Image Understanding with Organic Computing

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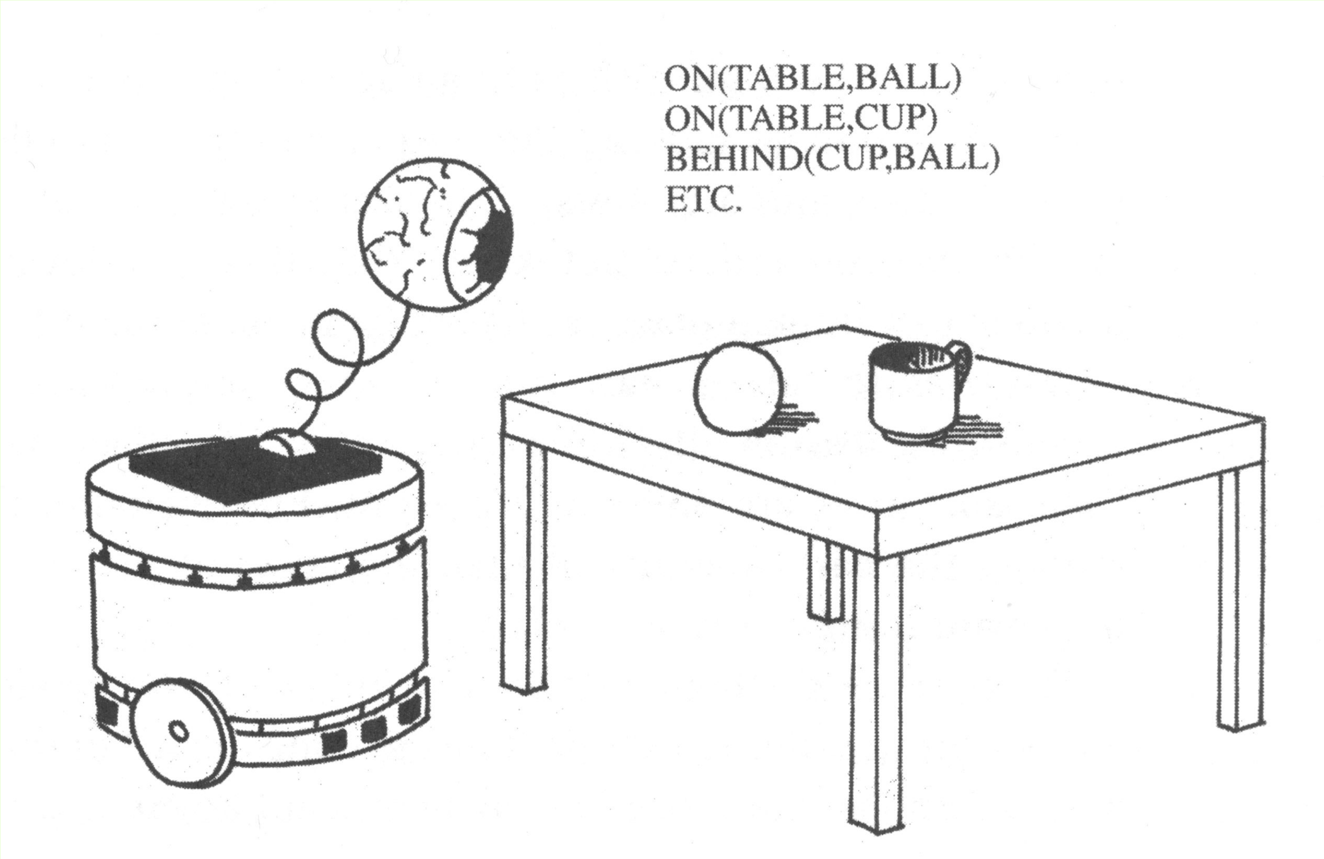
Overview

- Introduction
- Problem of image understanding
- Controlled generalization in face recognition
- General object recognition
- Learning of articulated models
- Where to go from here

