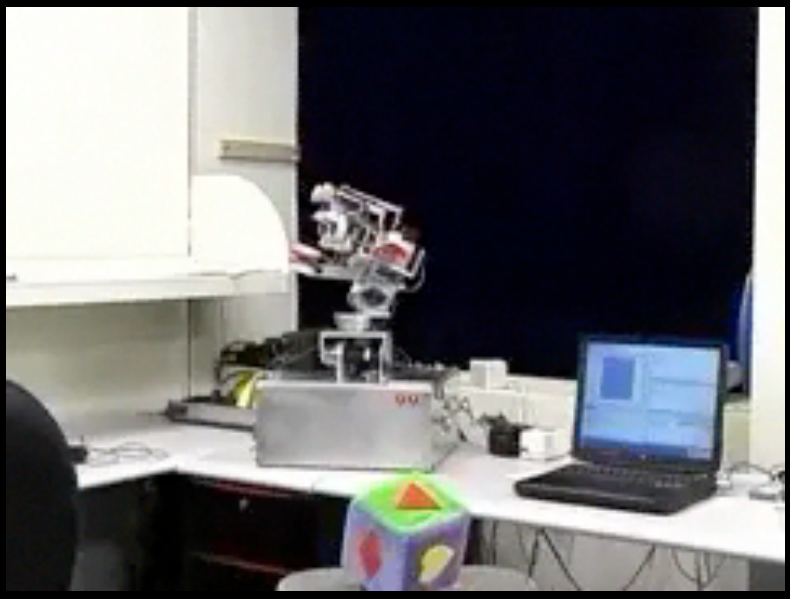
Situating vision in the world



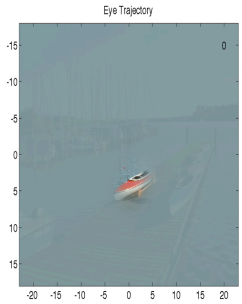
Situating vision in the world



Situating vision in the world



Modelli di attenzione visiva //livelli di spiegazione



Qual è il goal della computazione?

Quale rappresentazione e quale algoritmo?

Come realizzarla fisicamente?

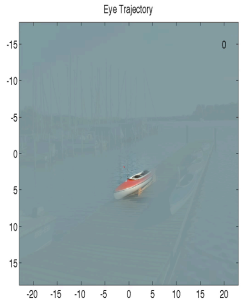
che cosa guardo

$\mathbf{I} \mapsto \mathcal{R}$

$\mathcal{R} \mapsto \{\mathbf{r}_F(1), \mathbf{r}_F(2), \cdots\}$

come guardo

Modelli di attenzione visiva //livelli di spiegazione: problema della variabilità



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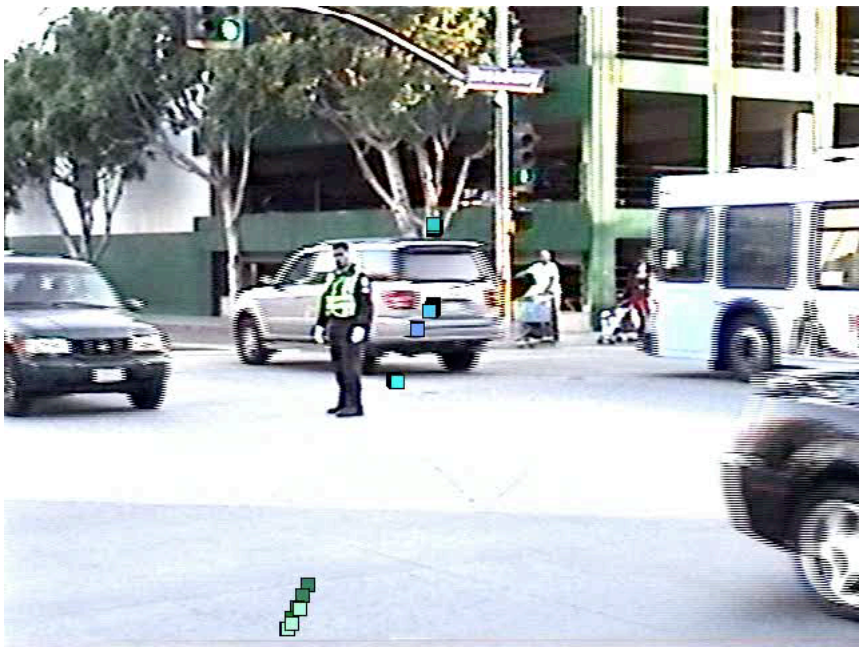
Modelli di attenzione visiva
//livelli di spiegazione: problema della variabilità

