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The part and the whole: relations in the scene of sensors' measurement space

Tamás Szirányi

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Budapest, Hungary

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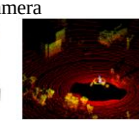
Our sensors for environment perception

High resolution video camera

Thermal camera

Kinect



MESA ToF camera Velodyne LIDAR laser scanner

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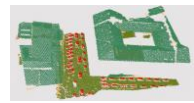
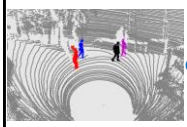
Recognising the things in motion

LIDAR based 3D reconstruction and recognition





Outdoor and indoor 3D video surveillance

Real time multi target tracking and target identification

Terrestrial target tracking

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- Relations among different views and scales in imaging
- Optimization strategies in the sensors' networks
- Graph-based features
- Clustering and recognition on connected features' structure
- Stochastic image alignment

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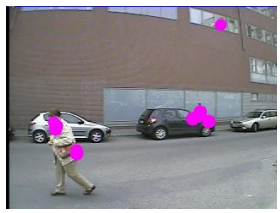
Eye tracking: Comparison of real-life measurement and saliency based estimation



Saliency points artificially inferred by my model

A real human gaze path from one of our subjects

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Content

- ❑ Scale-space axiomatic system
- ❑ What is in the background?
- ❑ Neighborhood connections
- ❑ Graph based Features
- ❑ Clustering and recognition
- ❑ Stochastic models

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"Scale-space" axioms

If zooming or rotating, the richness of details may change, but the essence not; give us rules:

- *Linearity:* $T_t(af + bh) = aT_t f + bT_t h$
- *Shift invariance*
- *Semi-group:* $g(x,y,t_1) * g(x,y,t_2) = g(x,y,t_1 + t_2)$ *(cascade filter)*
- *Local max/min relations do not change during scalig*
- *No new features (zero-crossings)*
- *rotation symmetry*

- Lindeberg & Haar Romeny: "Linear Scale-Space", Kluwers, 1994
- Babaud et al: "Uniqueness of the Gaussian kernel for scale-space filtering", IEEE PAMI, 1986

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A Scale-Space axioms to a new paradigm of image description

- Scale-Space theory: *scaling and* Gauss function
- *Anisotropic diffusion* → de-noising
- *Wavelet* description and uncertainty principle
- Image structure from scales: Lindeberg' iterations
- Finding the most featuring scale
- Descriptors around the key-points in 128 dimesions: SIFT

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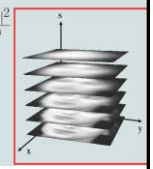
A Scale-Space axioms
- Linearity
- Shift invariance
- Isotropy
- Causality
- Separability

lead to the Gaussian smoothing.

Gaussian Scale Space

$$u(\mathbf{x}; s) = (f * \varphi_s)(\mathbf{x})$$

$$\varphi_s(\mathbf{x}) = \frac{1}{\sqrt{4\pi s}^n} e^{-\frac{\|\mathbf{x}\|^2}{4s}}$$



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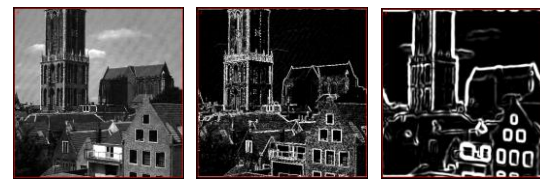
From fine details to overall features: Gaussian smoothing



Original | Gradient (scale 1 pixel) | Gradient (scale 4 pixels)

Scale induces an image hierarchy.

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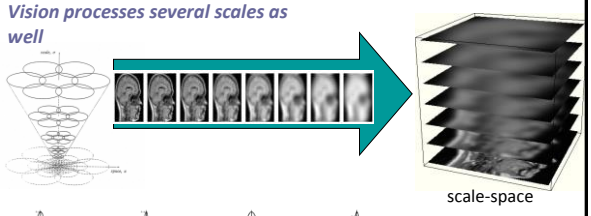
Looking for the most discriminative scale

The position and the detailness fulfils the uncertainty discipline

Vision processes several scales as well



scale-space

$$\Delta x \Delta y \geq \frac{1}{2} \frac{n}{4\pi}$$

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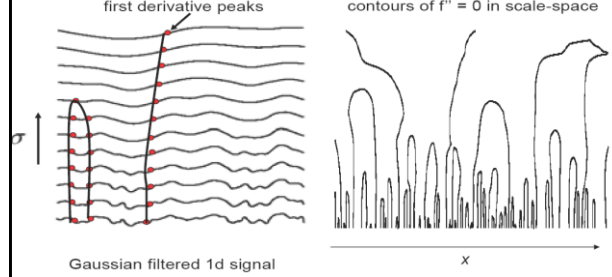
The edge transitions follow the axioms



Gradually smoothed signal

The positions of gradient-changes do not cross each other through scales

Scale space (Witkin 1983)

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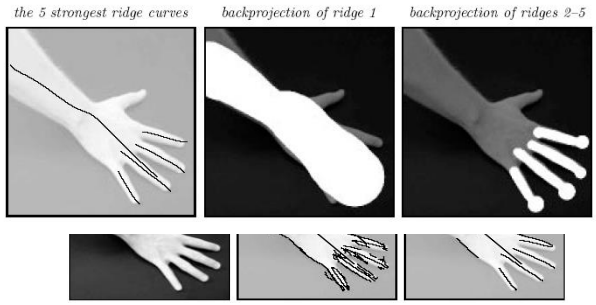
Defining edge, ridge and featuring scale



Tony Lindeberg: "Edge detection and ridge detection with automatic scale selection", IJCV, 1998

