Scale& Affine Invariant Interest Point Detectors

applied on particle disease detection in hip replacement

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Signal Processing Seminars, mars 2011

Outline

1. Motivation
   - Particle disease detection and extraction in hip replacement (ORTHOGEN)
2. Previous work : feature detection in Scale-Space
   - Scale Adapted Harris Detector
   - Laplacian of Gaussian for automatic scale selection
   - Isotropy measure
3. future work
   - planned improvements and fondamentals researches
   - Basic Ideas for Implementations

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Context : Orthogen

Orthogen

- definition
  - Integrated information system for tracking and managing multi-parameters of orthopedic infections
- goals
  - Easily collect and centralize patient informations (files and records from servers)
    - scans
    - laboratory results (biomolecular, hematology, etc.)
    - medical history
    - etc.
  - Process data, infer and deduce a probabilistic diagnosis

How to improve diagnosis by image processing ?

Diagnosing by image processing.

scans.

Procedure used for Orthogen :

- Learning about domain : Total Hip Arthroplasty.
  - pathology and disease symptom
- Looking for imaging tools performing those symptoms recognition
  - Finding visual extractable characteristics for the symptom
- designing an algorithm
  - adapted to the goal : able to extract visual characteristics
  - with fabrication constraints and performances
    - as fast as possible
    - interaction adapted to medical staff
    - the most automatic as possible

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Detection of characteristic : particle disease.

Short introduction to the Total Hip Arthroplasty Domain.

Simplified tree of pathologies.

- normal imaging findings
  - stable stresses
  - corrects alignements and positionning
- abnormal image findings
  - initial complications
  - complications at follow up

Example of case study

complications at follow up : particle disease

Figure: particle disease, basic scheme

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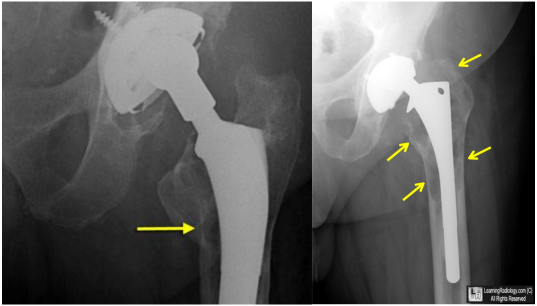


Figure: X-ray pictures, particle disease

main visual recognition criteria

focal luciency, darker than bones, ellipse form.

Outline

Scale Adapted Harris Detector

theory.

Definition

Harris hypothesis : Shifting a window in any direction should give a large change in intensity !

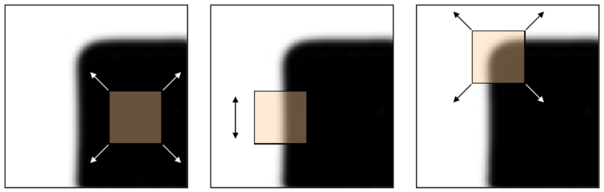


Figure: Harris theoric concept : on left, flat regions and no changes in any direction; in mid, edges and no change along the edge direction; on right, corner and we can see significant change in all directions.

Scale Adapted Harris Detector
theory.

Intensity change function E for a shift $(u,v)$of the window:
$E(u,v) = \sum_{x,y} w(x,y,\sigma_I)[I(x+u,y+v) - I(x,y)]^2$ where

- w is the window gaussian function with deviation σ_I.
- I is the intensity.

After Taylor and Mc Laurin polynomial approximation, assuming shifts to be small and bilinearity to be observed, we obtain

$$E(u,v) = \begin{bmatrix} u & v \end{bmatrix} M \begin{bmatrix} u \\ v \end{bmatrix},$$

$$M = \sum_{x,y} w(x,y,\sigma_I) \begin{bmatrix} I_x^2(\sigma_D) & I_x I_y(\sigma_D) \\ I_y I_x(\sigma_D) & I_y^2(\sigma_D) \end{bmatrix} \sigma_D^2$$

- I_i is the image derivative computed in the i direction, according to a gaussian kernel of deviation σ_D.
  - σ_D^2 is the normalization term, to be in Scale-space.
  - Derivatives are averaged or integrated in a neighborhood of the point by gaussian window.