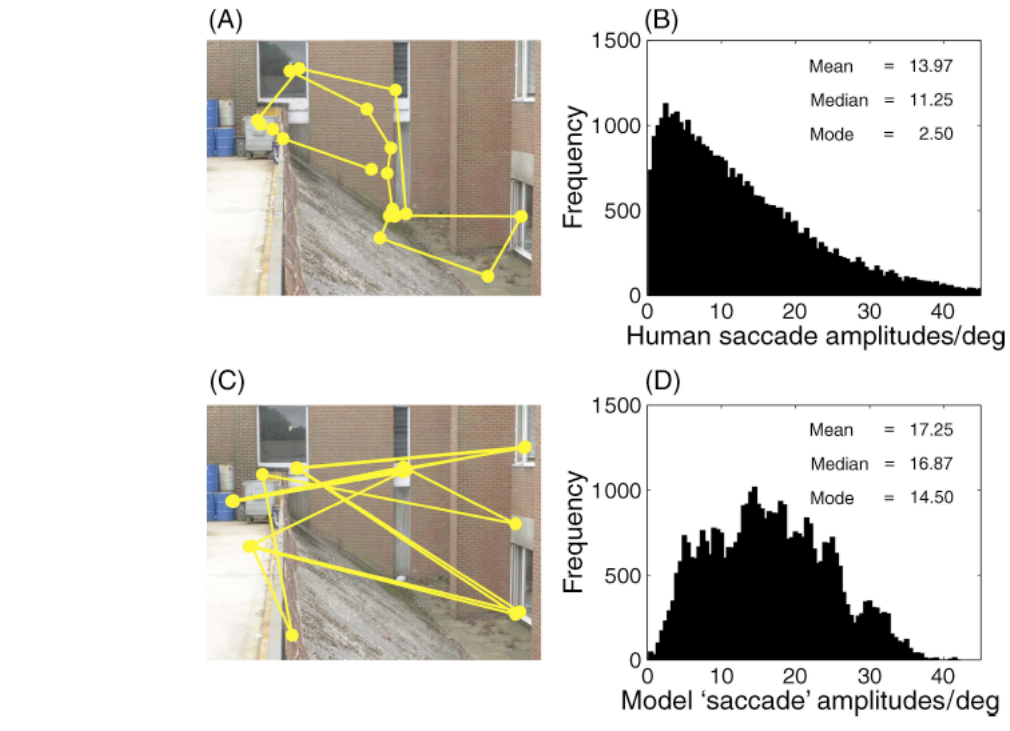


Modelli di attenzione visiva
//livelli di spiegazione: problema della variabilità

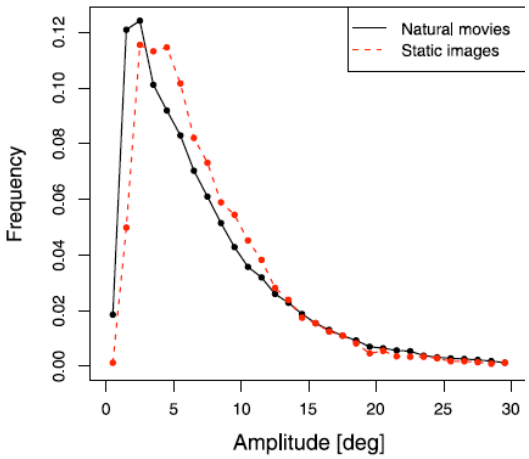
Modelli di attenzione visiva
//livelli di spiegazione: problema della variabilità

Modelli di attenzione visiva
//livelli di spiegazione: problema della variabilità

Journal of Vision (2011) 11(5):5, 1–23



Modelli di attenzione visiva
//livelli di spiegazione: problema della variabilità



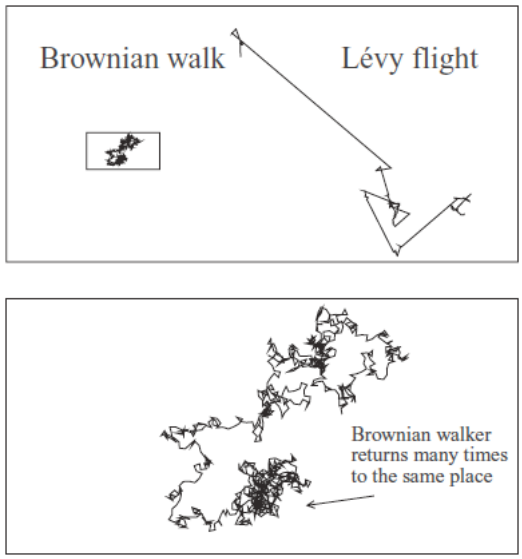
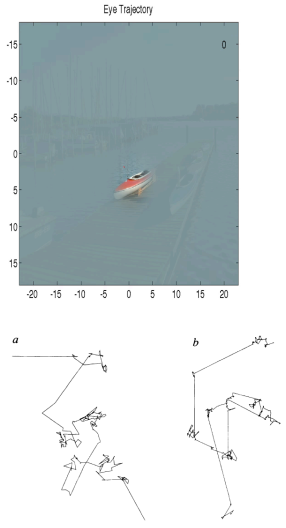
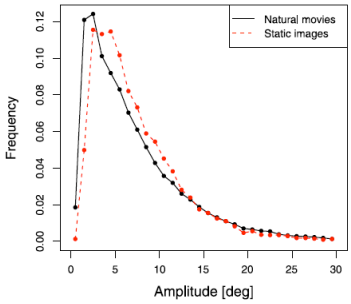
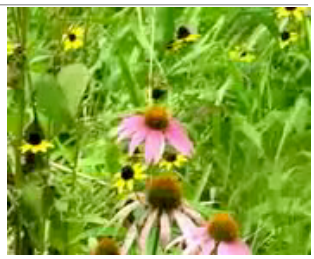


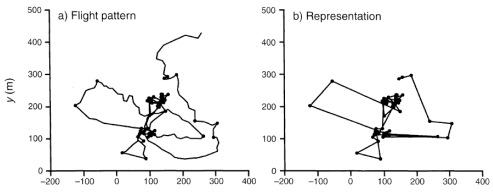
Figure 5.2 Two-dimensional Brownian random walk and Lévy flight of identical total length of 1000 units, shown to scale. (Bottom) Zoom of the Brownian walk. Note how the Brownian walker returns many times to previously visited locations, a phenomenon known as *oversampling*. In contrast, the Lévy flyer frequently takes ultralong jumps to virgin territory. This reduction in oversampling is part of the fundamental theoretical basis for interest in the Lévy flight foraging hypothesis.