Complexity problems

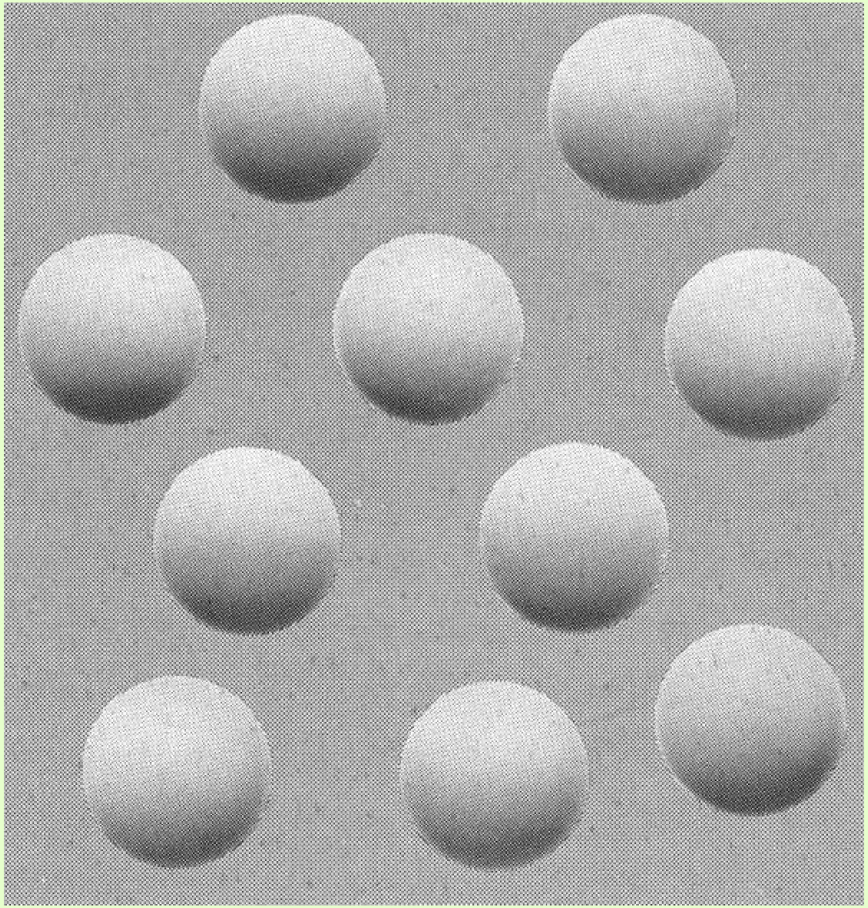
- Artificial systems are rapidly getting too complex to understand
- Desirable are complex systems with trivial interfaces
- This requires restrictions on possible behaviors
- This asks for self-organization

Image understanding . . .



. . . means establishing a symbolic description.

Image understanding . . .

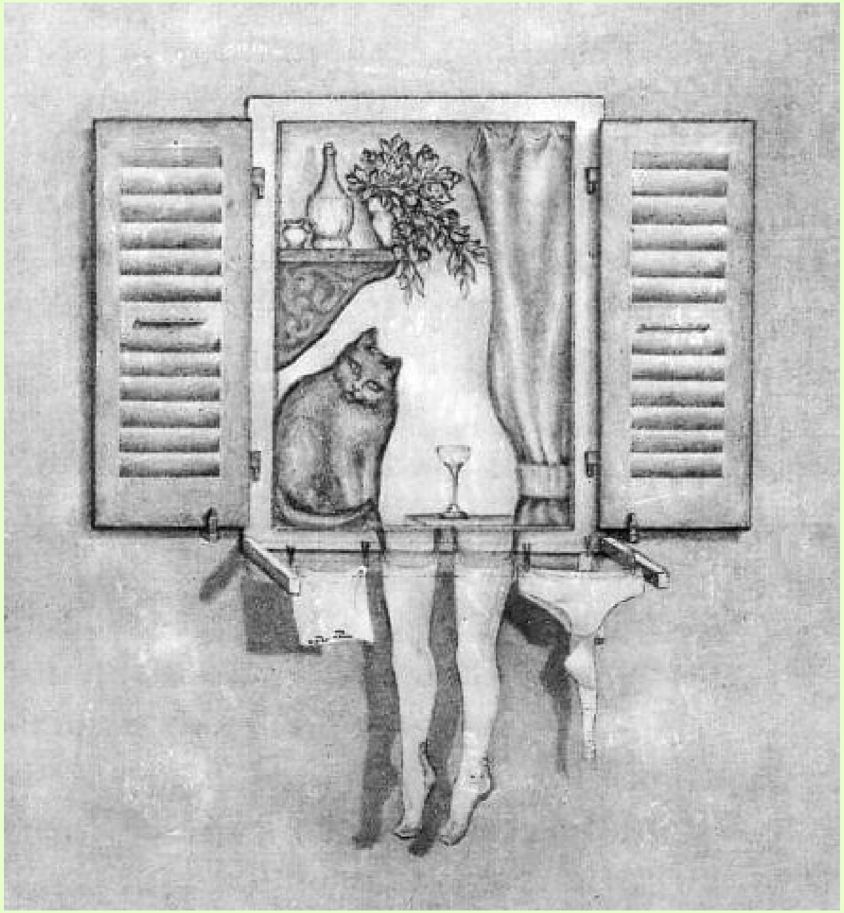


. . . in the brain is done under additional assumptions.

Image understanding . . .

. . . requires extensive world knowledge.

Image understanding . . .



. . . has a local-global problem.

Face recognition

Different situations yield very different images.

Invariance problem

All the same?

Invariance . . .

$$6 \neq 9$$

. . . is task-dependent.