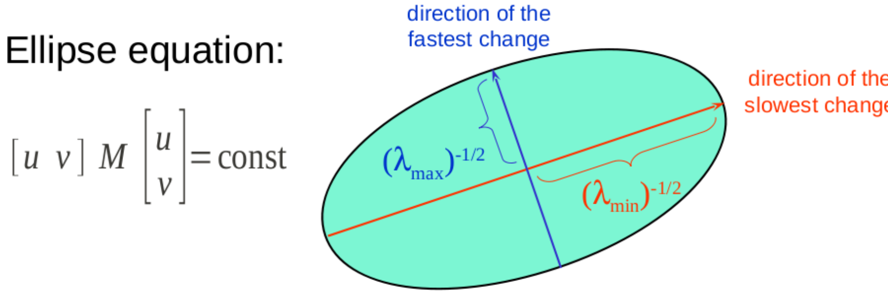
Scale Adapted Harris Detector

theory.

This auto-correlation matrix is symetric, so we found the diagonal expression :

$$M = R^{-1} \begin{bmatrix} \lambda_1 & 0 \\ 0 & \lambda_2 \end{bmatrix} R$$

This corresponds to an ellipse representation, for each point, with eigenvalues and eigenvectors :



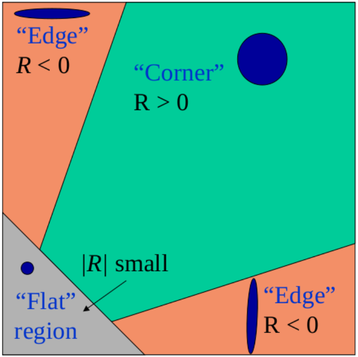
Scale Adapted Harris Detector

theory.

The Harris transfert function, based on eigen value, in order to have change along the two main directions :

$$R = \det(M) - \alpha \ \mathrm{trace}(M)^2 = \lambda_1 \lambda_2 - \alpha(\lambda_1 + \lambda_2)^2$$

α: constant (0.04 to 0.06)



Scale Adapted Harris Detector

Results applied to orthopedics X-ray images.

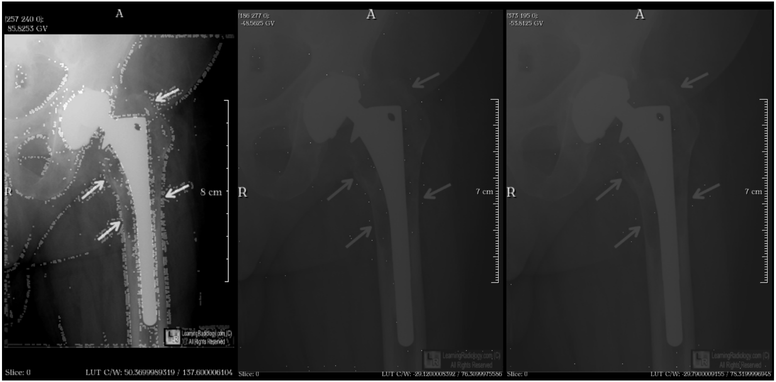


Figure: On left, Harris Edge Detection, $\sigma_I = \sigma_D = 0.5mm$. On mid, Corner detection with $\sigma_I = \sigma_D = 1.0mm$ and $1.6mm$ on right.

Outline

Laplacian of Gaussian for automatic scale selection

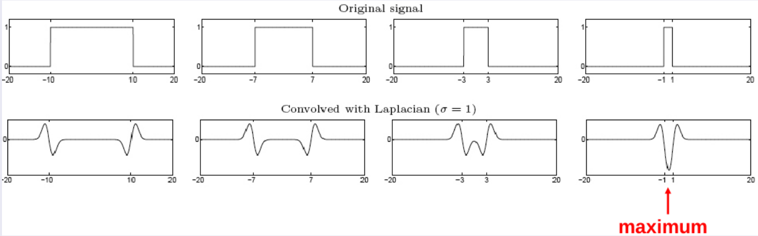
Theory, introduction to blob

We look for a method wich is invariant to scale

- we look for scale-invariant features : blob.

blob definition

- is the superposition of two ripples (>< edges).



