real-time salt & pepper noise removal based on the properties of the human visual system…
… and…
… Soft Tissue Filter (STF)
A new algorithm to enhance visibility in cephalometric radiography

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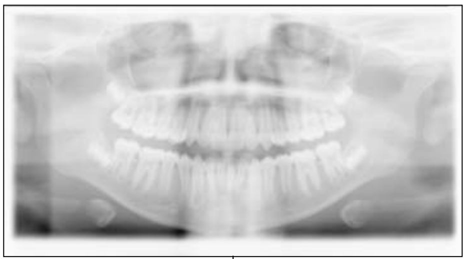
Overview…

- A.i.s. lab activity in digital radiography
- Real-time salt & pepper noise removal based on the properties of the human visual system
- Soft Tissue Filter (STF): a new algorithm to enhance visibility in cephalometric radiography

Applied Intelligent systems (A.I.S.) LAB (university of milan)

- Dental digital radiography…



Local exposure correction

Applied Intelligent systems (A.I.S.) LAB (university of milan)

- Dental digital radiography…

Sensor response correction

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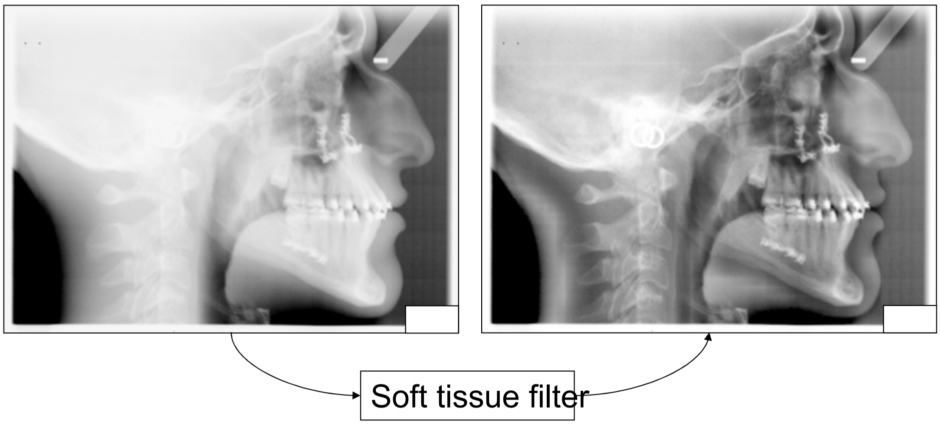
- Dental digital radiography…



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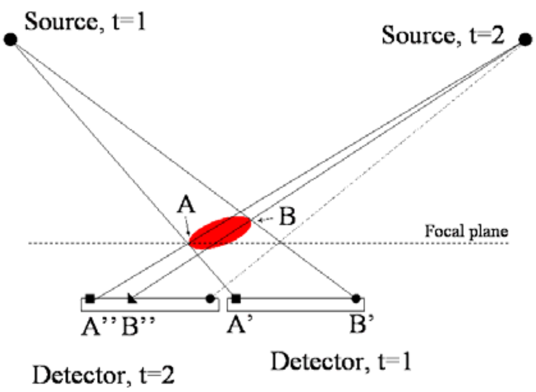
- Dental digital radiography…
- … and 3D reconstruction (tomosynthesis)