List of tasks

- We *do* need a formal model of images, but we don't have any

- We do not even have a formalization of the problem
- Required is an imitation of human capability

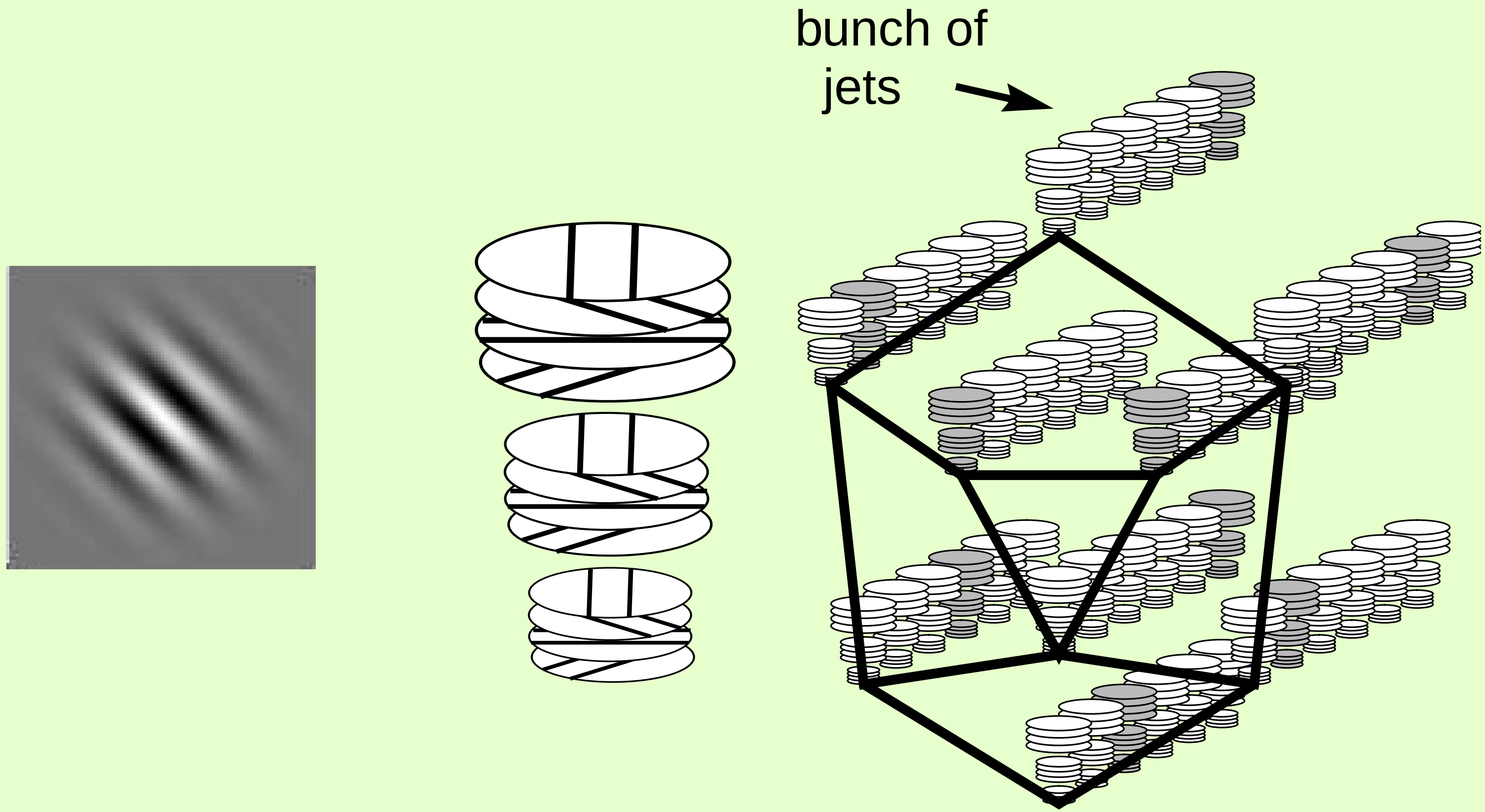
- Identify constraints of visual data autonomously
- Learn computer vision routines from examples
- Start a positive feedback loop of learning vision
- Control generalization

Controlled generalization

- Neural networks learn complicated functions from examples
- They can generalize, but not always in the desired way
- Visual invariances must be built in explicitly
  (Neocognitron, Convolutional NN, . . .)
- Exception: Slow feature analysis (Wiskott & Sejnowski, 2002)

- Goal: Learn generalization dimensions from examples!