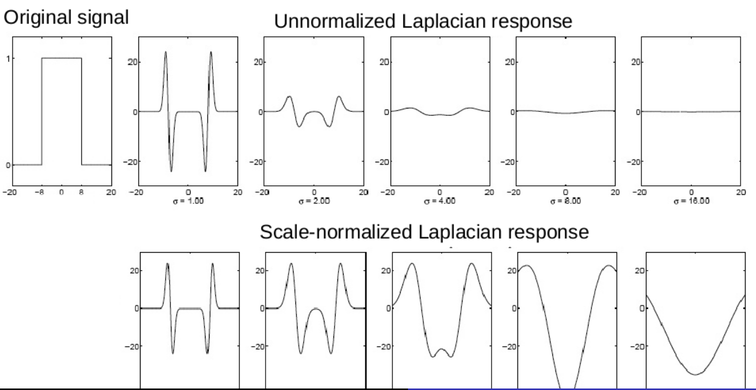
To automaticaly select scale, select maximum of the convolution with $|LoG(x,\sigma_n)| = \sigma_n^2|I_{xx}(x,\sigma_n) + I_{yy}(x,\sigma_n)|$.

Laplacian of Gaussian for automatic scale selection

Theory, normalization

what about gaussian fading with σ increasing?

- thanks to normalization, peaks respect scale-adapted blob detection.

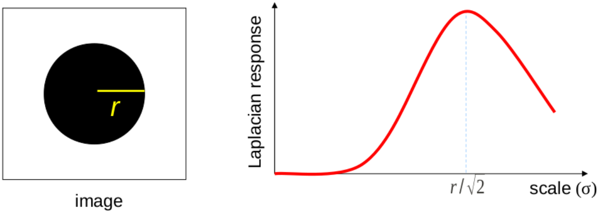


Laplacian of Gaussian for automatic scale selection

Theory, normalization

What's the link between scale factor σ and the dimension of the blob?

- a 2D Laplacian is given by the expression
  - $(x^2+y^2-2\sigma^2)e^{(-\frac{(x^2+y^2)}{2\sigma^2})}$
- so, according to ripples addition schemes, $\sigma = \frac{r}{\sqrt{2}}$



Laplacian of Gaussian for automatic scale selection

Results applied to orthopedics X-ray images.

The pipeline thresholds results after local maximums detection.

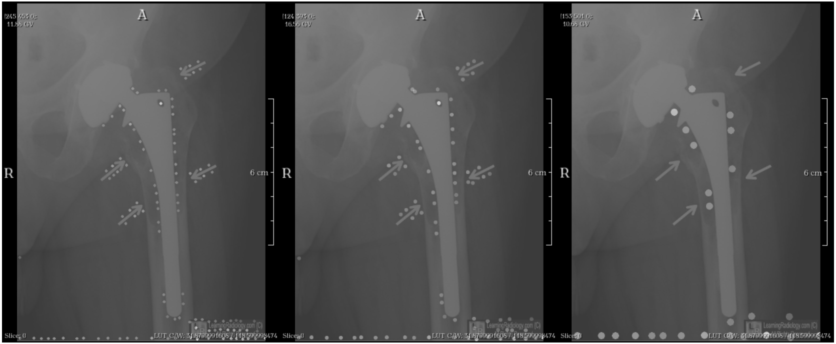


Figure: Selection of particule disease for $\sigma = 5, 7, 11.5$ voxels

Outline

Isotropy Measure
Theory.

We have shown that

- the second moment matrix can be visualised as an ellipse.
- The eigenvalues values of this matrix represent two principal signal changes in the neigboorhood of a point.

As a result :

- if we find the corrects σ_I and σ_D in the correlation matrix, we can learn how anisotropic are structures or features.
  - the normalized measure of the anistropy is the eigenvalue ration : $\rho = \frac{\lambda_{min}(\mu)}{\lambda_{max}(\mu)}$ where
    - blobs have a ratio almost equal to 1.
    - edges have a big ration.
  - this ration has been employed by the MevisLab communauty into a blob detection function transfert $1 - e^{-\frac{\rho^2}{2\sigma_r^2}}$
    - σ_r gives the authorized deviation for the "equal to 1" ratio.

