V INTERNATIONAL CONFERENCE ON INFORMATION TECHNOLOGY AND NANOTECHNOLOGY (ITNT - 2019)

Target identification for photon counting image sensors, inspired by mechanisms of human visual perception

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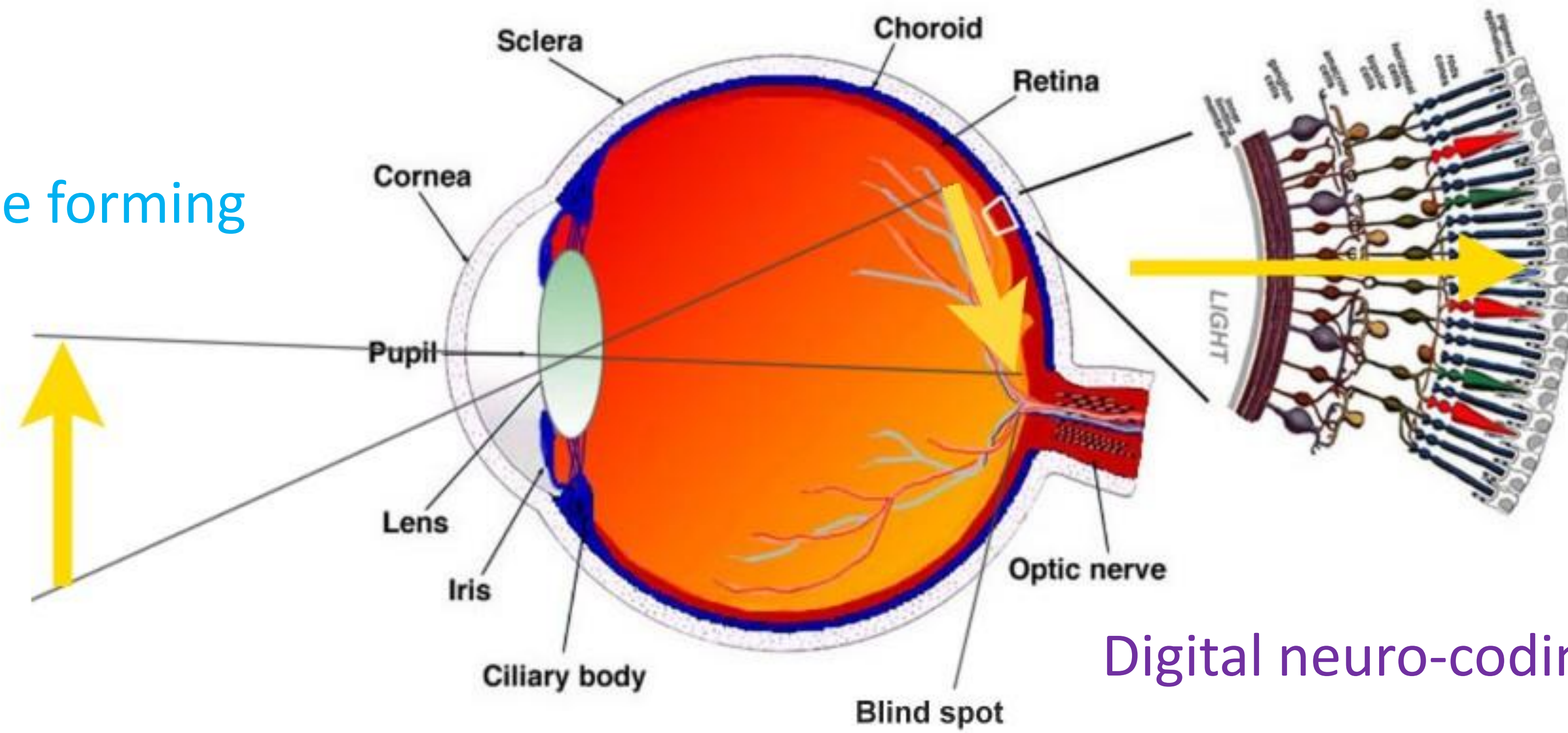
Key Points

- Mechanisms of human visual perception
- Examples of modern Photon–Counting Sensors
- Physical bases of Photon-Counting Registration
- Statistical bases of Photon-Counting Registration
- GMM model for registered intensity shape
- Forming the set of descriptions by precedents (training objects)
- Identification of objects by precedent descriptions (testing objects)
- EM algorithm for low-count objects identification
- Simple experiments on objects identification