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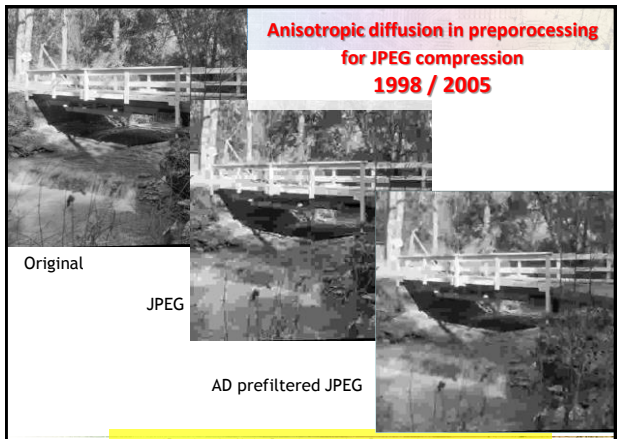
Anisotropic diffusion (de-noising)

$$\partial_t u = w_K \left(|\nabla G_\sigma * u| \right) \left((1-\alpha)\, u_{\parallel} + \alpha\, u_{\perp} \right)$$

- Perona & Malik: "Scale-space and edge detection using anisotropic diffusion", 1987
- Alvarez, Guichard, Lions, Morel: "Axioms and fundam. eqs. of image proc.", 1993

Anisotropic diffusion in preporocessing for JPEG compression 1998 / 2005



Kopilovic & Szirányi; Optical Engineering, 2005

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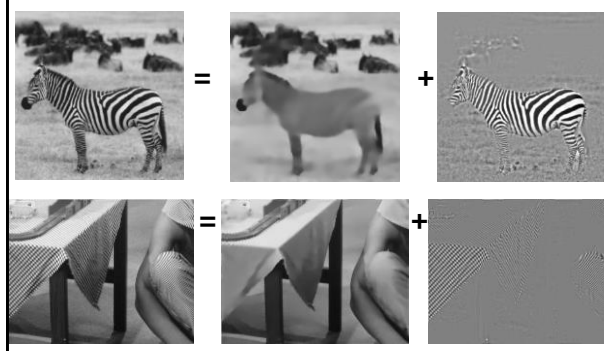
Cartoon/Texture separation with TV and adaptive anisotropic diffusion - *2012*



Szolgay D & Szirányi T: IEEE Tr. ImProc, 2012

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Scale Invariant Feature Transform

- Local features are specific for shape and less information loss in case of occlusion
- Main steps:
  - Keypont definitions,
  - Featuring areas,
  - Descriptors.

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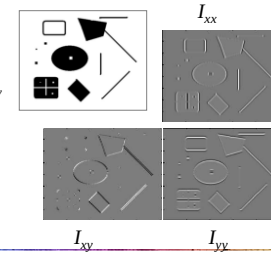
Hessian detector *(Beaudet, 1988)*

- Search for strong derivatives in two orthogonal directions:

$$Hessian(I) = \begin{bmatrix} I_{xx} & I_{xy} \\ I_{xy} & I_{yy} \end{bmatrix}$$

$$\det(Hessian(I)) = I_{xx} I_{yy} - I_{xy}^2$$



Responses mainly on corners and strongly textured areas.

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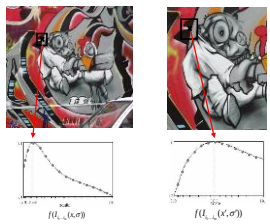
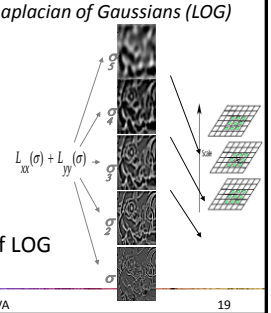
Automatic scale selection: *LOG*

- Function response of scale signature



Laplacian of Gaussians (LOG)



- Local maxima in scale-space of LOG

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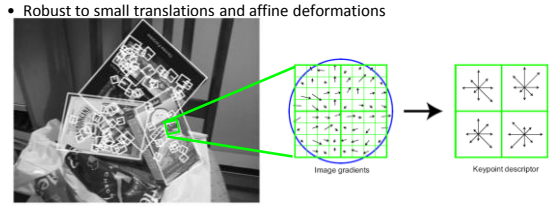
SIFT descriptor *(Lowe, ICCV, 1999)*

- Histogram of oriented gradients
- Captures important texture information
- Robust to small translations and affine deformations



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Keypoint detection based methods:

Harris detector as main feature

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Alternative for keypoint descriptors: Filtering keypoint candidates with Local Contours

- Generating Harris keypoints for difference map
- Generating Local Contour with Gradient Vector Field (GVF) around keypoints in the Harris-based image: $f_{|R|}(x,y) = G_\sigma(x,y) * |R(x,y)|$
- Calculating Modified Fourier Descriptor for the estimated closed curve
- Describe the contour by a limited set of Fourier coefficients
- Comparing descriptors with a symmetric distance computation
  - D_i: similarity value between descriptor for p_i on old and new image
  - if $D_i > \varepsilon_3$ p_i is supposed to be a changed point

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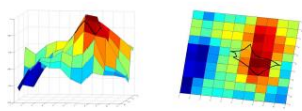
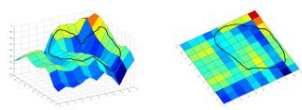


(a) Contour in 3D (b) Contour from top view

Fig. 1. Significant contour



(a) Contour in 3D (b) Contour from top view

Fig. 2. Not significant contour

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Results

Older image

Newer image with detected changing objects

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Harris function based active contour external force for image segmentation

Pattern Recognition Letters, 2012

Andrea Kovács, Tamás Szirányi

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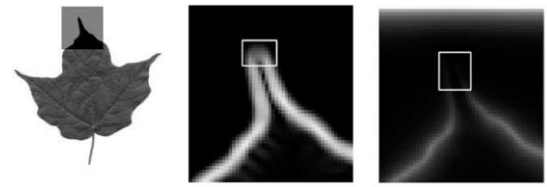
The original f edge map for high curvature boundary: (a) shows the original image, region of interest is in gray; (b) is the f edge map of the marked area. The white rectangle indicates the decreased f values of the high curvature boundary; (c) is the fVFC map of the marked area. The white rectangle indicates the decreased fVFC values of the high curvature boundary.