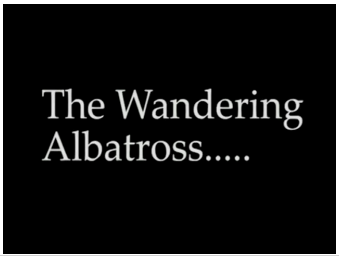
Modelli di attenzione visiva
//livelli di spiegazione: problema della variabilità

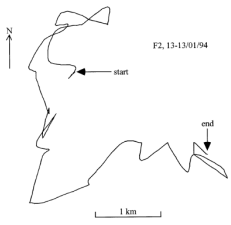




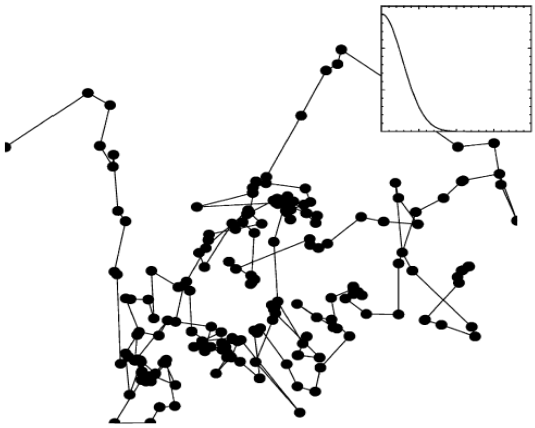




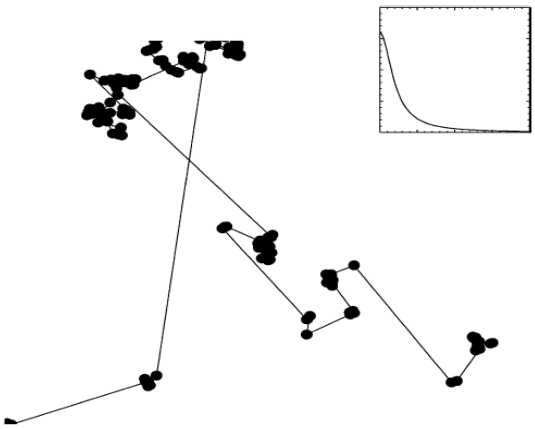




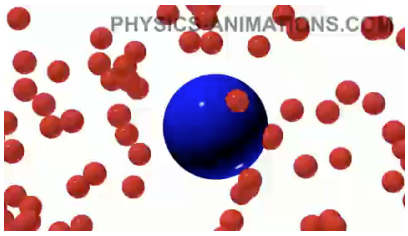
Modelli di attenzione visiva
//livelli di spiegazione: problema della variabilità



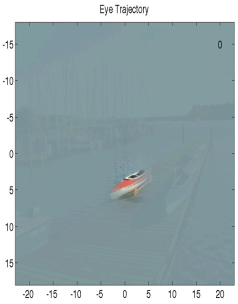
random walk Browniano



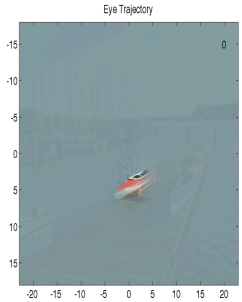
volo di Levy



$$\mathbf{r}_{new}(t) = \mathbf{r}(t) - \nabla V + \boldsymbol{\eta}$$



Modelli di attenzione visiva
//livelli di spiegazione: problema della variabilità



che cosa guardo

$\mathbf{I} \mapsto \mathcal{R}$

$\mathbf{r}_{new}(t) = \mathbf{r}(t) - \nabla V + \boldsymbol{\eta}$

come guardo

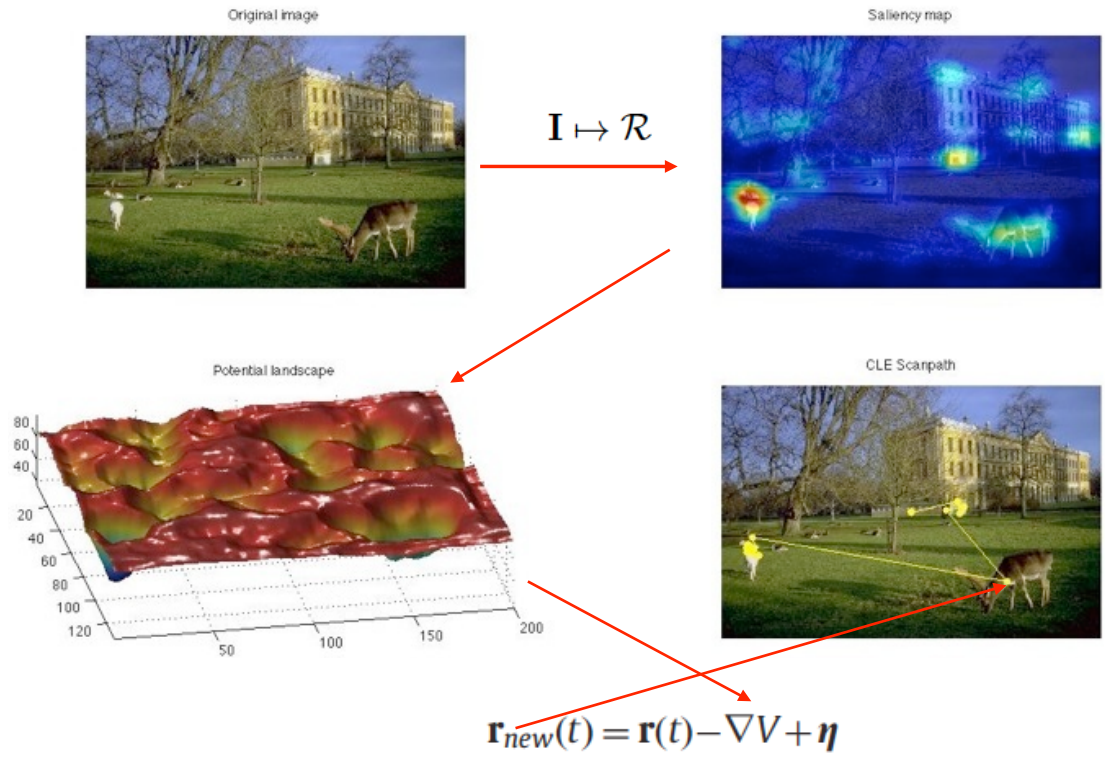
Qual è il goal della computazione?