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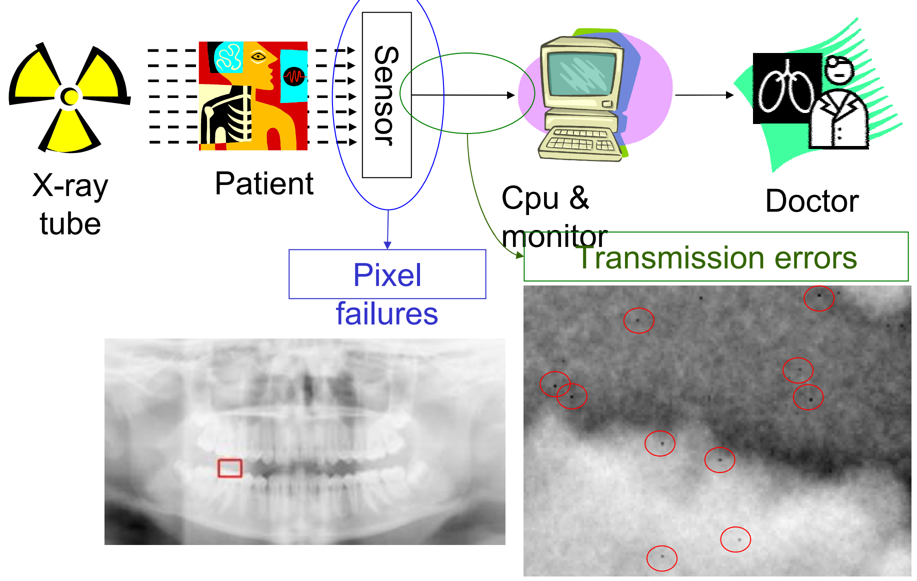
Salt & pepper noise in digital radiography



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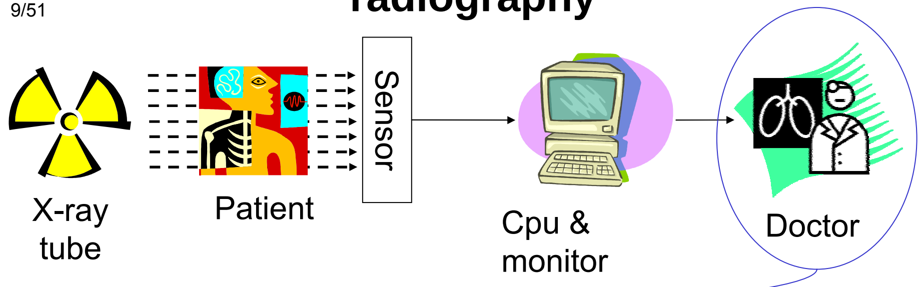
Salt & pepper noise in digital radiography



Salt & pepper noise…
…is Annoying for the human eye…
… may cause degradation in the image content.

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The task

…Also computational intensive filters are annoying…

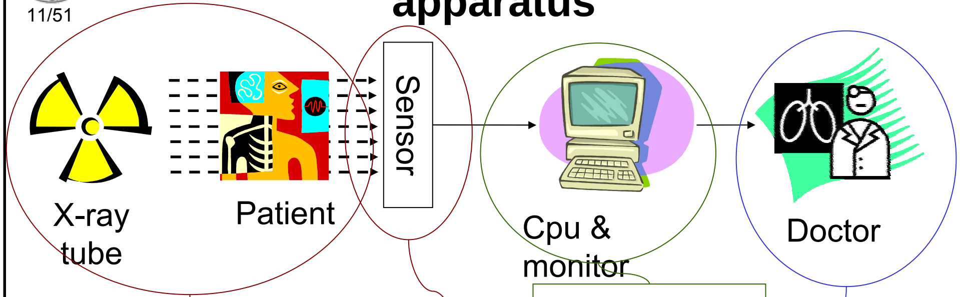
Development of a REAL TIME filter for SALT & PEPPER NOISE REMOVAL before DISPLAYING DIGITAL RADIOGRAPHIES.

Salt & pepper noise is annoying…

…A human operator observes the image…

…The properties of the digital radiographic apparatus influence the image charactheristics.

Description of the radiographic apparatus



5Mpixel, 12bpp image

Linear sensor:
Sensor gain and offset: G (<0), O (≅ 4095)
Image gray level (luminance): b = G·p+O

Photonic noise (Poisson):
Average number of photons: p.