(a) (b) (c)

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Harris corner detector

- Harris detector is based on the second moment (autocorrelation) matrix M:

$$M = \begin{bmatrix} A & C \\ C & B \end{bmatrix}$$

  - $A = \dot{x}^2 \otimes w$, $B = \dot{y}^2 \otimes w$, $C = \dot{x}\dot{y} \otimes w$
  - $\dot{x}$, $\dot{y}$: first order derivatives; w: Gaussian window
- Eigenvalues of M (λ_1 and λ_2) are proportional to the principal curvatures and separate the following cases:
  - both of them are large in corner regions
  - one of them is large in edge regions
  - both of them are small in homogeneous (flat) regions

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Modified Harris: corners+edges

- **A. Kovács**, T. Szirányi: "High Definition Feature Map for GVF Snake by Using Harris Function," *Conference on Advanced Concepts for Intelligent Vision Systems (ACIVS), Lecture Notes in Computer Science 6474*, 2010, pp. 163 – 172.
- Emphasizing corners and edges equally:
  - $\max(\lambda_1, \lambda_2)$ separates flat and non-flat regions
- After compressing and rescaling the dynamics to get a balanced distribution:

$$R_{\text{logmax}} = \max(0, \log[\max(\lambda_1, \lambda_2)])$$

- Proposed feature map for Harris based VFC (HVFC):
  - Applying $R_{\text{logmax}}(x, y)$ instead of $I(x, y)$

$$\mathbf{f}_{\text{HVFC}} = \left|\nabla(G_\sigma(x, y) * R_{\text{logmax}}(x, y))\right| * \mathbf{k}(x, y)$$

f_{VFC}

f_{HVFC}

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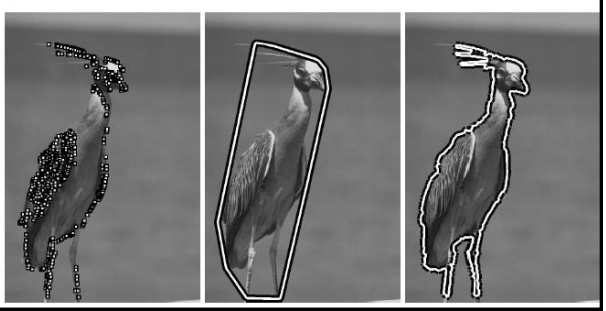
Initial contour + detection

- Feature points: local maxima of R_{logmax}
- Initial contour: convex hull of the point set
- Iterative active contour method



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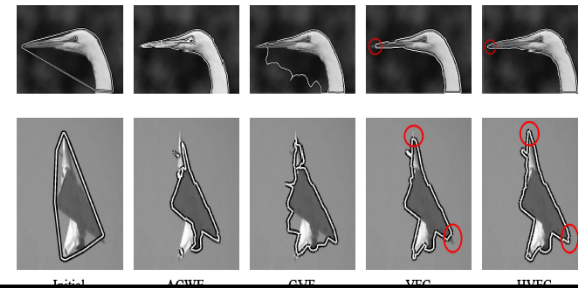
F(HVFC) = 0.91 > F(VFC) = 0.86
F(HGFV) = 0.87 > F(GVF) = 0.79

- Specific images to test accuracy
- ACWE *(Chan, 2001)*, GVF *(Xu, 1997)*, VFC *(Li, 2007)* and HVFC (proposed) were compared



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Harris, orientation and Shearlet trf. based segmentation

- Contour detection based on feature points and edge map

A. Kovács, T. Szirányi: "Orientation Based Building Outline Extraction in Aerial Images," *XXII ISPRS Congress*, (under revision).

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Improved feature point set for orientation sensitive urban area detection(*2013*)

7/14/20 **Kovács A & Szirányi T; IEEE GeoSci RemoteSensing L**

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Improved segmentation of a series of remote sensing images by using a fusion MRF model

Tamás Szirányi and Maha Shadaydeh

IEEE GRSL, 2014

7/14/2015

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1984

2000

2005

2007

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Proposed method:

- Color and texture features
- Cross-image featuring
- Multi-Layer Markovian adaptive fusion
- Single layer segmentation based on fusion clusters
- Segmentation and detection of changes

Detecting details in rarely scanned remote sensing areas, where trajectory analysis or direct comparison is not applicable.

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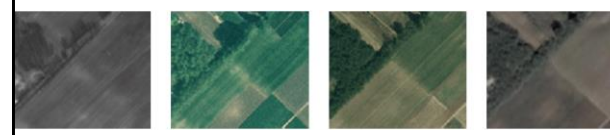
Fused segmentation of the different subclasses



More images

More information

More complex details

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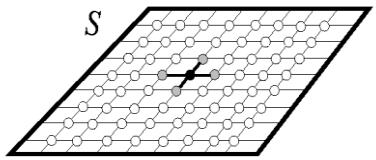
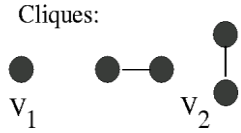
Markov Random Field Optimization
Local steps – global optimum



Cliques:



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MRF models and segmentation levels:

- *Single layer*

  single year - some supervision is needed

- *Multiple layers* (stack of years' layers):

  the source of supervision for single layer step

$$\hat{\Omega} = \text{argmin}_{\Omega} \sum_{s \in S} \underbrace{-\log P(\overline{x}_s|\omega_s)}_{\epsilon_{\omega_s}(s)} + \sum_{r,s \in S} \Theta(\omega_r, \omega_s)$$

$$\Theta(\omega_r, \omega_s) = \begin{cases} 0 & \text{if } \omega_r = \omega_s \\ +\beta & \text{if } \omega_r \neq \omega_s \end{cases}$$

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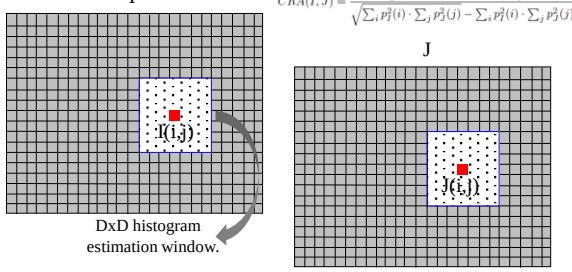
CRA Calculation

$$CRA(I,J) = \frac{\sum_{i,j} p^2_{I,J}(i,j) - \sum_i p^2_I(i) \cdot \sum_j p^2_J(j)}{\sqrt{\sum_i p^2_I(i) \cdot \sum_j p^2_J(j) - \sum_i p^2_I(i) \cdot \sum_j p^2_J(j)}}$$



Marginal and joint histograms can be estimated from subsets of the images. The window size can be varied according to the required scale of change detection.