Mechanisms of human visual perception

Optical preprocessing

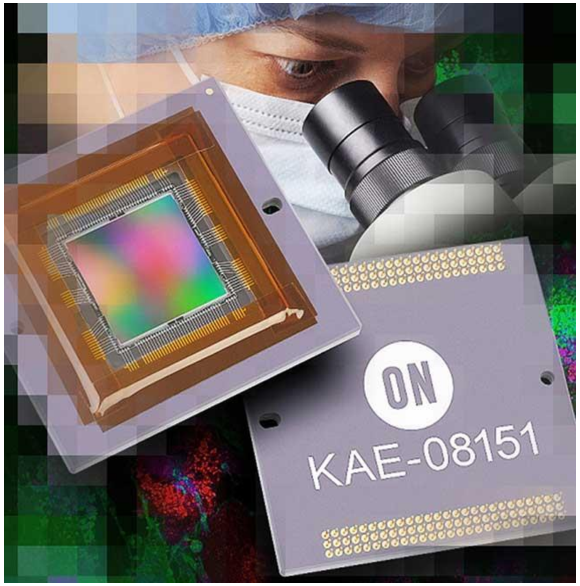
Image forming



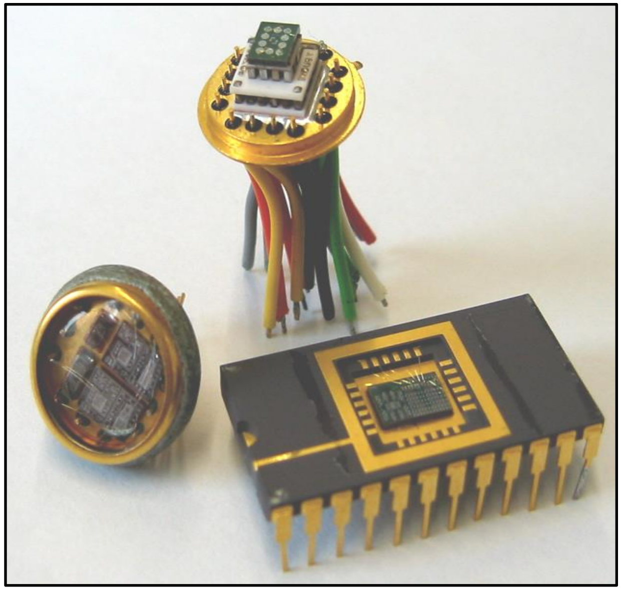
Digital neuro-coding

A SCHEMATIC SECTION THROUGH THE HUMAN EYE WITH A SCHEMATIC ENLARGEMENT OF THE RETINA

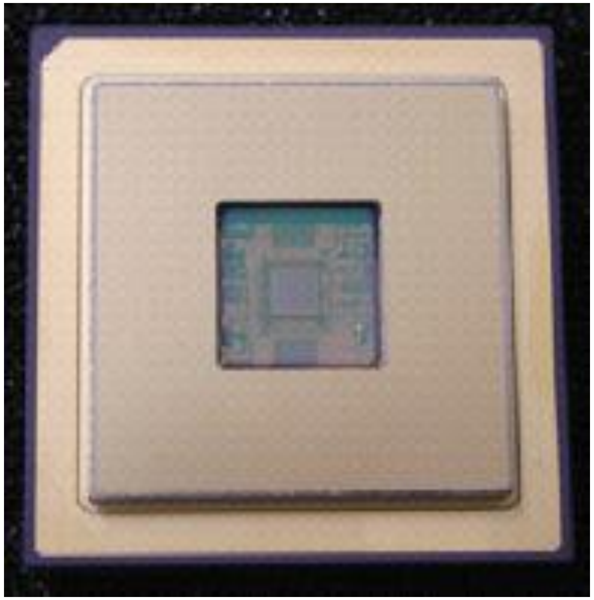
Examples of modern Photon–Counting Sensors



The Electron Multiplying Charge Coupled Device (EMCCD) image sensor provides high imaging performance in extreme-low-light applications and direct sunlight.