Human Visual System (HVS) properties:
Weber's law (contrast)
Rose's criterion (signal to noise

Noise std (σ_b) vs. image gray level (b)

	Sensor	Image	
Signal	p_b	$b = G \cdot p_b + O$	(1)
Noise std	$\sqrt{(p_b)}$	$\sigma_b = \lvert G\rvert \cdot \sqrt{(p_b)}$	(2)

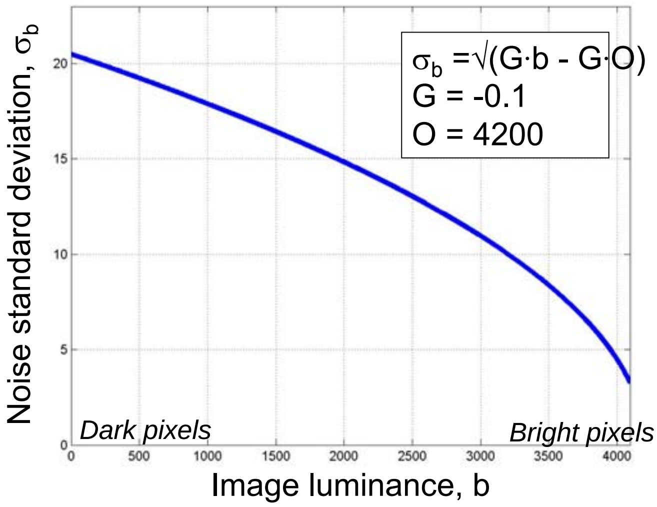
From (1) : $p_b = (b - O) / G$ (3)

From (2), (3) : $\sigma_b^2 = G \cdot b - G \cdot O$ { $\sigma_b = \mathrm{sqrt}(G \cdot b - G \cdot O)$ } (4)

Observations

- Poisson noise std (σ_b) is a function of the image gray level (luminance b).
- Poisson noise std is higher in the darkest zones of the image.
- Poisson noise std is lower in the brightest zones

Noise std (σ_b) vs. image gray level (b)



Salt & pepper noise removal

Median filtering removes impulsive noise, but…

… Low pass filtering of the entire image is also obtained…

… because pixels not corrupted by impulsive noise are modified.

A local filter, which "cleans" only the pulses, is required. The filter has to be optimal for a typical human observer in ideal conditions.

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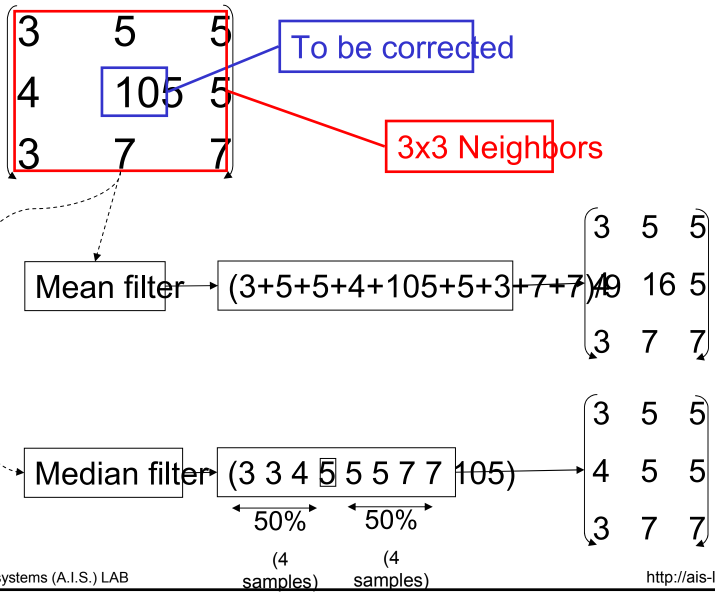
Mean & median filter