Bunch Graphs



a: Gabor wavelet **b: jet** **c: bunch graph**

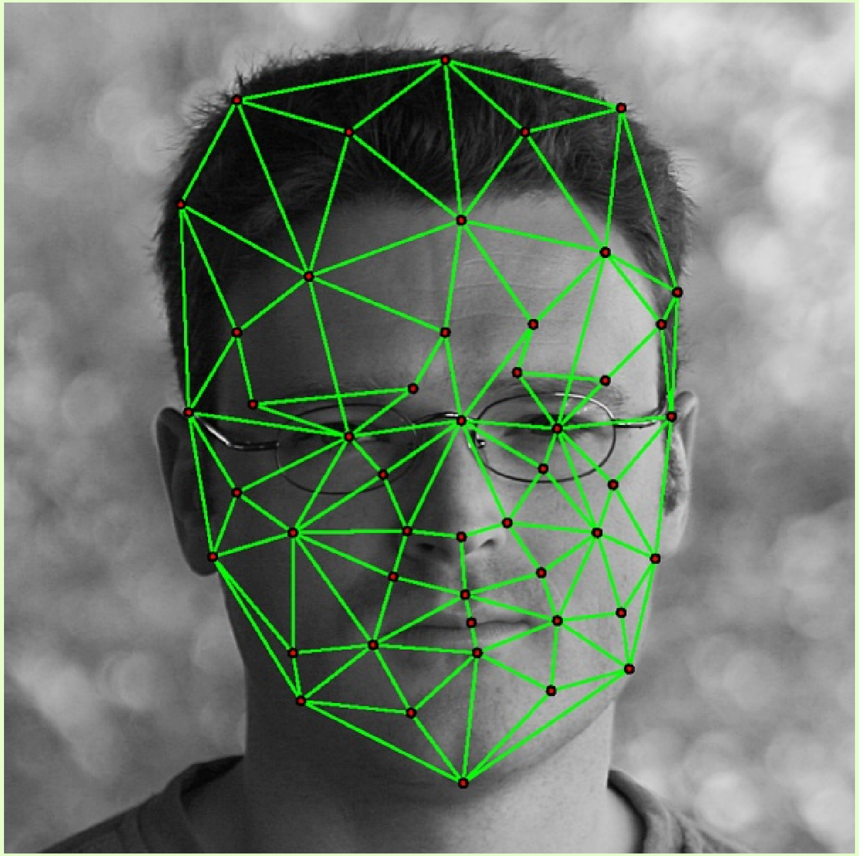
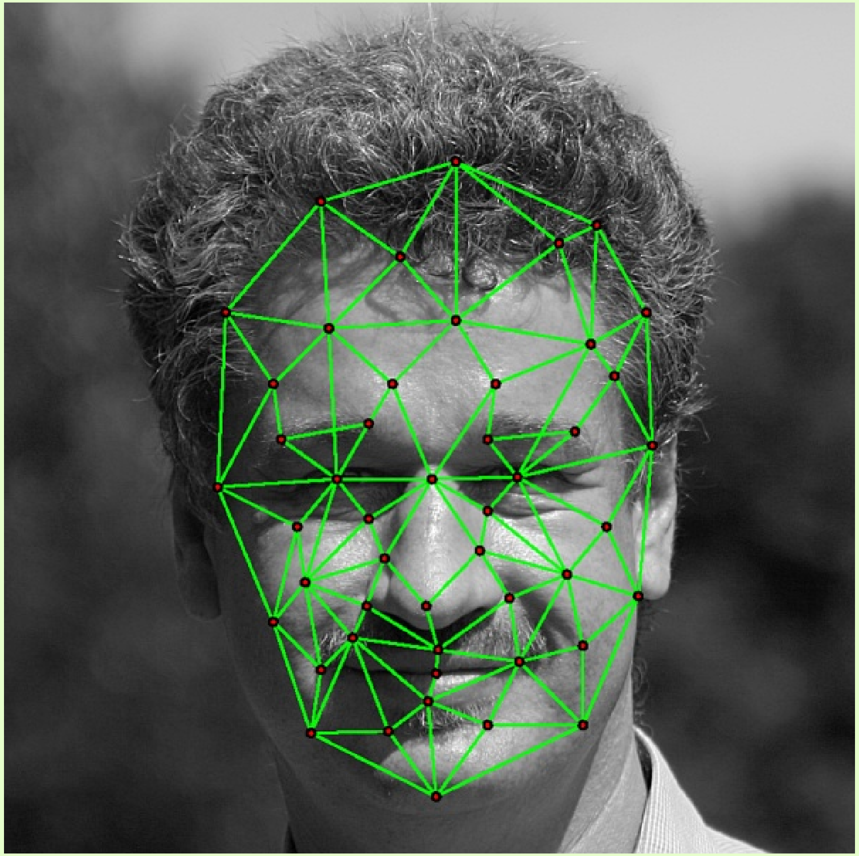
Wiskott et al., 1997