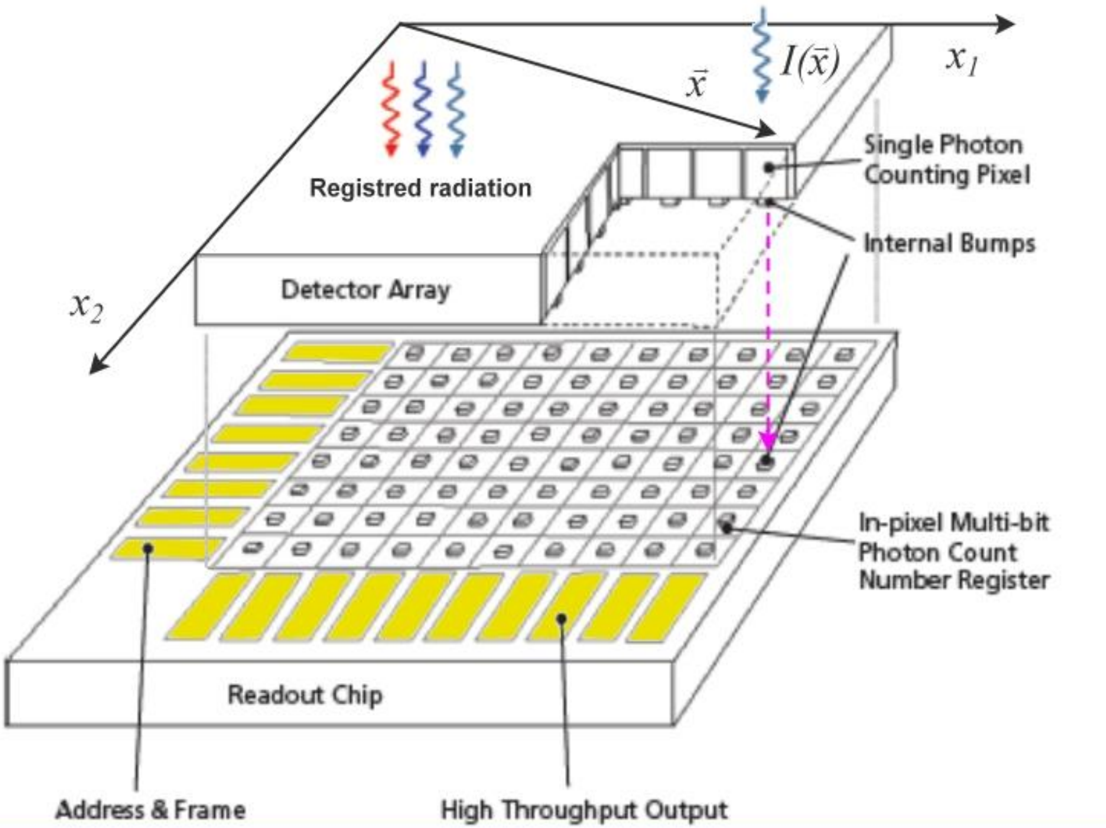


The Single-Photon Avalanche Diode (SPAD) defines a class of photodetectors able to detect low intensity signals (down to the single photon).



Geiger counter mode Avalanche Photo Diodes (GmAPD) provide true single photon sensitivity with high photon detection efficiency and low dark count rates.

Physical bases of Photon-Counting Registration



Continuous model of the photodetection process (PPP):

$$\rho(n, \vec{x}_1, \dots, \vec{x}_n) =$$

$$= \frac{1}{n!} \prod_{i=1}^{n} \lambda(\vec{x}_i) \times \exp\left\{ - \int_{\Omega} \lambda(\vec{x}) d\vec{x} \right\}$$

$(\vec{x}_1, \dots, \vec{x}_n)$ – coordinates of n photocounts, $\lambda(\vec{x})$ – PPP intensity:

$$\lambda(\vec{x}) = \eta T I\,(\vec{x}) / h\,\bar{\nu}$$

η – quantum efficiency of the detector material;
T – frame readout time;
$I(\vec{x})$ – radiation intensity;
$\bar{\nu}$ – central radiation frequency;
h – Planck constant;

Statistical bases of Photon-Counting Registration

The main paradigm of math. statistics:

Observed iid data $\{\vec{x}_1, \vec{x}_2, \dots, \vec{x}_n\}$

Statistical decision procedure

Best explaining model $P_k(\vec{x})$

Set of distributions, models $\{P_1(\vec{x}), P_2(\vec{x}), \dots, P_m(\vec{x}), \dots\}$

Formalization: Param family model $P_k(\vec{x}) = P(\vec{x}, \vec{\lambda}_k)$

Formalization: Best explaining params $\vec{\lambda}_k$

Maximum Likelihood Estimate (MLE) of Ronald Fisher:

$$\hat{k} = \underset{k}{\operatorname{argmax}} \ln P\left(\vec{x}_1, \vec{x}_2, \dots, \vec{x}_n, \vec{\lambda}_k\right)$$

GMM model for registered intensity shape

What is to model?

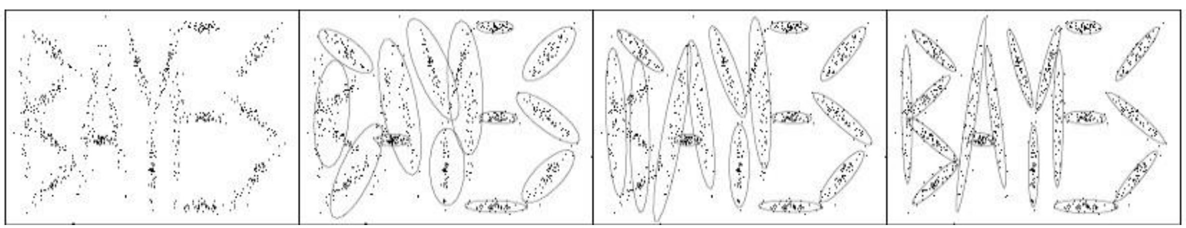
Conditional distribution of photocount coordinates for a given total number n of counts:

$$P(\vec{x}_1, \vec{x}_2, \dots, \vec{x}_n | n, k) = \prod_{i=1}^{n} p_k(\vec{x}_i), \quad p_k(\vec{x}) = \frac{I_k(\vec{x})}{\int I_k(\vec{x}) d\vec{x}}$$