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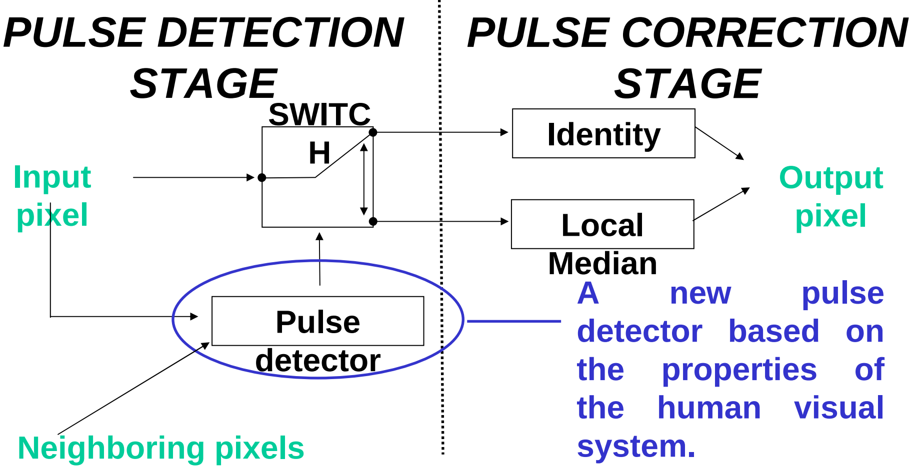
Switching median filter

Two stages filtering



Pulse detection: general framework

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- Let (b) be the background luminance, and (b+Δb) the luminance of an object (pixel).
- The Just Notable Difference (JND) is defined as the minimum difference of luminance (Δb) which is necessary to distinguish an object from the background.
- The luminance of the pixel (x,y) has to be compared to the luminance of its neighbor pixels to establish if (x,y) is a visible object (pulse) or not.
- if Δb>JND, the pixel (x,y) is classified as "pulse".

Pulse detection: weber's law

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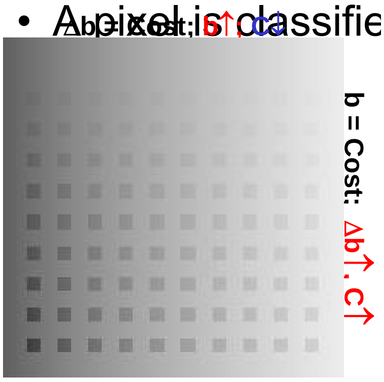
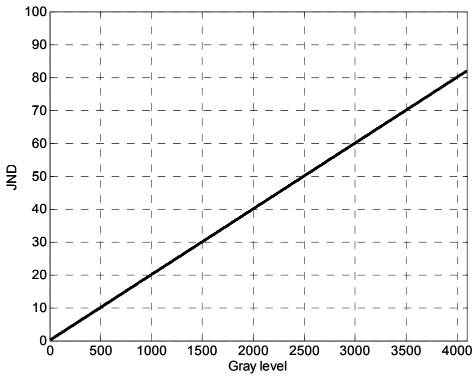
- A minimum contrast, C_t, is necessary to distinguish an object (pulse) from the background.
- A pixel is classifie





Pulse detection: Rose's criterion

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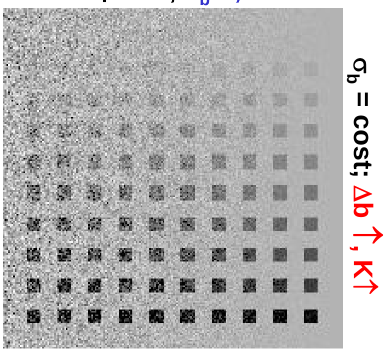
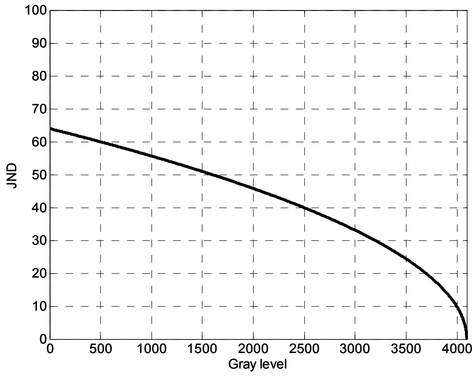
- Object visibility is also limited by the presence of noise. A minimum signal (Δb) to noise (σ_b) ratio, K_t, is required to distinguish an object (pulse) from the background.
- A pixel is classified as