Isotrop Measure
Results.

Figure: Femur, blob detection based on anistropic ratio, $\sigma_I = \sigma_D = 1.8mm$ et $3mm$, $\sigma_r = 3$.

Outline

More optimal Scale invariant detector : Harris-Laplace Detector

Mikolajczyk, K. and Schmidt, C. proposed in 2004 an interative scale invariant feature detection.

Harris-Laplace detector principle

- cumulation of
  - Harris and corner detection
  - Laplacien of gaussian method to automatically choose the matched scale
- the iterative process , at step k, is
  1. Finding a local extremum over scale σ_I^k of the LoG for a point $x^{(k)}$
  2. Detect the spatial location $x^{(k+1)}$of a maximum of the Harris measure nearest $x^{(k)}$ for the selected σ_I^k.
  3. Go to step 1 if $\sigma_I^{k+1} \neq \sigma_I^k$.

More optimal Scale invariant detector : Harris-Laplace Detector

For all the solutions in scale space for Harris method, LoG can choose the matched one.

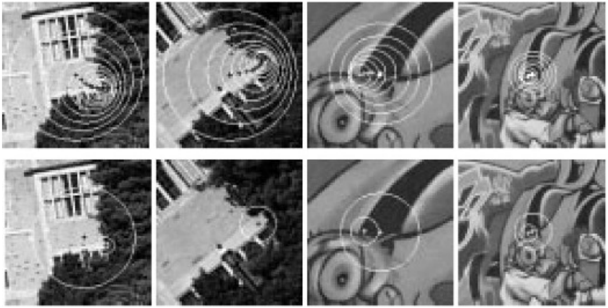
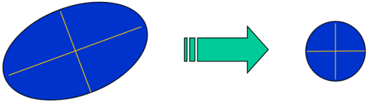


Figure: Harris-Laplace detector. Top : Harris scale-space solutions. Bottom : Interests points selected with the simplified Harris-Laplace approach

Affine Invariant Interest point Detector

Mikolajczyk, K. and Schmidt, C. proposed in 2004 an interative Affine invariant feature detection.
the idea is the determine affine transformation thanks to two basic operations

- find orientation ambiguity
- find an affine adaptation (most important one because a rotated circle is still a circle)

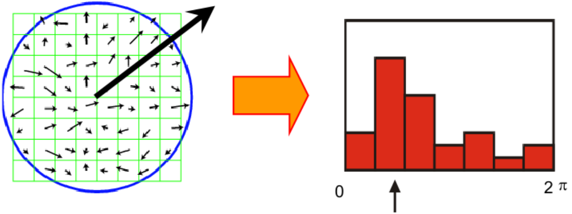


- loop
  - until you converge to matched region.

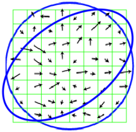
Affine Invariant Interest point Detector

Find orientation ambiguity :

- create an histogram of local direction gradients in the patch
  - assign canonical orientation at peak of smoothed histogram



Affine Invariant Points Detector



Create an affine adaptation

- the correlation matrix must **match** the characteristic shape of the region
  - by LoG, you can find the integration scale σ_I
    - by maximazing the normalized isotropy ratio, you find the differential scale factor $\sigma_D$to match the region
  - iterativ process
    - Use a circular window to compute second moment matrix
    - Perform affine adaptation to find an ellipse-shaped window
    - Recompute second moment matrix using new window and iterate
    - the convergence criterion is $1 - \frac{\lambda_{min}(\mu)}{\lambda_{max}(\mu)} \leq \varepsilon_C$

Affine Invariant Points Detector

Results.

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Ideas from medical cluster of last week

- localisation by Harris (after scale selection by LOG)
  - selection of seeds according to the distance to the prosthesis
- extraction of the particles thanks to other algorithms
  - fast marching
  - region growing
  - watershed
- discussion if any idea =)

end

Thank you for you attention

- questions?

For Further Reading I

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IEEE Transactions on Image Processing,9(12):2027-2042, 2000.

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