Note: count distribution $p_k(\vec{x}_i)$ coincides directly with the (normalized) intensity $I_k(\vec{x})$ and does not depend on $\eta, T, \bar{\nu}$.

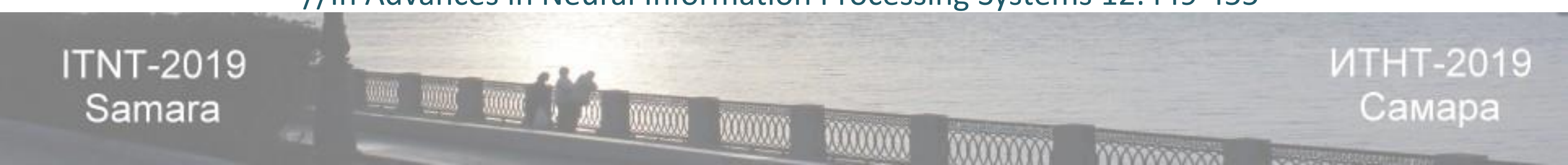
How to model?

Gaussian mixture model (GMM) approximation of counts image



$$p_k(\vec{x}) = \sum_{j=1}^{N_k} \pi_{k,j} N(\vec{x} | \vec{\mu}_{k,j}, \sigma_{k,j})$$

Ghahramani, Z. and Beal, M.J. (2000) Variational Inference for Bayesian Mixtures of Factor Analyzers. //In Advances in Neural Information Processing Systems 12:449-455



Forming the set of descriptions by precedents (training objects)

Param family model:

$$p(\vec{x}|\vec{\lambda}) = \sum_{j=1}^{N} \pi_j N(\vec{x}|\vec{\mu}_j, \sigma_j) \text{: } \vec{\lambda}=\{(\pi_j, \vec{\mu}_j, \sigma_j)\}$$

Precedent params MLE calculation:

$$\{x_1, x_2, \ldots, x_n\} \rightarrow \text{EM algorithm for GMM} \rightarrow \vec{\lambda}_k=\{(\pi_{k,j}, \vec{\mu}_{k,j}, \sigma_{k,j})\}$$

E-step:

$$Q_{k,j}^{(m)}(\vec{x}_i) = \left(\vec{x}_i - \vec{m}_{k,j}^{(m)}\right)^T A_{k,j}^{(m)} \left(\vec{x}_i - \vec{m}_{k,j}^{(m)}\right) \;;$$

$$V_{j|i}^{(m+1)} = \frac{1}{\Sigma_V} p_{k,j}^{(m)} \sqrt{\det\left\{A_{k,j}^{(m)}\right\}} \exp\left\{-\frac{1}{2} Q_{k,j}^{(m)}(\vec{x}_i)\right\};$$

$$\Sigma_V = \sum_{j=1}^{N_k} p_{k,j}^{(m)} \sqrt{\det\left\{A_{k,j}^{(m)}\right\}} \exp\left\{-\frac{1}{2} Q_{k,j}^{(m)}(\vec{x}_i)\right\};$$

M-step:

$$p_{k,j}^{(m+1)} = \frac{1}{n} \sum_{i=1}^{n} V_{j|i}^{(m+1)},$$

$$\vec{m}_{k,j}^{(m+1)} = \frac{1}{n p_{k,j}^{(m+1)}} \sum_{i=1}^{n} V_{j|i}^{(m+1)} \vec{x}_i \;;$$

$$\left[A_{k,j}^{(m+1)}\right]^{-1} = \frac{1}{n p_{k,j}^{(m+1)}} \sum_{i=1}^{n} V_{j|i}^{(m+1)} \times$$

$$\times \left(\vec{x}_i - \vec{m}_{k,j}^{(m+1)}\right) \left(\vec{x}_i - \vec{m}_{k,j}^{(m+1)}\right)^T$$

Identification of objects by precedent descriptions (testing objects)

Direct application of Fisher's MLE to precedent descriptions ???

$$\hat{k} = \underset{k}{\operatorname{argmax}} \ln P\left(\vec{x}_1, \vec{x}_2, \dots, \vec{x}_n, \vec{\lambda}_k\right)$$

The problem of direct use of MLE - a huge number of precedents.