Quale rappresentazione e quale algoritmo?

Come realizzarla fisicamente?

simulazione Monte Carlo con accettazione Metropolis

Modelli di attenzione visiva
//livelli di spiegazione: problema della variabilità



Modelli di attenzione visiva
//livelli di spiegazione: problema della variabilità

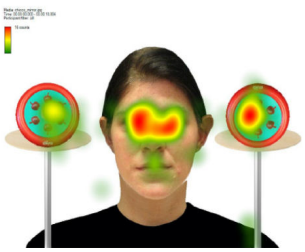
Free Matlab Code:

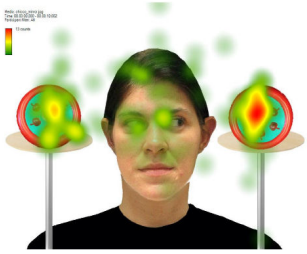
toolbox ufficiale su Matlab Central:

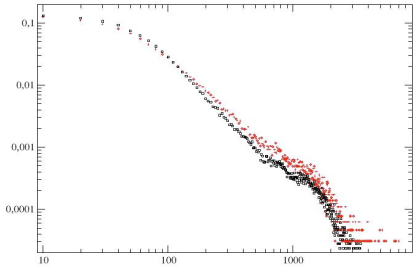
http://www.mathworks.com/matlabcentral/fileexchange/38512-visual-scanpaths-via-constrained-levy-exploration-of-a-saliency-landscape

Modelli di attenzione visiva
//livelli di spiegazione: problema della variabilità

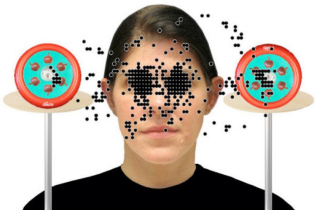
- Caratterizzazione di pazienti autistici

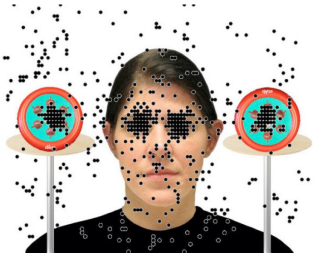






Experimental heat maps: TDs (left) and ASDs (right)





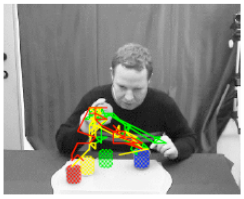
1000 points generated by the model for T=10 (left) and T=100 (right) placed over a stimulus.

T is a sort of "attentional temperature", which seems to be able to describe the transition from TDs to ASDs visual behavior

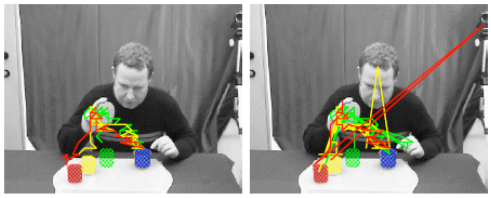
//the iCub

Modelli di attenzione visiva //livelli di spiegazione: problema della variabilità

- Apprendimento stocastico nei robot



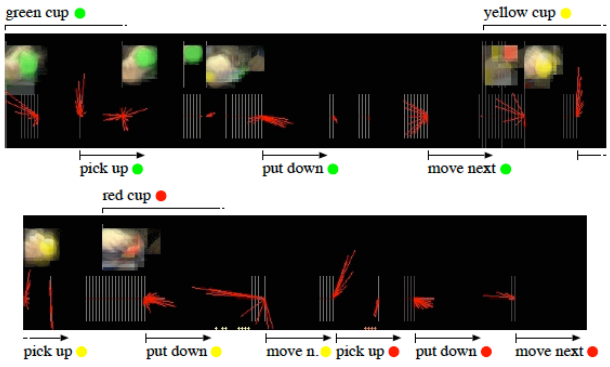
(a) Stochastic algorithm *with* retinal filter



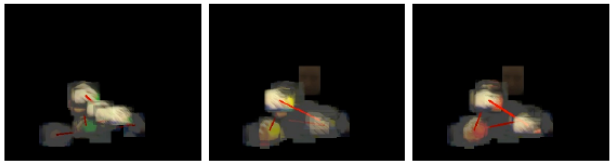
(b) Winner-take-all algorithm *with* retinal filter

(c) Winner-take-all algorithm *without* retinal filter

Fig. 7. Transition of attention of proposed model (a) and two comparative models, (b) and (c). The line color corresponds to the cup color.