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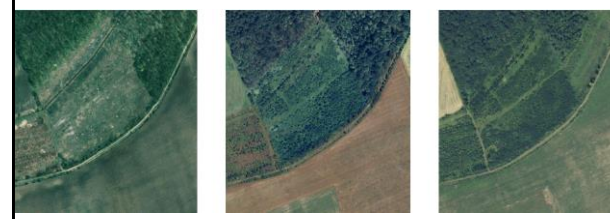
Forest / Meadow changes: 2000 - 2005 - 2007



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Unsupervised segmentation and change detection by using CRA cross-layer measure and color info

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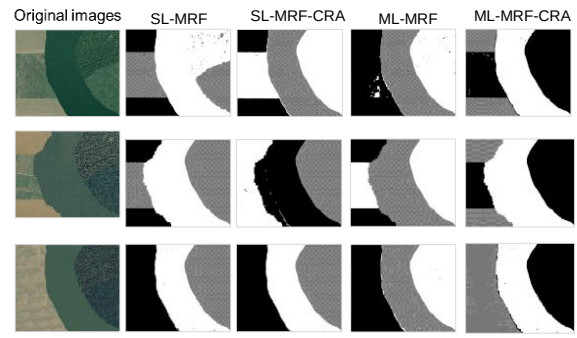
Segmentation Results on Ground-Truth samples



(unsupervised using K-means)

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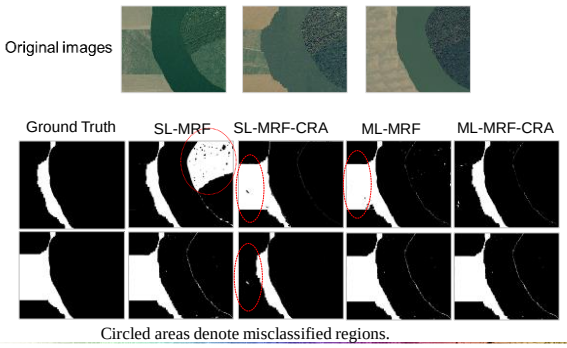
Change Detection Results on Ground-Truth



Circled areas denote misclassified regions.

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- Fusion in 3D

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What is in the background?

Stochastic and physical models for background discrimination:

- Gaussian models
- Doppler measurement for passive radars

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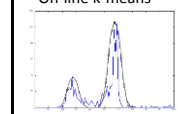
Background filters

Stauffer and Grimson IEEE Tr. PAMI, 2000
Benedek and Szirányi, IEEE Tr. IP, 2008

- Mixture of Gaussians
- On-line k-means



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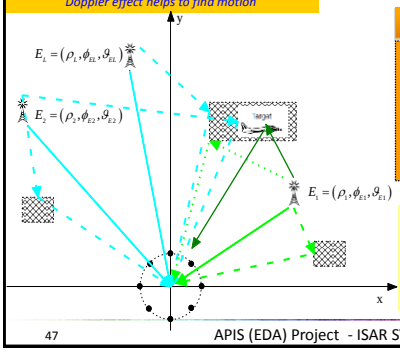
Background filter from „radar" signatures

Passiv reflections
Doppler effect helps to find motion



Target signal
Interferences
Hot clutter
Direct signal
Multipath
Ground clutter

Array received signal vector

$$s(\mathbf{r}_k,t)=s_L(t)e^{i2\pi f_0(t-\tau_k)}$$

$$\tau_k=\frac{\mathbf{k}(\phi,\vartheta)\mathbf{r}_k}{c}=\frac{\cos(\phi)\sin(\vartheta)x_k+\sin(\phi)\sin(\vartheta)y_k}{c}$$

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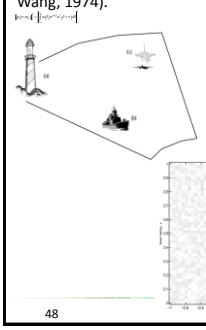
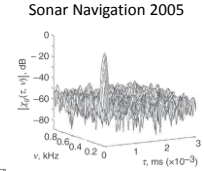
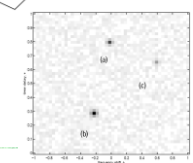
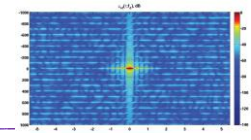
Ambiguity function describes how correlated a signal is with itself delayed in time by τ and shifted in Doppler (Sinsky and Wang, 1974).

Saini, Cherniakov, "DTV signal ambiguity function analysis for radar application", IEE Proc.-Radar Sonar Navigation 2005









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Neighborhood and geometrical relations

- Sensor networks
- Geometry based relations

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Neighborhood and geometrical relations

- Sensor Networks
- Geometry based relations

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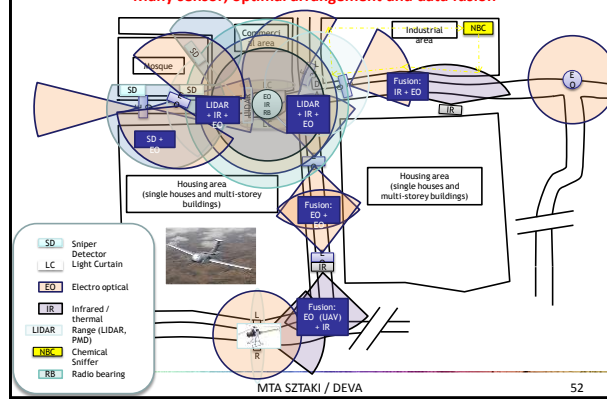
Many sensor, optimal arrangement and data fusion



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Stochastic methods, correlation models

Bayes iterations

- Lucy-Richardson algorithm for blind deconvolution
- *Image registration through correlation calculus*

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Stereo registration through random motion