The solution is the test auditory image data $\{\vec{x}_i\}$ identification not with a specific description of a precedent $\vec{\lambda}_k$=$\{(p_k^j, \mu_{k,j}, \sigma_{k,j})\}$, but with a whole class of similar descriptions, obtained from each registered using some group of transformations, for example, an affine group $\vec{x} \to (\vec{x} + \vec{t})/s$ (change in time origin on $\vec{t}$ and change of time scale on *s*).

$$\ln P\left(\vec{x}_1, \vec{x}_2, \dots, \vec{x}_n, \vec{\lambda}_k\right) = \ln \prod_{i=1}^{n} p_k(\vec{x}_i) \to \ln\left[\int\int \rho_{apr}\left(\vec{t}, s\right) \prod_{i=1}^{n} p_k\left(s\vec{x} - \vec{t}\right) s^2 \, d\vec{t} ds\right]$$

EM algorithm for low-count objects identification

Hidden variables:

Instead of $\vec{\lambda}_k$={($\pi_{k,j}$,$\vec{\mu}_{k,j}$, $\sigma_{k,j}$)} – precedent description params, $\vec{t}$ and s are considered as unknown params - parameters of a affine group of transformations, identifying object in a class k of similar precedents.

$\vec{t}$ and s params MLE calculation:

$$\{x_1, x_2, \ldots, x_n\} \rightarrow \text{EM algorithm for GMM} \rightarrow \vec{t} \text{ and } s$$

E-step:

$$Q_{k,j}^{(m)}(\vec{x}_i) = \left(\bar{S}^{(m)}\,\vec{x}_i - \vec{T}^{(m)} - \vec{m}_{k,j}^{(*)}\right)^T \times$$
$$\times\, A_{k,j}^{(*)}\left(\bar{S}^{(m)}\,\vec{x}_i - \vec{T}^{(m)} - \vec{m}_{k,j}^{(*)}\right);$$

$$V_{j|i}^{(m+1)} = \frac{1}{\Sigma_V} p_{k,j}^{(*)} \sqrt{\det\left\{A_{k,j}^{(*)}\right\}} \exp\left\{-\frac{1}{2} Q_{k,j}^{(m+1)}(\vec{x}_i)\right\}$$

$$\Sigma_V = \sum_{j=1}^{N_k} p_{k,j}^{(*)} \sqrt{\det\left\{A_{k,j}^{(*)}\right\}} \exp\left\{-\frac{1}{2} Q_{k,j}^{(m+1)}(\vec{x}_i)\right\};$$

M-step:

$$\sigma^{(m+1)} = \cdots, \Sigma^{(m+1)} = \cdots, \varepsilon = \cdots,$$

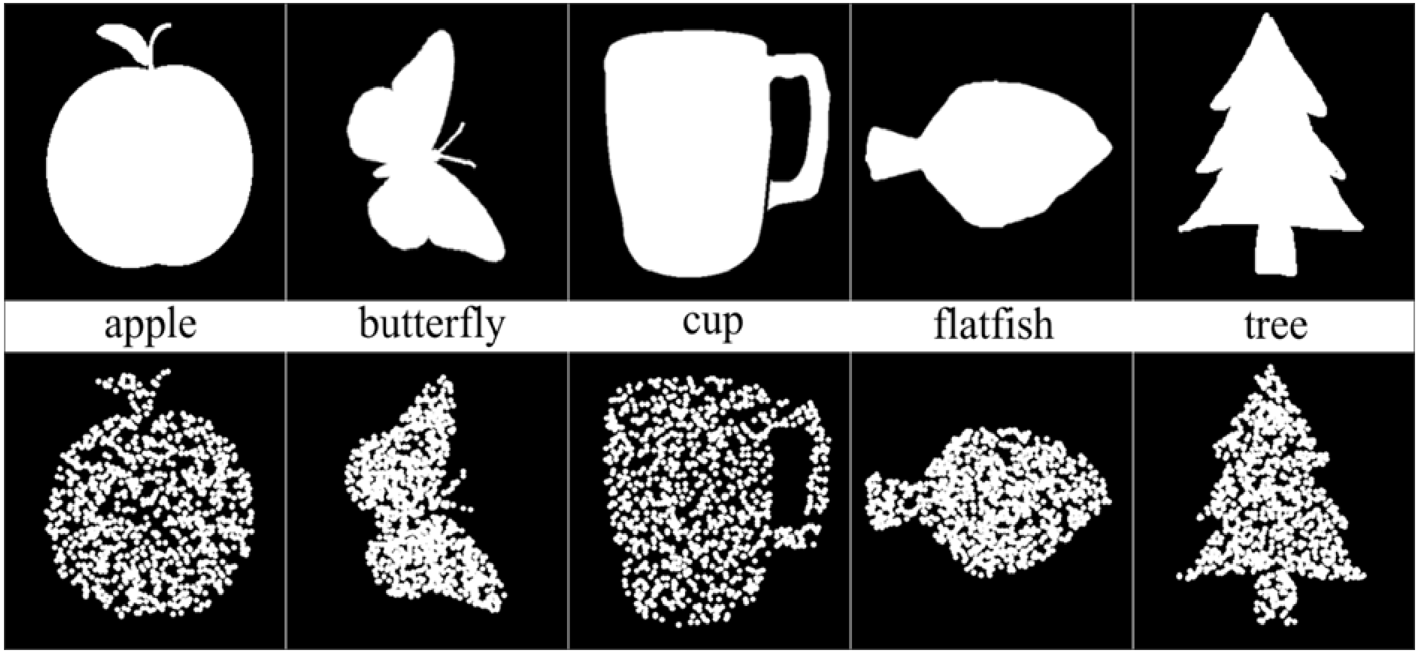
$$\mu_\sigma = \frac{\varepsilon}{1+\varepsilon}; \quad \mu_\Sigma = \frac{1}{1+\varepsilon}$$