(a) Object and motion chunks created through task demonstration

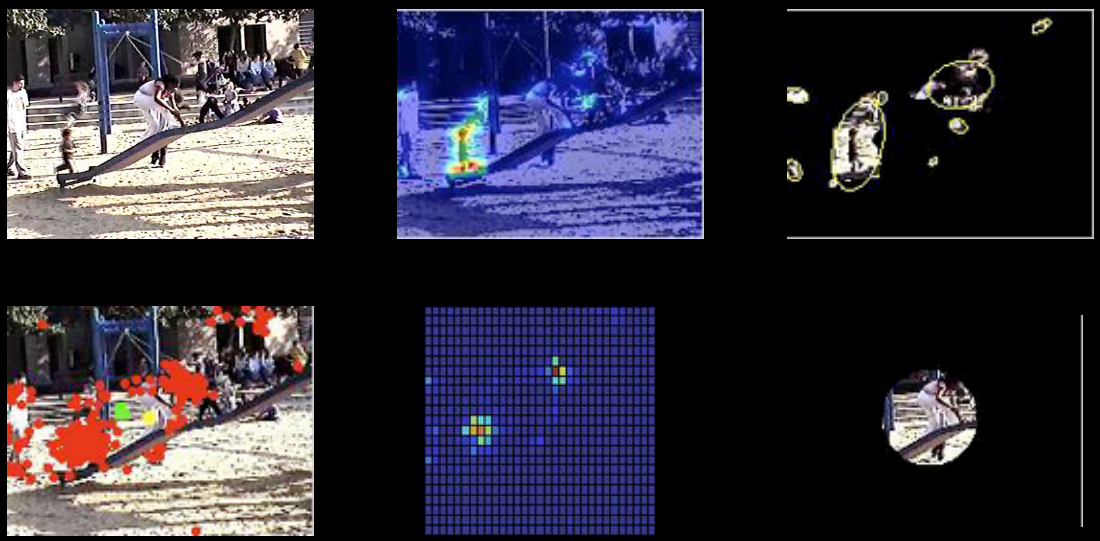


(b) Action map for moving green, yellow, and red cups

IEEE TRANS. ON SMC-B

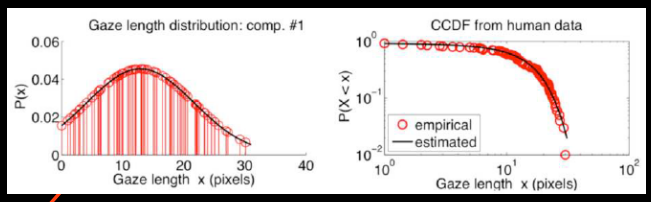
Ecological Sampling of Gaze Shifts

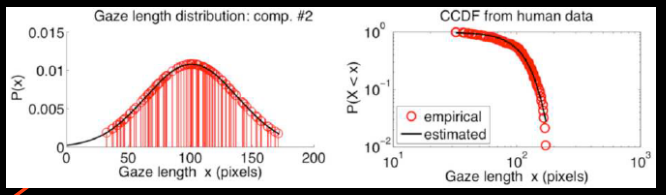
Giuseppe Boccignone and Mario Ferraro

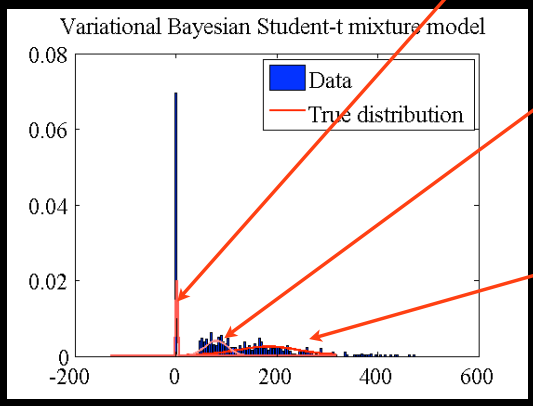


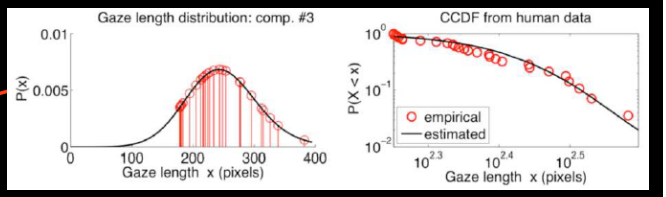
Matlab simulation code:
http://boccignone.di.unimi.it/Ecological_Sampling.html