Δb = cost; $\sigma_b \downarrow$, $K\uparrow$





Pulse visibility: Weber's law + Rose's criterion

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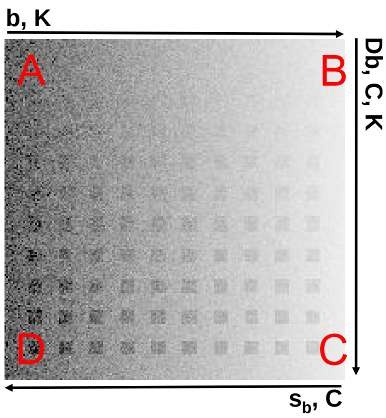
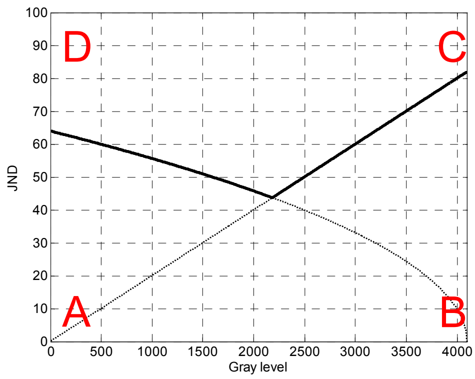




$$JND(b) = \max(C_T \cdot b, K_T \cdot \sigma_b)$$

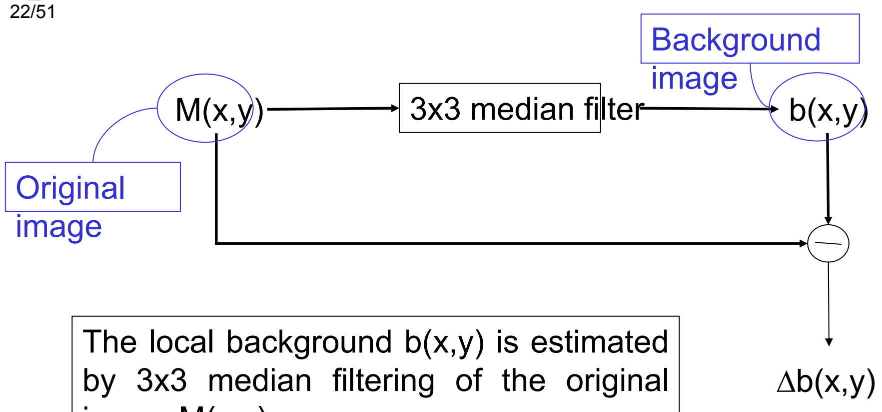
Pulse detection: parameters estimation

A Pulse is detected in (x,y) if the absolute value of the difference between the measured gray value of the pixel, M(x,y), and the local background, b(x,y), is greater than the local Just Notable Difference, JND (x,y).

Since JND is a function of local background and noise, the following parameters have to be estimated:

b(x,y) [local image background];
Δb(x,y) [difference between M(x,y) and b(x,y)];
σ_b [function of b, G and O];
G and O [sensor gain and offset]

Estimation of *b(x,y)* and *Δb(x,y)*



The local background b(x,y) is estimated by 3x3 median filtering of the original image M(x,y);

The local difference Δb(x,y) is estimated by subtracting the background b(x,y) from the original image M(x,y).

Estimation of σ_b - I

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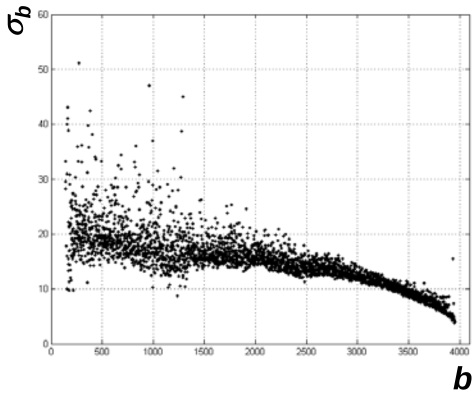
A rough estimation of s_b for each gray level b can be obtained as follow:



- Consider all the N_b pixel (x,y) such that: M(x,y) = b;
- Estimate Poisson noise, n(x,y), in all these points (x,y) as the difference between measured and estimated value: n(x,y) = Δb(x,y);
- Compute σ_b as: $\sigma_b = \sqrt{\frac{\sum_{(x,y)} n(x,y)^2}{N_b}} \quad \forall (x,y) \ s.t. \ b(x,y) = b$