$$\bar{S}^{(m+1)} = \mu_\sigma \sigma^{(m+1)} + \mu_\Sigma \Sigma^{(m+1)};$$

$$\vec{T}^{(m+1)} = \bar{S}^{(m+1)} \vec{X}^{(m+1)} - \vec{M}^{(m+1)};$$

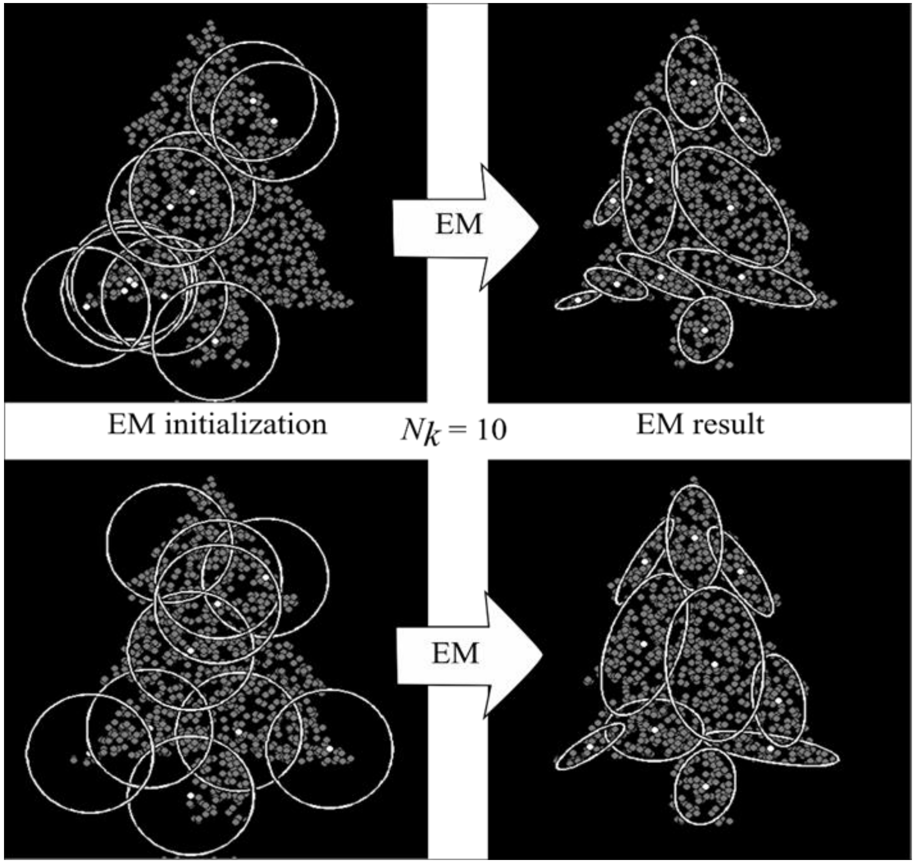
Simple experiments on objects identification I

Precedents from the “MPEG-7” database represented by 500 × 500 binary images (top) and their registration model data as 1000 samples, uniformly distributed over their shapes (bottom).