Ecological sampling: //data analysis

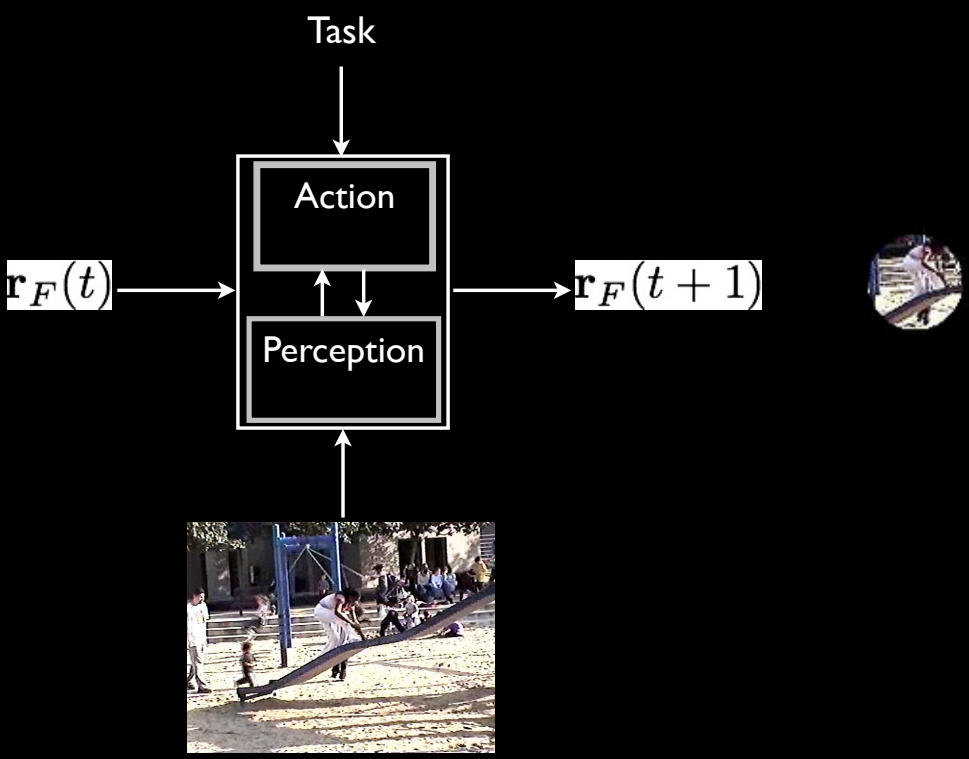




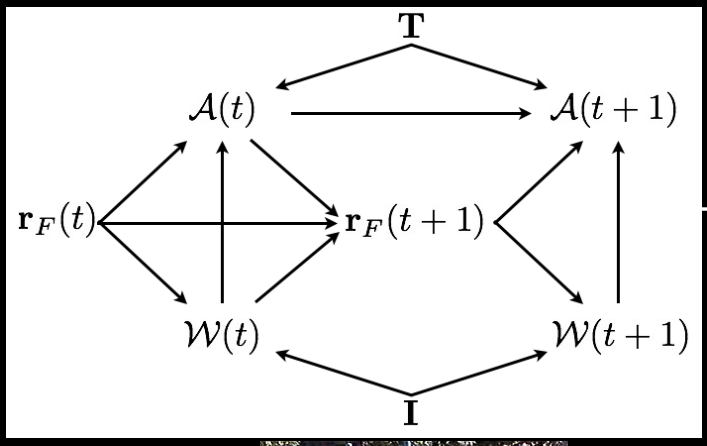




Ecological sampling of gaze shifts



Ecological sampling of gaze shifts //unfolding the action-perception loop



Ecological sampling of gaze shifts //sampling the action-perception loop

- Sampling the natural habitat

$$\mathcal{W}^*(t) \sim P(\mathcal{W}(t)|\mathbf{r}_F(t), \mathbf{F}(t), \mathbf{I}(t))$$

- Sampling the appropriate motor behavior

$$\mathcal{A}(t)^* \sim P(\mathcal{A}(t)|\mathcal{A}(t-1), \mathcal{W}^*(t))$$

- Sampling where to look next

$$\mathbf{r}_F(t+1) \sim P(\mathbf{r}_F(t+1)|\mathcal{A}(t)^*, \mathcal{W}^*(t), \mathbf{r}_F(t))$$

Ecological sampling of gaze shifts //sampling the natural habitat

- Sampling the saliency

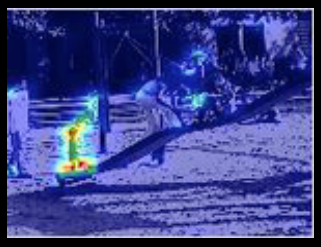
$$\mathcal{S}^*(t) \sim P(\mathcal{S}(t)|\mathbf{F}(\widehat{\mathbf{I}(t)}))$$

- Sampling patches...

$$\mathcal{M}^*(t) \sim P(\mathcal{M}(t)|\mathcal{S}^*(t))$$

- ...and their parametric descriptions

$$\text{for } p = 1, \cdots, N_P$$
$$\theta_p^*(t) \sim P(\theta_p(t)|\mathcal{M}_p^*(t) = 1, \mathcal{S}^*(t))$$



Ecological sampling of gaze shifts //sampling the natural habitat

- Sampling "preys" from patches (food items / Interest Points)

$$O_p^*(t) \sim P(O_p(t)|\theta_p^*(t), \mathcal{M}_p^*(t) = 1, \mathcal{S}^*(t))$$

$$O(t) = \bigcup_{p=1}^{N_P} \{\mathbf{r}_{i,p}(t)\}_{i=1}^{N_{i,p}}$$

$$\mathbf{r}_{i,p} \sim \mathcal{N}(\mathbf{r}_p; \mu_p(t), \Sigma_p(t)), i = 1, \cdots, N_{i,p}$$

Ecological sampling of gaze shifts //sampling the motor behavior

- Motor action $\mathcal{A}(t) = (z(t), \pi_t)$ determines the choice of oculomotor behavior
- Markov assumption $\mathcal{A}(t-1) \rightarrow \mathcal{A}(t)$

$$P(\mathcal{A}(t)|\mathcal{A}(t-1), \mathcal{W}^*(t))$$

oculomotor choice action

oculomotor choice prior

$$P(z(t)|\pi(t))P(\pi(t)|\pi(t-1), O(t))$$

$$Mult(z(t)|\pi(t)) = \prod_{k=1}^{K} [\pi_k(t)]^{z_k(t)}$$

$$Dir(\pi(t); \nu(t)) = \frac{\Gamma(\sum_k \nu_k(t)}{\prod_k \Gamma(\nu_k(t))} \prod_k \pi_k(t)^{\nu_k(t)-1}$$

Ecological sampling of gaze shifts //sampling the motor behavior

- Motor action $\mathcal{A}(t) = (z(t), \pi_t)$ determines the choice of oculomotor behavior
- Markov assumption $\mathcal{A}(t-1) \rightarrow \mathcal{A}(t)$

prior hyperparameters

oculomotor prior

$$\pi^*(t) \sim Dir(\pi|\nu(O(t)))$$

oculomotor choice sampling

$$z^*(t) \sim Mult(z(t)|\pi^*(t))$$

Ecological sampling of gaze shifts //sampling the motor behavior

- Motor action $\mathcal{A}(t) = (z(t), \pi_t)$ determines the choice of oculomotor behavior
- Markov assumption $\mathcal{A}(t-1) \rightarrow \mathcal{A}(t)$

$$\pi^*(t) \sim Dir(\pi|\nu(O(t)))$$

$$\nu_k(t) = \nu_k(t-1) + \left[E_{\mathcal{C}(t)} = k\right], k = 1, \cdots, K$$

prior hyperparameters

$$\mathcal{C}(t) = \Delta(t) \cdot \Omega(t)$$

Ecological sampling of gaze shifts //sampling the motor behavior

- Taking into account the complexity of the landscape in natural habitats

no cues

some cues

too many cues

$$\mathcal{C}(t) = \Delta(t) \cdot \Omega(t)$$

Ecological sampling of gaze shifts //sampling the motor behavior

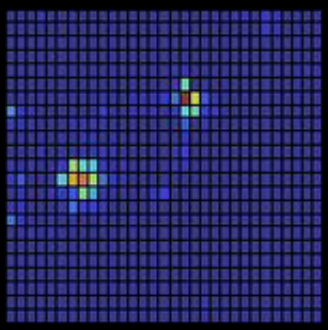
- Motor action $\mathcal{A}(t) = (z(t), \pi_t)$ determines the choice of oculomotor behavior
- Markov assumption $\mathcal{A}(t-1) \rightarrow \mathcal{A}(t)$