Estimation of σ_b - II

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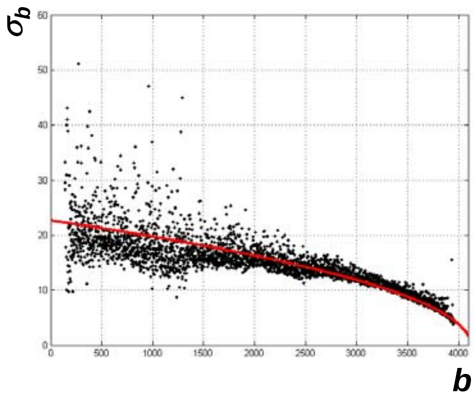
Regularization of the estimate can be obtained by fitting the sensor curve (in red). This is obtained by considering also the sensor equation (with G and O).

It results:

$\sigma_b^2 = G \cdot b - G \cdot O$ (4)



This is a system of 4096 equations, which can be solved by adoption of a least squares approach.

The resulting $\sigma_b = \sigma(b)$ is smooth; it can be used to reliably estimate σ ... from

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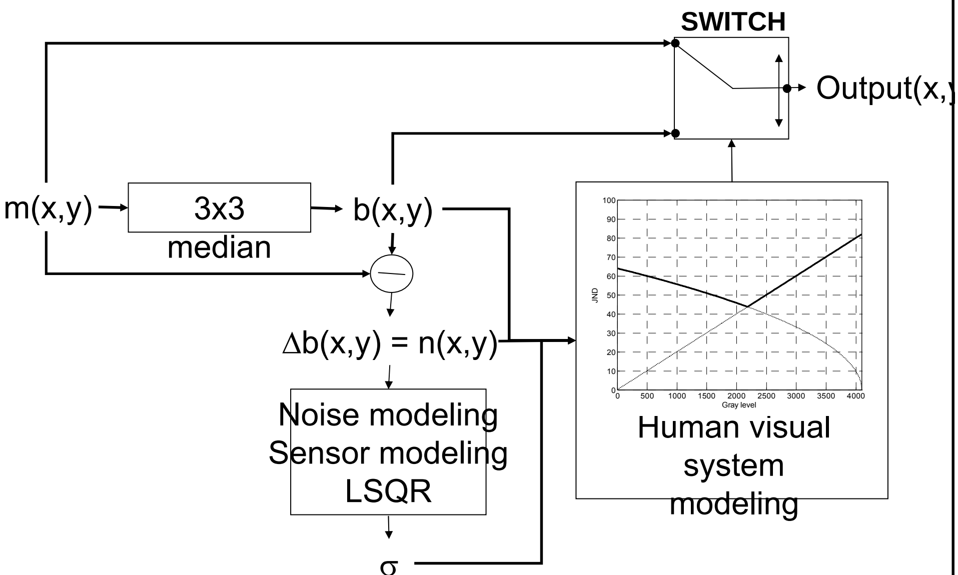
Switching median filter flow chart



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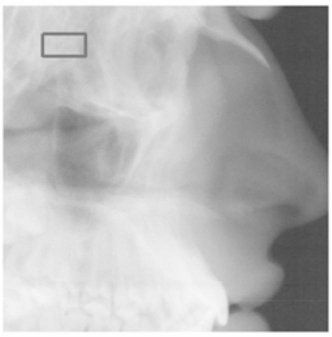
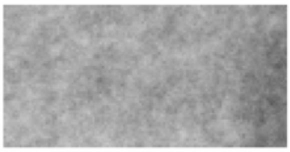
Result 1



Original image:

Our filter:



Rank conditioned 13x13:

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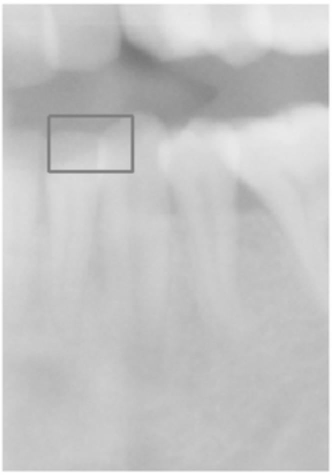
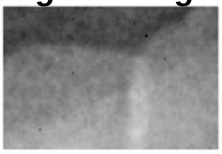
Result 2