Szlavik, Sziranyi, Havasi - IEEE Tr. Image Processing, 2007

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Ergodic regular Markov chain has a unique stationary distribution

$$\left(\underline{p}_1 \quad \underline{p}_2\right) = \left(\underline{p}_1 \quad \underline{p}_2\right)\underline{\underline{\Pi}}$$

$$P(m_{1i})_{r+1} = P(m_{1i})_r \sum_k \frac{P(m_{2k} \mid m_{1i})P(m_{2k})_r}{\sum_j P(m_{2k} \mid m_{1j})P(m_{1j})_r}$$

$$P(m_{2k})_{r+1} = P(m_{2k})_r \sum_i \frac{P(m_{1i} \mid m_{2k})P(m_{1i})_r}{\sum_j P(m_{1i} \mid m_{2j})P(m_{2j})_r}$$

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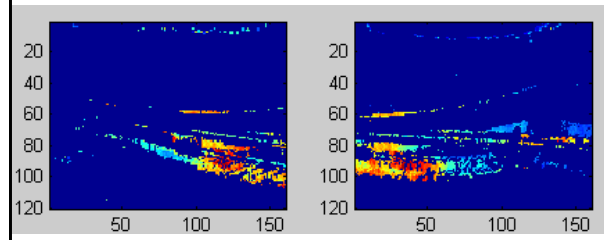
Bayesian iterations of Ergodic regular Markov chain

with a unique stationary distribution



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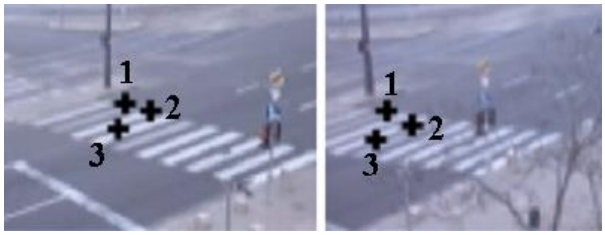
Point pairs



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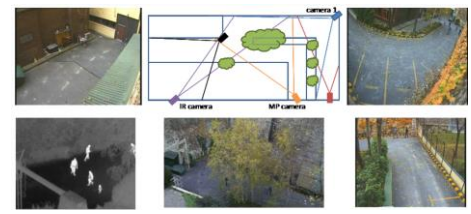
Fusion of different partly overlapping modalities

- Calibration of sensors or basic surfaces
- Localisation in the world coordinate system



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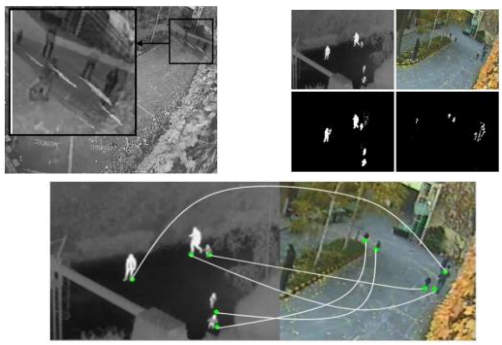
Localisation



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Sensor connection system:

From parts to the whole

Sensors should be arranged in optimal arrangement

- Random search accomodating to the priority levels
- Criterion for network building

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Swarm optimization

- Many models:
  - ABC (Artificial Bee Colony) — Karaboga, Akay – A survey: algorithms simulating bee swarm intelligence, 2009.
  - Intelligent water drops — Duan,Liu,Wu – Novel Intelligent Water Drops Optimization Approach to Single UCAV Smooth Trajectory Planning, 2009.
- Firefly/ glowworm algorithm : — Krishnanand,Ghose – Glowworm Swarm Optimisation: A New Method for Optimising Multi-Modal Functions, 2009.
  - Lightness related to the fitness
  - The most lighter effects the weakers
  - Without lighting neighbors, the motion is random

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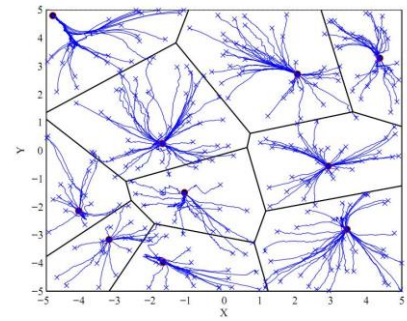
Glowworm algorithm for grouping



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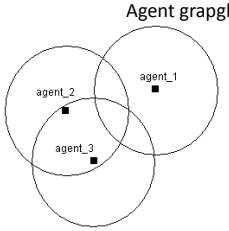
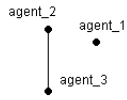
Connection test

Az *agent_2* and *agent_3* related cto each other, while *agent_1* is not connected.

Agent grapgh





$$L = \begin{bmatrix} 0 & 0 & 0 \\ 0 & 1 & -1 \\ 0 & -1 & 1 \end{bmatrix}$$

$$L_{ij} := \begin{cases} \deg(v_i), & \text{if } i = j \\ -1, & \text{if } i \neq j \text{ and } (v, v_j) \in E \\ 0, & \text{else} \end{cases}$$

Goal:
Calculating the sign of the ***2. smallest eigenvalue*** *of L* Laplace matrix

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Connection test from local calculus

1. $\dot{x} = -E(\{x_i\})1$
2. New direction : $\dot{x} = -Lx$
3. Normalised: $\dot{x} = -(E(\{(x_i)^2\}) - 1)\,x$

Three steps together:

$$\dot{x} = -k_1 E(\{x_i\})1 - k_2 Lx - k_3(E(\{(x_i)^3\}) - 1)\,x$$

Convergence criterion:

$$k_1, k_2, k_3 > 0$$
$$k_1 > k_2 \lambda_2$$
$$k_3 > k_2 \lambda_2$$

Eigenvalue from local info:

$$\lambda_2^i = -\frac{\sum_{j \in N_i} L_{ij} x_j}{x_i}$$

Yang et al, "Decentralized Estimation and Control of Graph Connectivity for Mobile Sensor Networks", American Control Conference, 2008

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Content

- ❑ Scale-space axiomatic system
- ❑ What is in the background?
- ❑ Neighborhood connections
- ❑ *Graph based Features*
- ❑ Clustering and recognition
- ❑ Stochastic models
- ❑ Fusion in 3D