$$H(t) = -k_B \sum_{c=1}^{N_w} P(c,t) \log P(c,t)$$

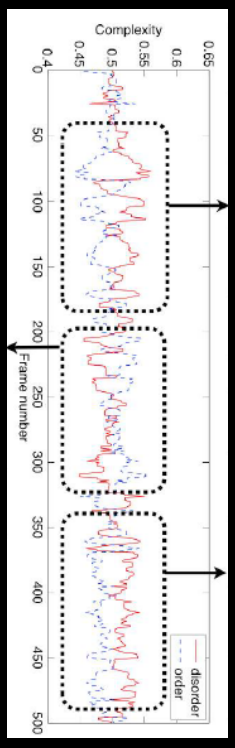
$$\Delta \equiv H/H_{sup}$$

$$\Omega = 1 - \Delta$$

$$\mathcal{C}(t) = \Delta(t) \cdot \Omega(t)$$



Ecological sampling of gaze shifts //sampling the motor behavior



no cues

some cues

too many cues

$$\mathcal{C}(t) = \Delta(t) \cdot \Omega(t)$$

Ecological sampling of gaze shifts //sampling where to look next

- Motor action $\mathcal{A}(t) = (z(t), \pi_t)$ determines the choice of oculomotor behavior
- Sampling the next FOA

$$\mathbf{r}_F(t+1) \sim P(\mathbf{r}_F(t+1)|z^*(t) = k, \theta^*(t), \eta, \mathbf{r}_F(t))$$

- Langevin - Smoluchowski

$$d\mathbf{r}_F(t) = -\nabla V(\mathbf{r}_F, t)dt + \mathbf{D}(\mathbf{r}_F, t)\boldsymbol{\xi}_k(t)dt$$

Ecological sampling of gaze shifts //sampling where to look next

- Motor action $\mathcal{A}(t) = (z(t), \pi_t)$ determines the choice of alpha stable parameters $f(\boldsymbol{\xi}; \alpha, \beta, \gamma, \delta)$
- Sampling the next FOA $\boldsymbol{\xi} \sim$

$$d\mathbf{r}_F(t) = -\nabla V(\mathbf{r}_F, t)dt + \mathbf{D}(\mathbf{r}_F, t)\boldsymbol{\xi}_k(t)dt$$

$$-\nabla V(\mathbf{r}_F, t) = -\sum_{p=1}^{N_V}(\mathbf{r}_F(t) - \mathbf{r}_p(t))$$

$$\mathbf{r}_F(t_{n+1}) \approx \mathbf{r}_F(t_n) - \sum_{p=1}^{N_V}(\mathbf{r}_F(t_n) - \mathbf{r}_p(t_n))\tau + \gamma_k \mathbb{I}\tau^{1/\alpha_k}\boldsymbol{\xi}_k.$$