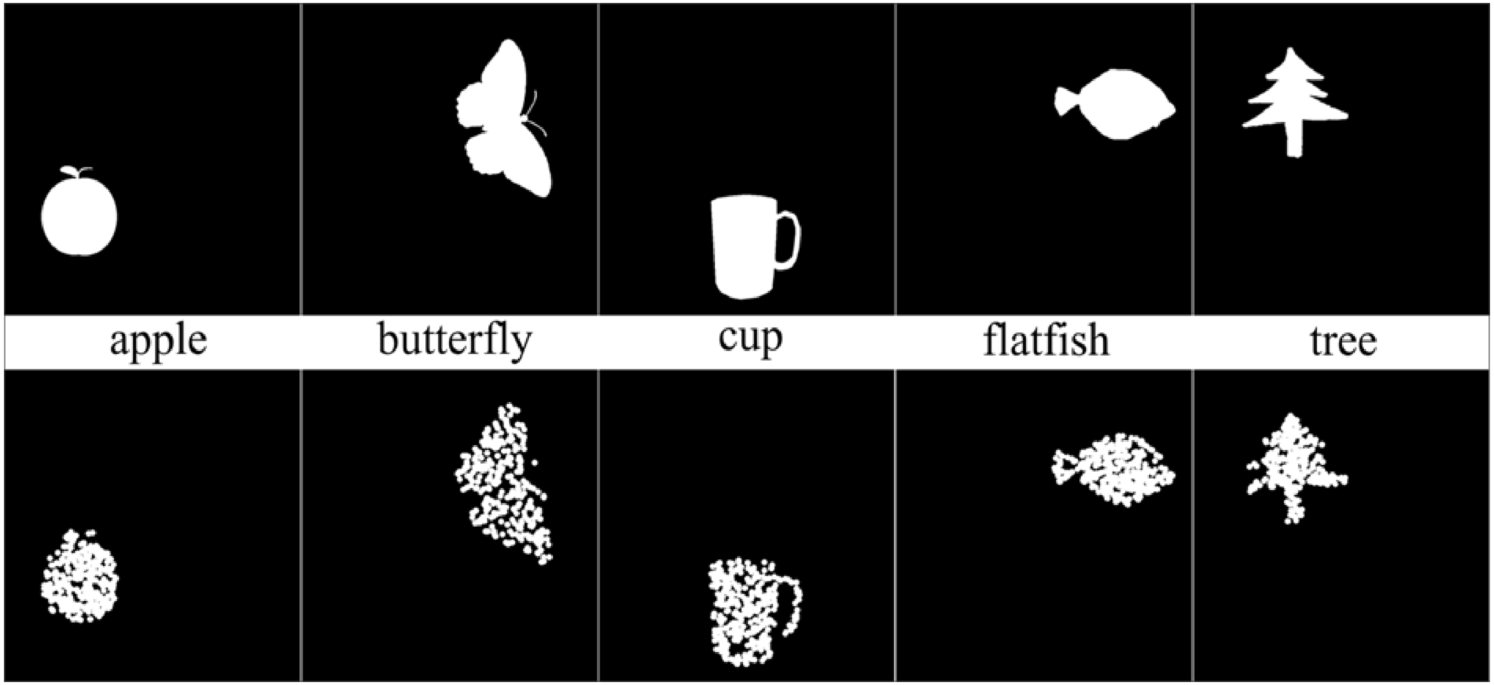
Simple experiments on objects identification II

The results of initialization (on the left) and the application (on the right) of the EM – algorithm. The components of the corresponding mixtures are represented by their centres (points) and lines (ellipses) of a constant level



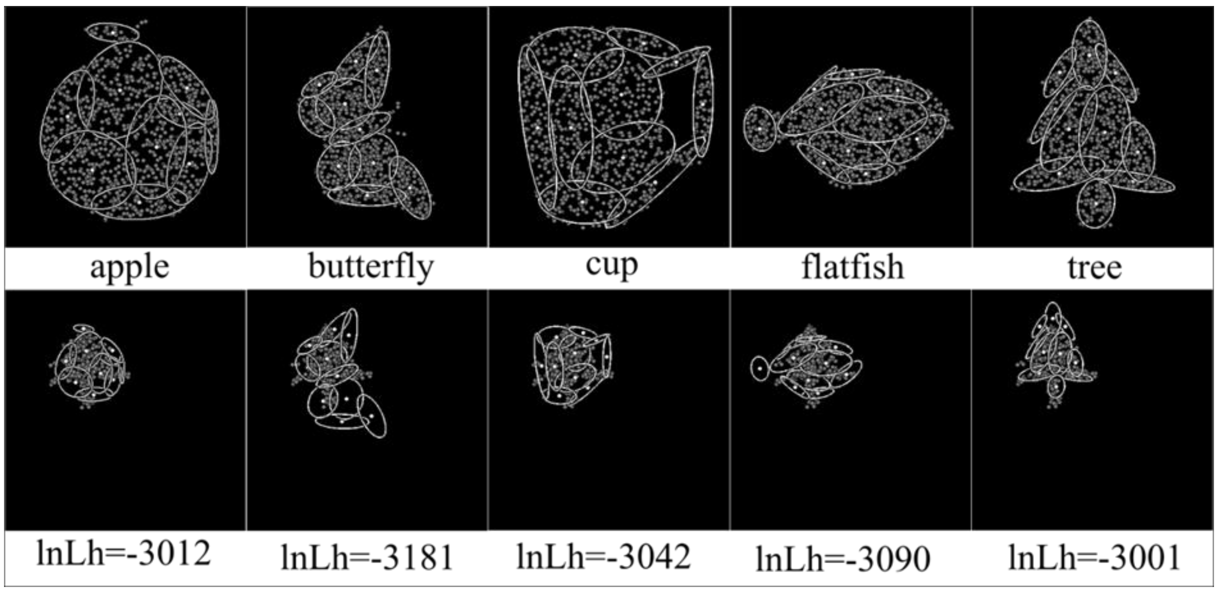
Simple experiments on objects identification III