Graph similarity

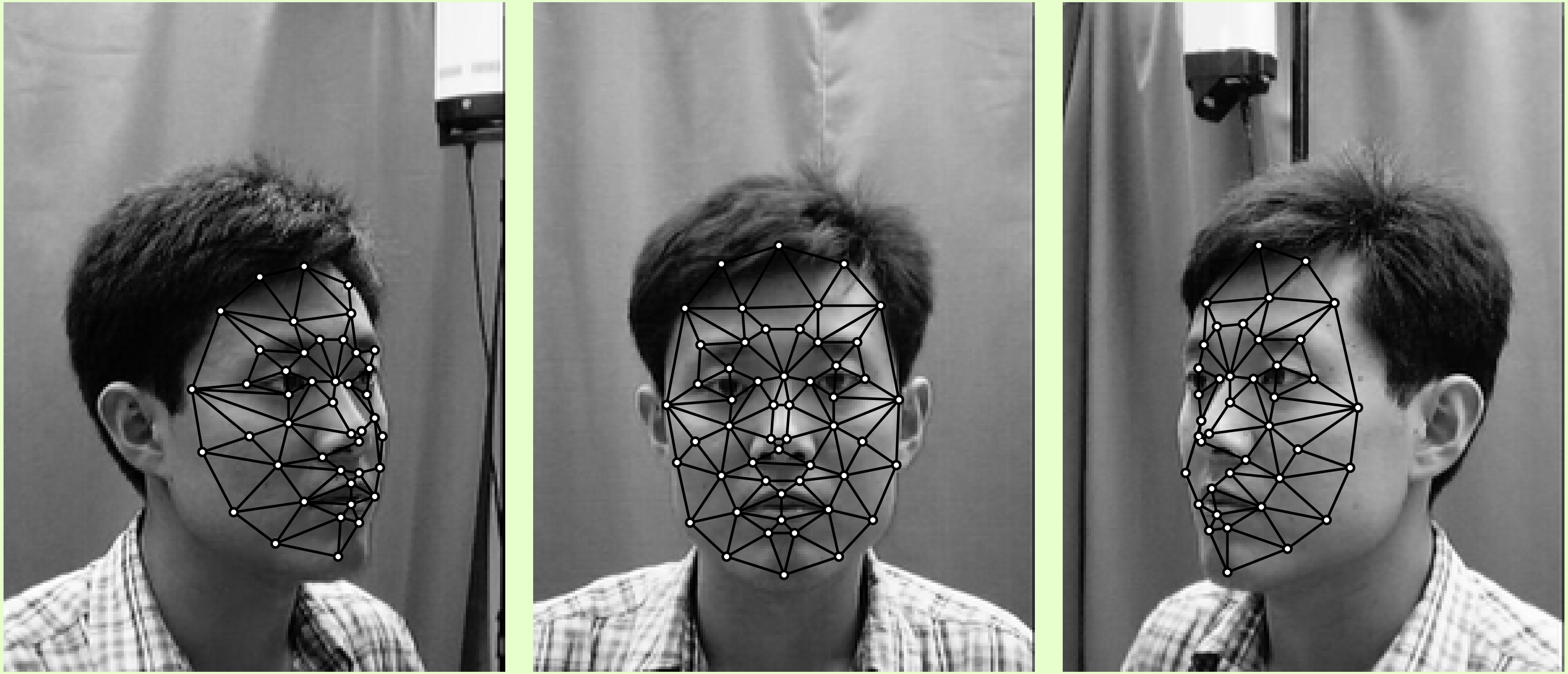
- Jet similarity function S_J
- Probe graph P with N nodes P_n
- Gallery graphs G_g with N nodes $G_{g,n}$ each