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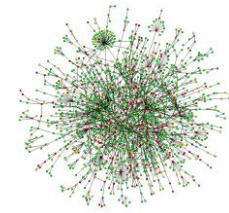
Graph based features

- Scale-space
- Texture
- Graph-cut for segmentation
- Biometrical recognition



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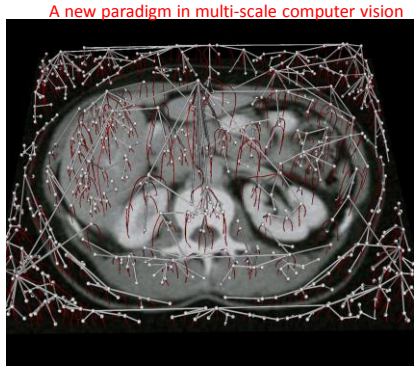
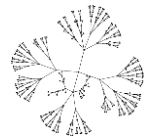
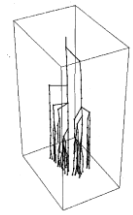
Scale-space based interpretation:

A new paradigm in multi-scale computer vision







Bart M. ter Haar Romeny, TU/e

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Graph based features

- Scale-space
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- Graph-cut for segmentation
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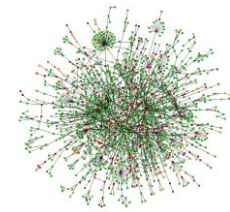

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Graph based segmentation on textured areas

In high resolution, **textural and geometric properties** emerge:

- Entities of interest appear at **multiple scale**
  - Surfaces, Vegetation, Buildings, Urban Areas, etc.
- Visual appearance and significant information change across the scales.

- The **scale** can be fixed (extraction of specific entities):
  - Vegetation → **NDVI index** + binary segm. …
  - Buildings → (**MPP**) Marked Point Processes, …
  - Roads → **Active Contours & HOAC**, …

*R. **Gaetano, G. Scarpa, T. Szirányi**: "Graph-based Analysis of Textured Images for Hierarchical Segmentation", LNCS, **BMVC 2010***

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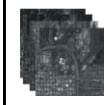


Pixel level processing

Region level processing

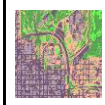
Color Based Classification

Spatial Context Based Clustering

Region Merging

fragmentation

reconstruction



hierarchical map

Color Based Classification

- Based on the **Tree-Structured Markov Random Fields**
- **Robustness to noise**, control over initial **spatial scale**

Fragment Features for SBC

$S_\omega = \bigcup_{k=1}^{N_\omega} S_{\omega_k}$ *region associated to state* ω

$\forall$ *fragment* ω_k *we can compute a feature matrix*

$A_{\omega_k}{}^{(L)}(\omega', j) = p_j{}^{(L)}(\omega'|\omega_k)$ [L × 8]

$p_j{}^{(L)}(\omega'|\omega) = \sum_{k=1}^{N_\omega} p_j{}^{(L)}(\omega'|\omega_k)\Pr(\omega_k)$

Texture Score for Region Merging

$TS^\omega = p(\omega) \cdot p(\bar{\omega}|\omega)^{-1} \cdot [p(\bar{\omega}|\omega) \cdot \max_{\omega' \neq \omega} p(\omega'|\omega)^{-1}]$

- **Area**, **compactness** and **nearest neighbor dominance**
- **Region** with **lowest TS** are sequentially merged

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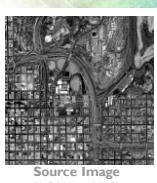
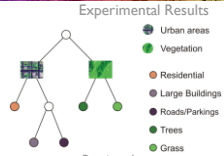


Source Image (1 PAN + 4 MS)

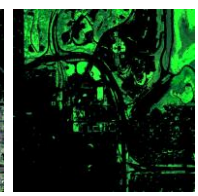
Manually segmented

Experimental Results



Retrieved Hierarchical Structure

5-class Map
Overall Acc. **73,4%**



Urban class Overall Acc. **97,5%** **Vegetation** class

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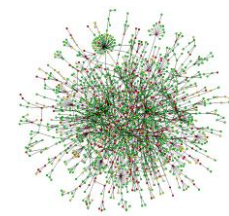
Graph based features

- Scale-space
- Texture
- Biometrical recognition



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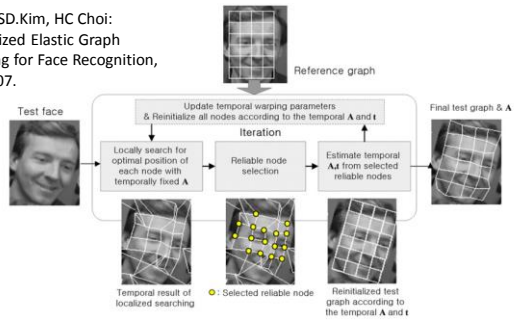
Graphs in face recognition

H.Shin, SD.Kim, HC Choi:
Generalized Elastic Graph Matching for Face Recognition, PRL, 2007.



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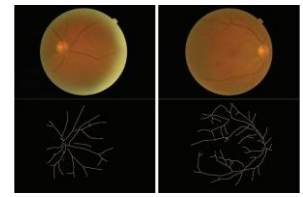
Graphs in retina comparison



Tree/forest edge comparison

M. Zaslavskiy, F.Bach, JP. Vert :
A path following algorithm for the graph matching problem,
PAMI, 2009.

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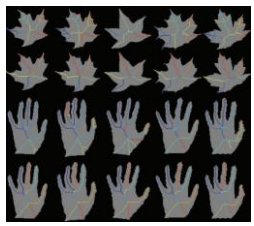
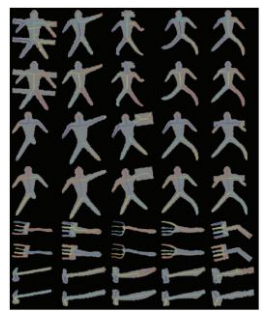
Silhouette based graph comparison

A.D.Ward, G. Hamarneh:
The Groupwise Medial Axis Transform for Fuzzy Skeletonization and Pruning, PAMI, 2010.