Ecological sampling of gaze shifts //sampling where to look next

no cues

#Levy flights > #Gaussian flights

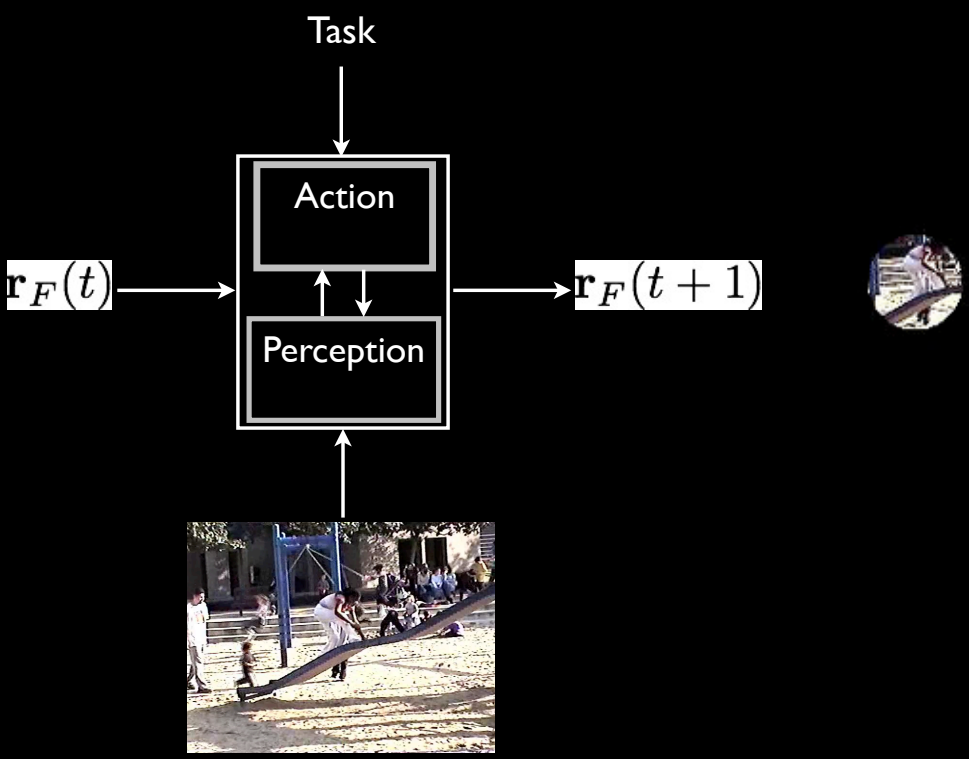
some cues

#Gaussian flights > #Levy flights

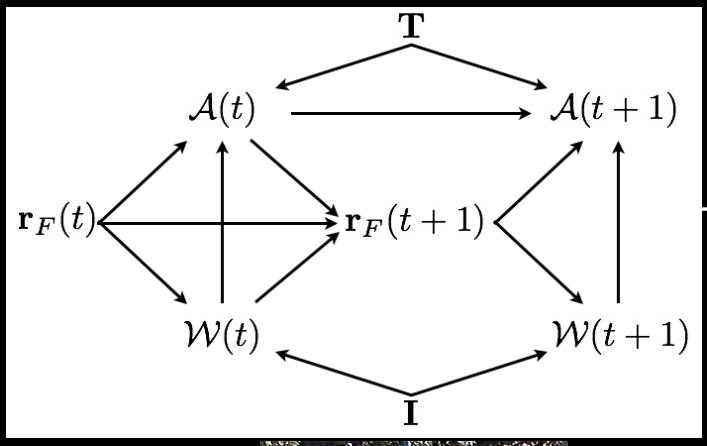
too many cues

#Levy flights > #Gaussian flights

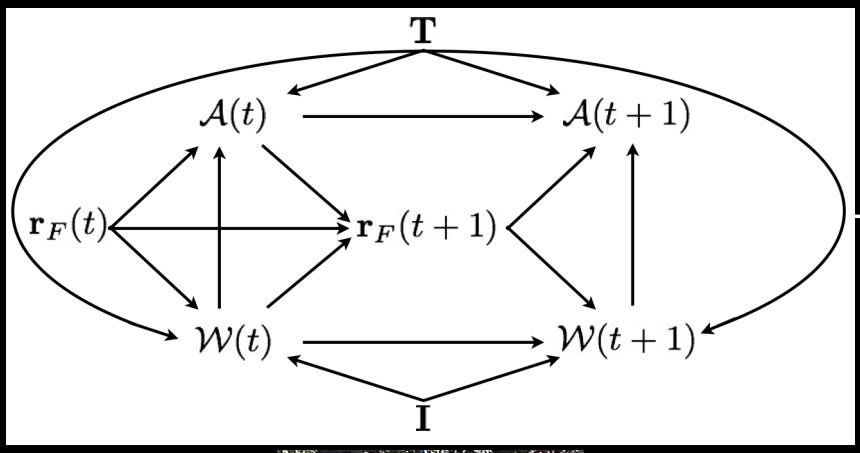
Ecological sampling of gaze shifts



Ecological sampling of gaze shifts //accounting for task

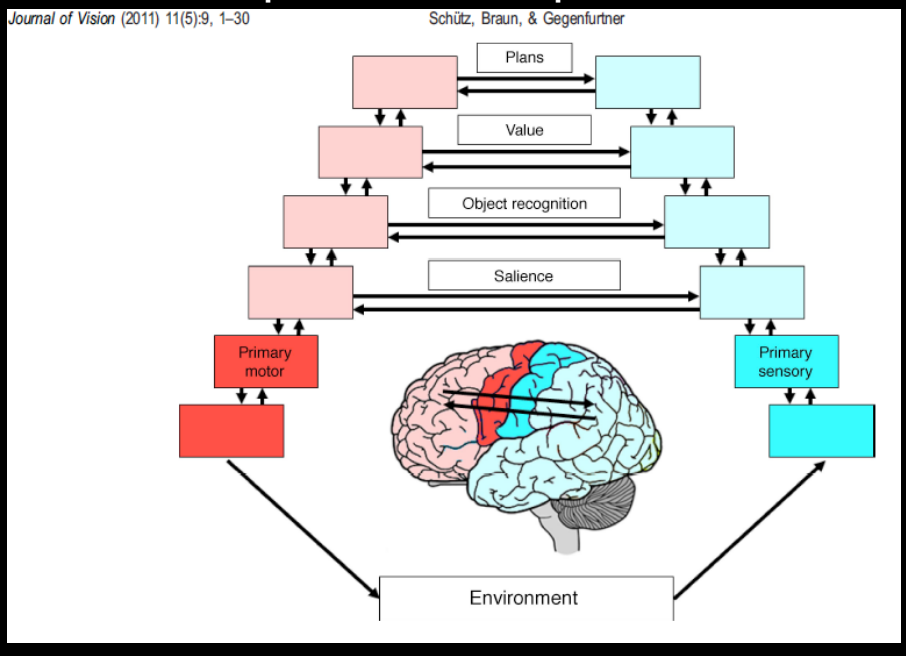


Ecological sampling of gaze shifts //accounting for task

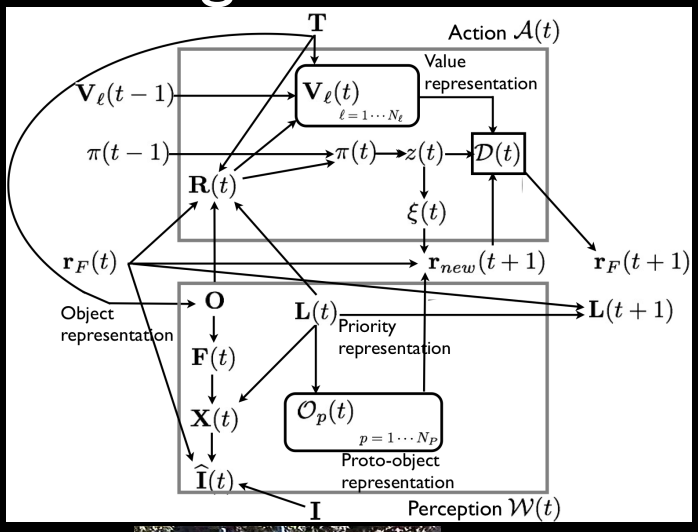


Ecological sampling of gaze shifts //accounting for task

- There are multiple levels of representation



Ecological sampling of gaze shifts //accounting for task



every gaze shift is a decision