$$g_{rec} = \arg\max_g \frac{1}{N} \sum_{n=1}^{N} S_J(P_n, G_{g,n}) \, .$$

Face Graphs

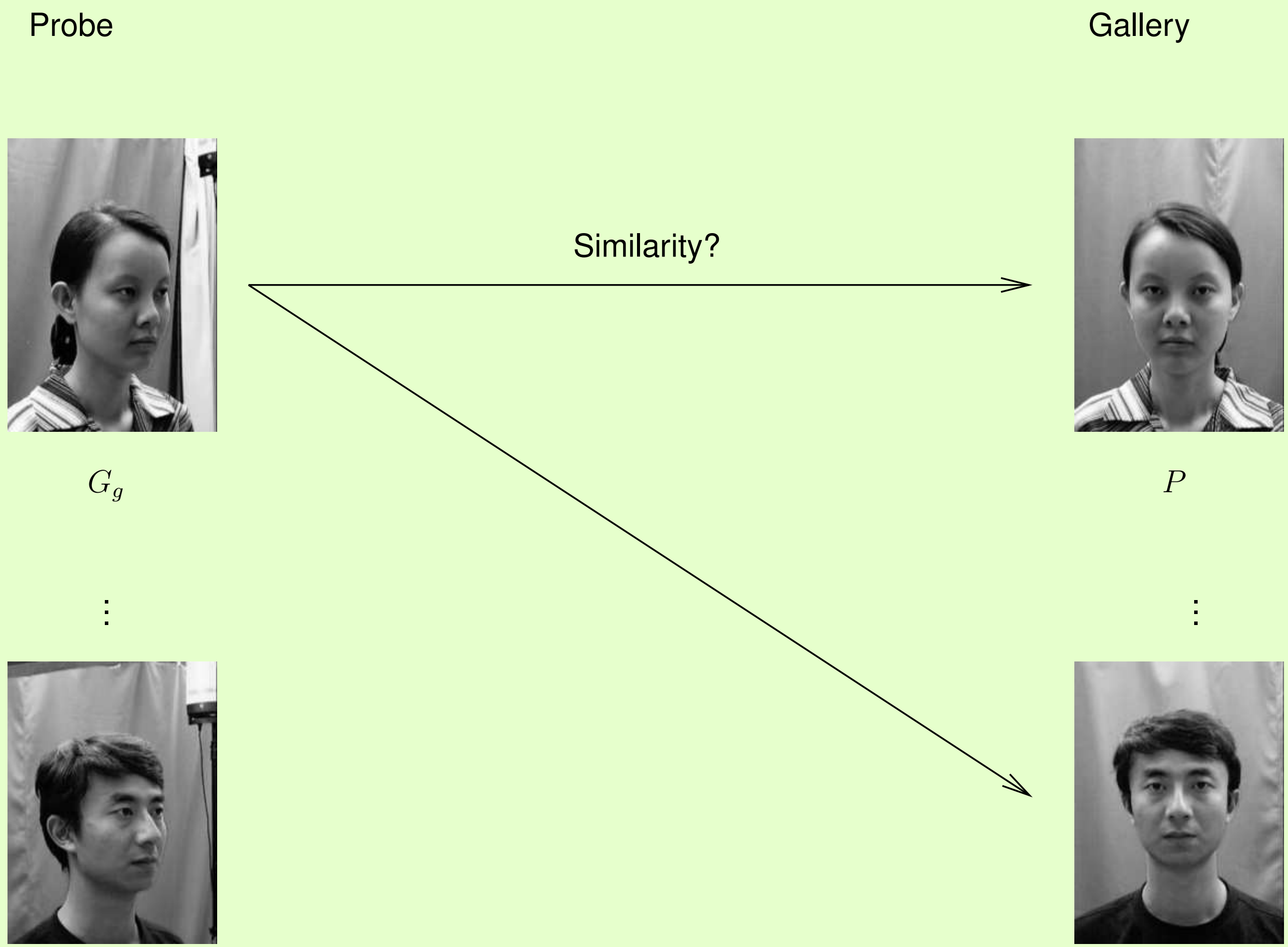



Pose Variation



PM+45 PM+00 PM−45

Pose Variation



Rank Correlation

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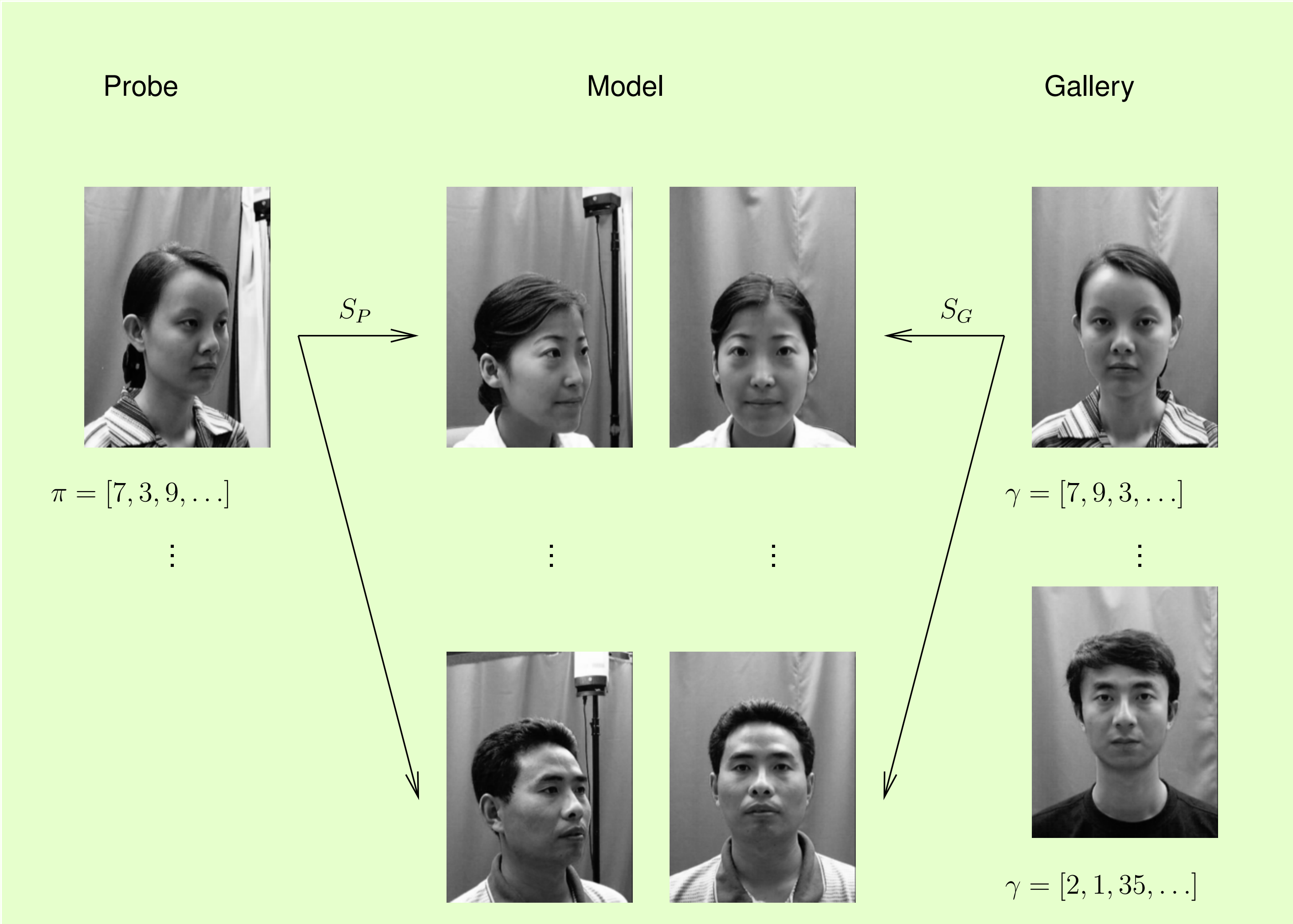