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Image/cluster comparison by graphs

- BoW
- Related images constitutes society

Resulted clusters:

S. Papadopoulos, C. Zigkolis, et al. - Image Clustering Through Community Detection on Hybrid Image Similarity Graphs , ICIP, 2010.

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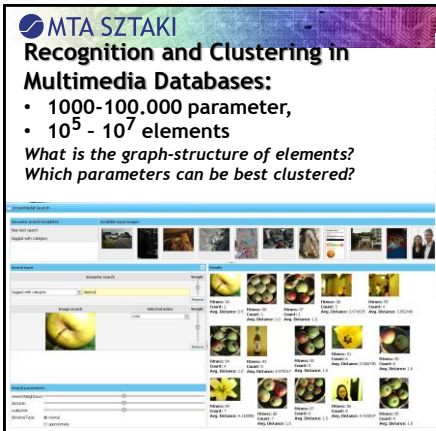
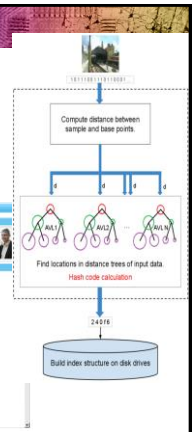
Recognition and Clustering in Multimedia Databases:

- 1000-100.000 parameter,
- 10^5 - 10^7 elements

What is the graph-structure of elements?
Which parameters can be best clustered?





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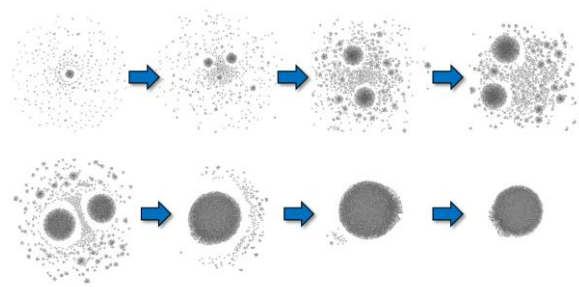
Clustering behavior of big databases follows the Giant Components (Erdős-Rényi) for random geometric graphs
CLEF, 2012



Keszler A. & Kovacs L. & Sziranyi T.

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Decision and recognition tasks

Kleinberg, 2002 – „impossibility theorem"

f is a cluster function, from S set makes P partition, at d distance functions. P sets are the clusters.

Features of clustering:

1) Scale-invariance

For any d, α>0: f(d)=f(α·d)

2) Richness: any possible P might be a partition

3) Consistency

Proposition: For n≥2 no such clustering function may exist(2002).

For the Hierarchic case one and only one solution may exist!

(Carlsson & Mémoli, JMLR, **2010**).

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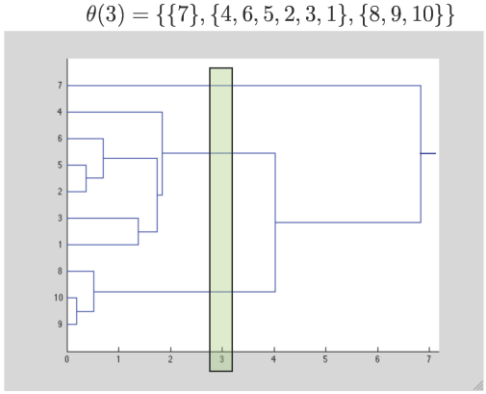
$$\theta(3) = \{\{7\}, \{4, 6, 5, 2, 3, 1\}, \{8, 9, 10\}\}$$



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Stochastic methods, correlation models

Bayes iterations

- *Lucy-Richardson algorithm for blind deconvolution*
- Image registration through correlation calculus

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Lucy-Richardson algorithm for blind deconvolution:

- Given observation *g*, give an estimation of the original image *f* and the blurring function (PSF) *h* : $g = f * h$
- Starting from Richardson's original formula based on Bayesians:

$$P(f_i|g) = [P(g|f)P(f_i)] / \sum_j [P(g|f_j)P(f_j)] \qquad P(f|g) = P(fg)/P(g)$$

$$P(f_i) = \sum_l P(f_i g_l) = \sum_l P(f_i|g_l)P(g_l) = \sum_l \frac{P(g_l|f_i)P(f_i)P(g_l)}{\sum_j P(g_l|f_j)P(f_j)}$$

$$P_{k+1}(f_i) = P_k(f_i) \sum_l \frac{P(g_l|f_i)P(g_l)}{\sum_j P(g_l|f_j)P_k(f_j)}$$

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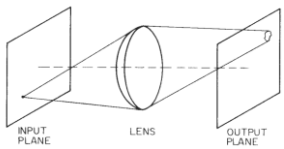
Lucy-Richardson algorithm for blind deconvolution:

- Probability is proportional to the luminance
- Conditional probability is prop. to the PSF

$$f_{i,k+1} = f_{i,k} \sum_l \frac{h_{i,l} g_l}{\sum_j h_{j,l} f_{j,k}} = f_{i,k} \sum_l h_{i,l} \frac{g_l}{\sum_j f_{j,k} h_{j,l}}$$

$$f_{k+1} = f_k \left(h_k \otimes \frac{g}{f_k \otimes h_k} \right)$$



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The double iteration

$$\begin{cases} f_{k+1}(r) = f_k(r) \left[h_k(r) * \frac{g}{g_k}(r) \right] \\ h_{k+1}(r) = \frac{h_k(r)}{\gamma} \left[f_k(r) * \frac{g}{g_k}(r) \right] \end{cases}$$

$g_k = f_k * h_k$

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- f and the PSF vary locally according to the amount of blur (distortion) present on the image locally
- Stop the double iteration at a finite step (here #5) and check the **error between the measured and the estimated blurred image** blocks: $\| g - g_k \|$
- Is MSE usable for comparison the BD residual errors of different blocks?