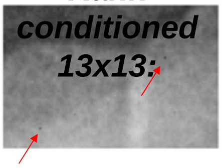


Original image:



Our filter:

Rank conditioned 13x13:



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Comparison with rank conditioned filter and notes

In comparison with a rank conditioned 13x13 filter, our filter removes a higher number of pulses;

In comparison with a rank conditioned 3x3 filter, our filter modifies a lower number of pixels.

Processing time for a 5MPixel image processing time is 0.67s on a Mobile AMD Athlon 2400+, 1.79GHz, 480M RAM).

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Conclusion & future works (We wish to thank referees for good suggestions)

- Optimal filter for a human observer;
- Tested on a clinical images dataset;
- IT consider the properties of noise and imaging apparatus;
- Competitive with more traditional approaches;
- Real time image processing allowed;

- Quantitative evaluation on synthetic data;
- ROC curves;
- Reliability of the parameters estimation;
- Display modeling;
- Extension to other kind of images.

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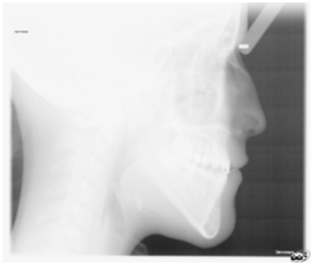
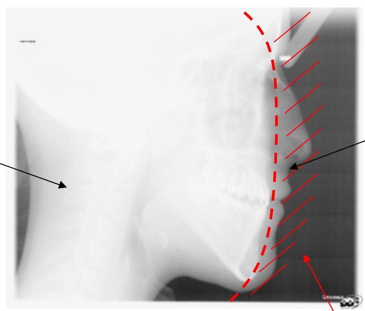
Exposure problems



- From film to phosphor film to CCD
- Underexposed radiographies: bone cannot be distinguished from soft tissue
- Overexposed radiographies: soft tissue tends to mix with background

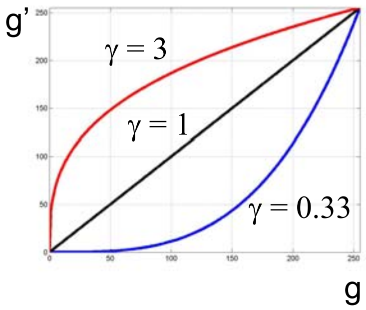
Typical HW solution



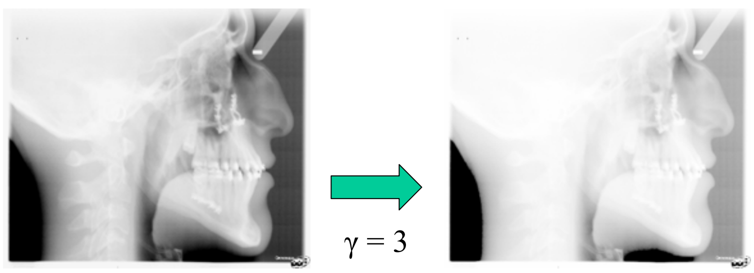
SW solution: gamma correction

- Gray level correction formula;
- Used for global exposure correction;
- For 8 bit image, gray level g is corrected to g' as:

$$g' = 255 \cdot [(g / 255)^{1/\gamma}]$$



Global γ correction



- Nowadays clinical practice: global γ correction
- γ = 0.25 (underexposed), soft tissue darkens!
- γ = 3 (overexposed), bone tissue mixes with soft tissue!

Global γ correction

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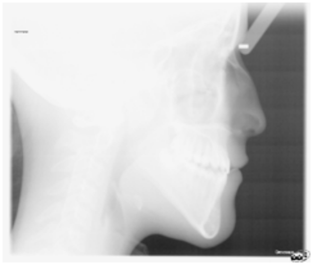

$\gamma = 0.25$

- Nowadays clinical practice: global γ correction
- $\gamma = 0.25$ (underexposed), soft tissue darkens!
- $\gamma = 3$ (overexposed), bone tissue mixes with soft tissue!