Neural rank list similarity

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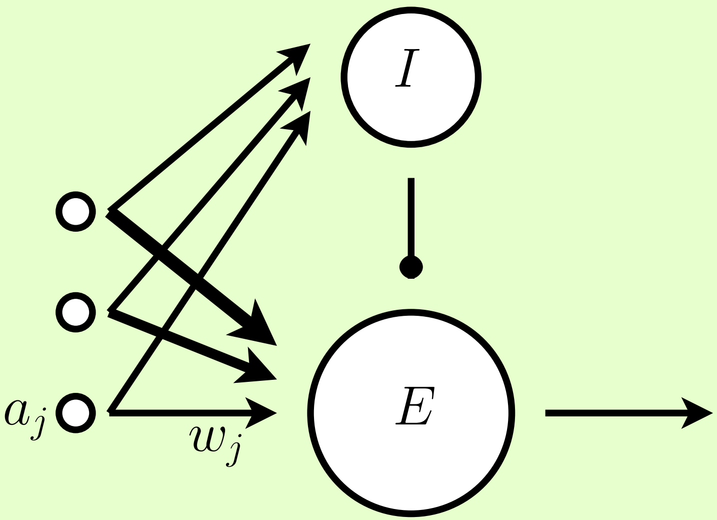

$$E = \sum_{j=1}^{K} \exp\left(-\frac{\text{order}(a_j)}{\lambda}\right) w_j$$

$$w_j = \frac{1}{K} \exp\left(-\frac{\text{order}(b_j)}{\lambda}\right)$$

Thorpe et al., 2001

Neural rank list similarity

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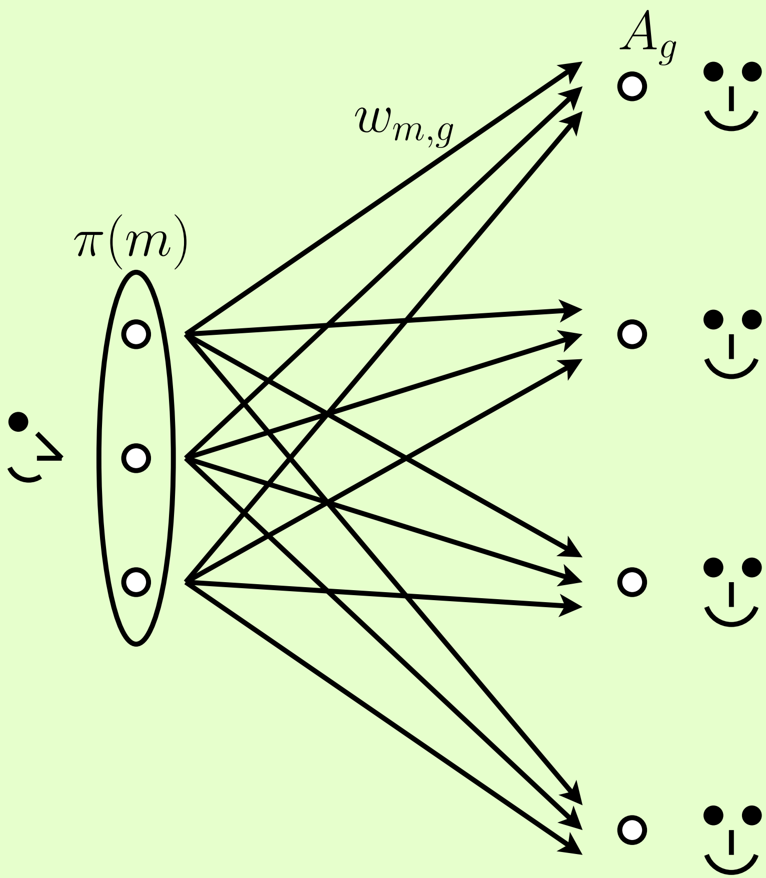
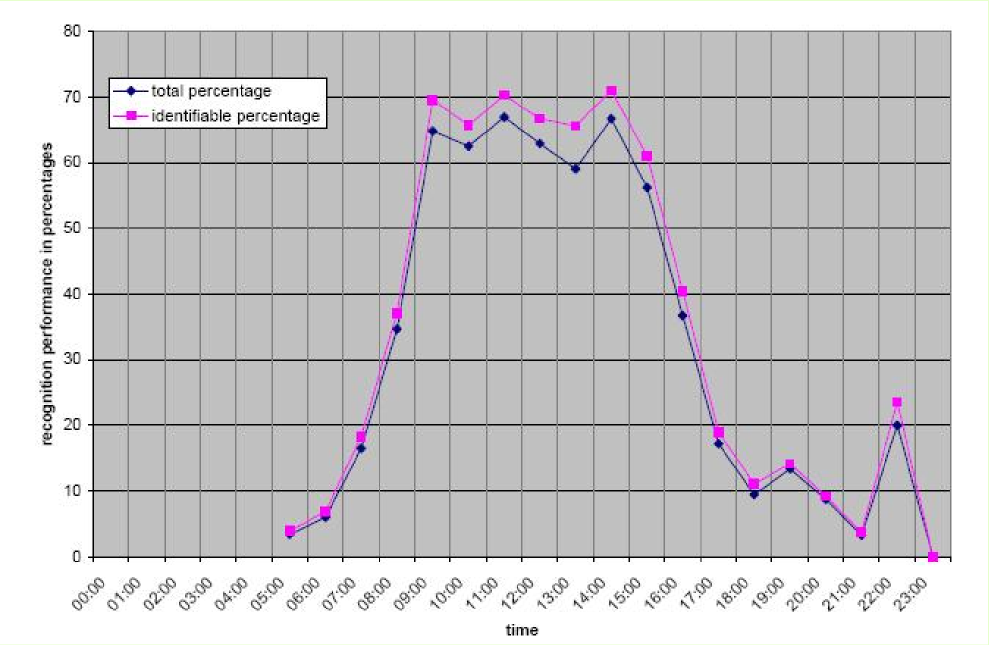