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Comparison of in-focus measures through convergence error

- Comparison of blocks is based on the $\| g - g_k \|$ error distance between the estimated g_k and measured g average values over a sample area
- The greater the error distance, the better in the focus: more effort is needed for convergence from the stopped iteration
- Problem: The residual error makes the comparison unbalanced
- A measure of zero theoretical residual is needed

The independence of signal and noise makes the orthogonality criterion usable as an error measure itself

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ADE : angle deviation error
Orthogonality criterion: signal and noise are independent

$$\left| \arcsin \frac{\langle g, g - g_k \rangle}{|g| |g - g_k|} \right|$$

In case of

$g - g_k = [+1, -1, -1, +1, -1, +1 \ldots\ldots -1, +1]$

$g = [10, 10, 10, 10, 10, 10 \ldots\ldots 10, 10]$

$\| g - g_k \|$ is high, while

$< g, g - g_k > \rightarrow$ zero

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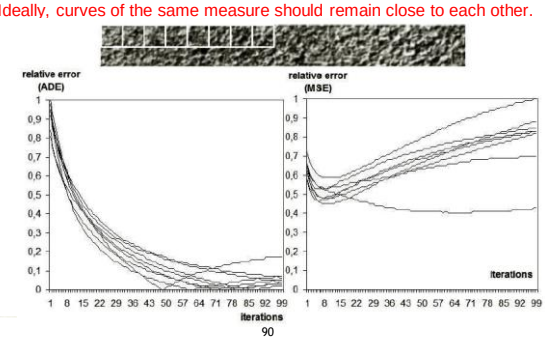
Error curves for 8 neighboring blocks (each curve stands for one block) on a blurred texture sample (top) for the same blur with **ADE** (left), and **MSE** (right) .

Ideally, curves of the same measure should remain close to each other.



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The weighted error function:

- Localised blind deconvolution for focus map estimation:
  - run local deconvolution with a low iteration count
  - calculate local residual errors, with contrast weighting

$$E_r(g, g_k) = arc\ sin \frac{< g - g_k, g >}{|g - g_k| \cdot |g|} \cdot \frac{C_r(g_r)}{max_r \{C_r(g_r)\}}$$

$$C_r(g_r) = \frac{g_{max\{x \in T_r\}} - g_{min\{x \in T_r\}}}{g_{max\{x \in T_r\}} + g_{min\{x \in T_r\}}}$$

- use the local residuals for relative classification of areas

$$F(r) = \frac{c \cdot (E_r(g, g_k) - min\{E_r(\cdot, \cdot)\})}{max\{E_r(\cdot, \cdot)\} - min\{E_r(\cdot, \cdot)\}}$$

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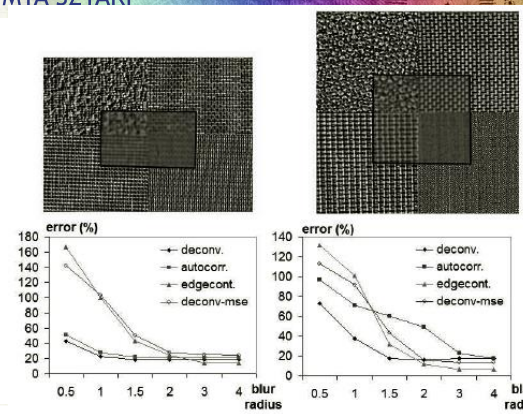

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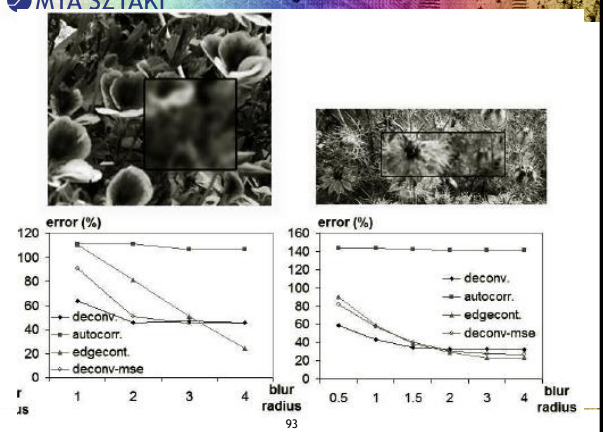

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Find images with similar relative focused objects:

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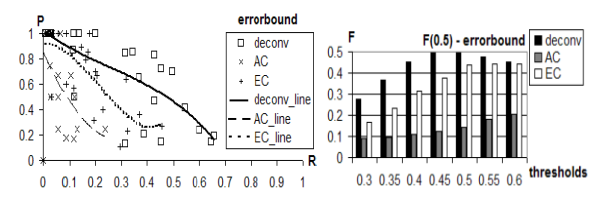
Local Relative Focus Map Estimation for Image and Video Indexing and Retrieval



L. Kovács , T. Szirányi

- "Focus Area Extraction by Blind Deconvolution for Defining Regions of Interest", **IEEE Tr. Pattern Analysis and Machine Intelligence, 2007**
- "Relative Focus Map Estimation Using Blind Deconvolution", **Optics Letters, 2005**

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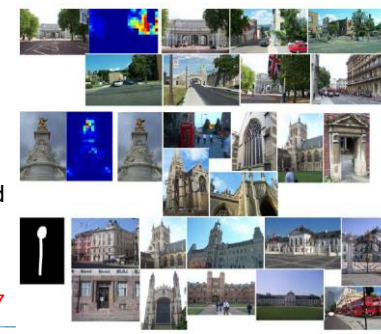
L. Kovács, T. Szirányi:

"Relative Focus Map Estimation Using Blind Deconvolution", Optics Letters, 2005

Focus Area Extraction by Blind Deconvolution for Defining Regions of Interest

IEEE Tr PAMI , 2007

Image / Video indexing matching sample image or semantic description



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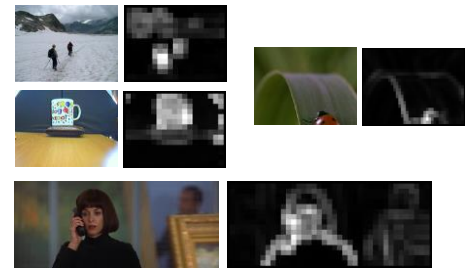

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Application in Non Photorealistic Rendering

Painting detail variation based on extracted relative focus maps

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Thank you for the attention !