The tested objects from the database "MPEG-7" are selected from the same categories as the processed precedents but shifted and reduced randomly (top) and model data of their registration in the form of uniformly distributed 300 counts (bottom).



Simple experiments on objects identification VI

Descriptions of precedents from the database (top) and their recalculated using the found maximum-likelihood parameters $\vec{T}^{(*)}$ and $S^{(*)}$ descriptions (bottom) for the registration data of the tested object “tree-9”. Below for each precedent the logarithm of the mean likelihoods denoted as “lnLh” are represented.

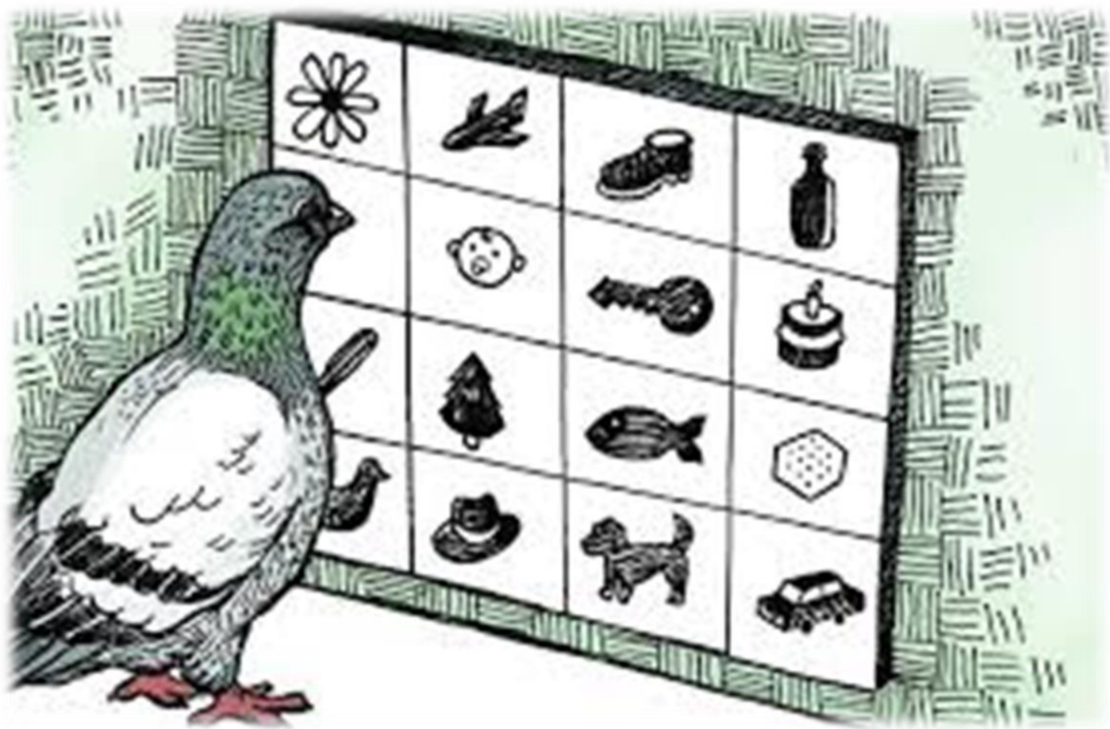


Simple experiments on objects identification V

Values of the similarity measure (log likelihood) for tested objects of different categories (300 samples data).

Tested objects ↓	Precedents				
	apple-10	butterfly-15	cup-19	flatfish-10	tree-14
apple-20	-2907	-3100	-2992	-3026	-2996
butterfly-13	-3202	-3117	-3227	-3320	-3186
cup-7	-3090	-3190	-3029	-3129	-3174
flatfish-3	-3122	-3304	-3175	-2949	-3193
tree-9	-3012	-3181	-3042	-3090	-3001

Thank you for attention,



Questions?