$$
\begin{aligned}
w_{m,g} &= \frac{1}{N_M} \exp\left(-\frac{\gamma_g(m)}{\lambda}\right) \\
A_g &= \sum_m \exp\left(-\frac{\pi(m)}{\lambda}\right) w_{m,g} \\
&= \frac{1}{N_M} \sum_m \exp\left(-\frac{\pi(m)+\gamma_g(m)}{\lambda}\right) \\
&= S_{neural}(\gamma_g, \pi)
\end{aligned}
$$

$$
g_{rec} = \arg\max_g \frac{1}{N} \sum_n S_{neural}(\gamma_{g,n}, \pi_n)
$$

Müller and Würtz, ICANN 2009

Face recognition Mainz Hbf.



CAS-PEAL Database

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PM+45


FM+00


FM−45


FM−90


PM+00


FD+00


FD−45


FD−90


PM−45


FU+00

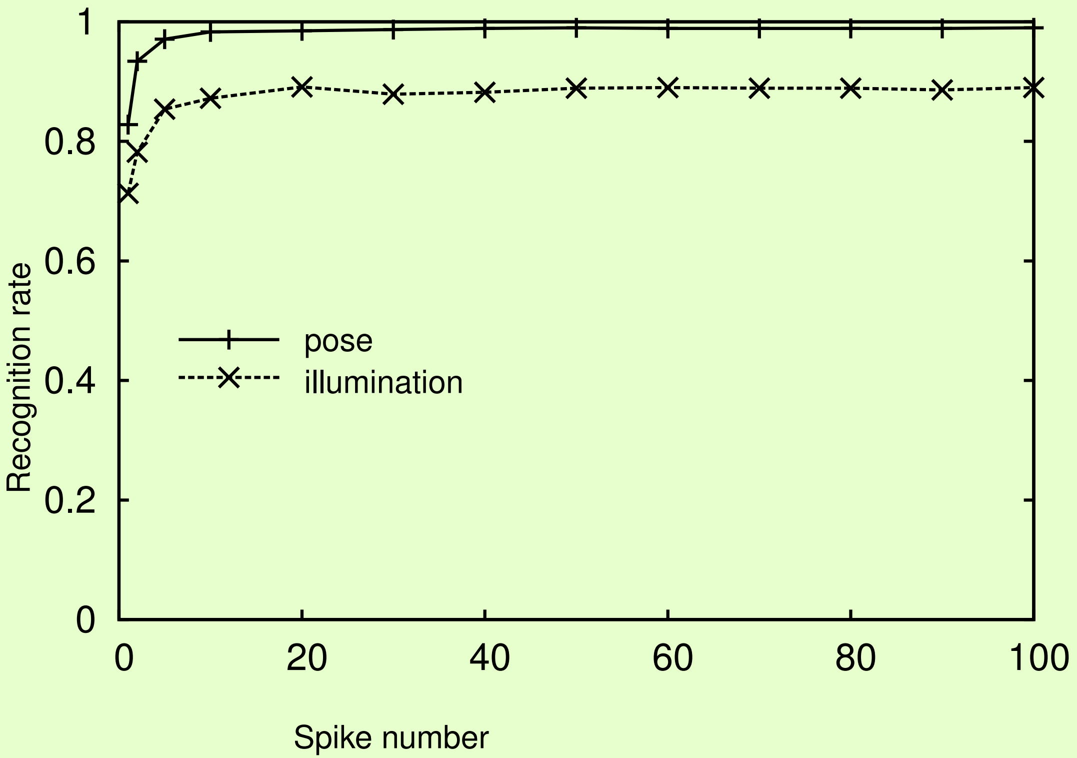

FU−45


FU−90

Rank Correlation: Results

	Pose	Illumination
Recognition percentage with given situation	99.02	89.01
Percentage of correct situation estimation	99.89 ± 0.09	91.96 ± 0.89
Recognition percentage with automatically determined situation	97.75 ± 0.50	89.97 ± 1.36
Best recognition percentage reported in database description	71	51

Rank Correlation: Early stopping



Thanks to

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