SW solution: unsharp masking

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- $I_{\text{unsharp masking}} = I_{\text{original}} + I_{\text{high frequencies}} * \text{Gain}$
- Underexposed images: $I_{\text{high frequencies}} \sim 0$, not effective!
- Overexposed images: soft tissue remain dark!

Typical histogram

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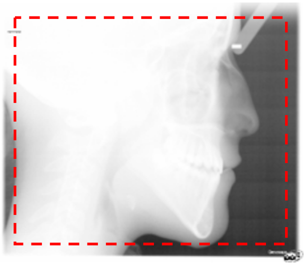

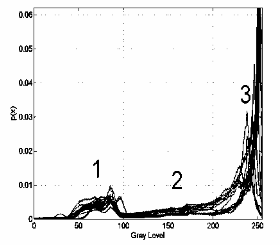

- Three characteristic gray zones: background (1), soft tissue (2), bone tissue (3)
- 5% boundary eliminated (white margins, logo)
- Gray level zero eliminated (saturated pixels)

Mixture model

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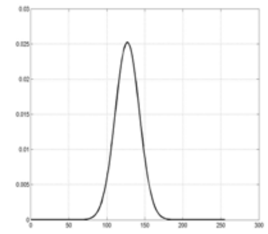
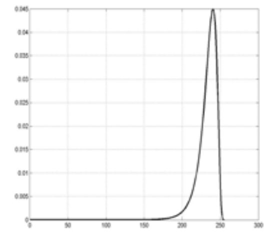
- A powerful technique to estimate complex probability densities distributions by using a restricted number of parameters
- Linear combination of M probability densities:

$$p_{MM}(x) = \sum_{j=1}^{M} P(j) \cdot p(x \mid j)$$

Two Gaussian, one Lognormal





- Mixture of three components (M = 3)
- Two Gaussians: background, soft tissue (symmetric peaks)
- One Inverted Lognormal: bone tissue (asymmetric peak)

Parameters estimation

- Parameters: P(j), μ_j, σ_j, j=1…3
- Negative log likelihood

$$E = -\ln L = -\sum_{n=1}^{N} \ln p_{MM}(x^n) = -\sum_{n=1}^{N} \ln\left\{p(x^n \mid j)P(j)\right\}$$

- E is minimized through the EM algorithm

Updating equations

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- Mixing parameters $$P(j)^{new} = \frac{1}{N} \sum_{g=0}^{N_{GL}-1} P^{old}(j \mid g) \cdot H(g)$$

- Gaussians $$\mu_j^{new} = \frac{\sum_{g=0}^{N_{GL}-1} P^{old}(j \mid g) \cdot g \cdot H(g)}{\sum_{g=0}^{N_{GL}-1} P^{old}(j \mid g) \cdot H(g)} \qquad \left(\sigma_j^{new}\right)^2 = \frac{\sum_{g=0}^{N_{GL}-1} P^{old}(j \mid g) \cdot \left(g - \mu_j^{new}\right)^2 \cdot H(g)}{\sum_{g=0}^{N_{GL}-1} P^{old}(j \mid g) \cdot H(g)}$$

- Lognormal $$\mu_j^{new} = \frac{\sum_{g=0}^{N_{GL}-1} P^{old}(j \mid g) \cdot \ln(N_{GL} - g) \cdot H(g)}{\sum_{g=0}^{N_{GL}-1} P^{old}(j \mid g) \cdot H(g)} \qquad \left(\sigma_j^{new}\right)^2 = \frac{\sum_{g=0}^{N_{GL}-1} P^{old}(j \mid g) \cdot \left[\ln(N_{GL} - g) - \mu_j^{new}\right]^2 \cdot H(g)}{\sum_{g=0}^{N_{GL}-1} P^{old}(j \mid g) \cdot H(g)}$$

Model Convergence

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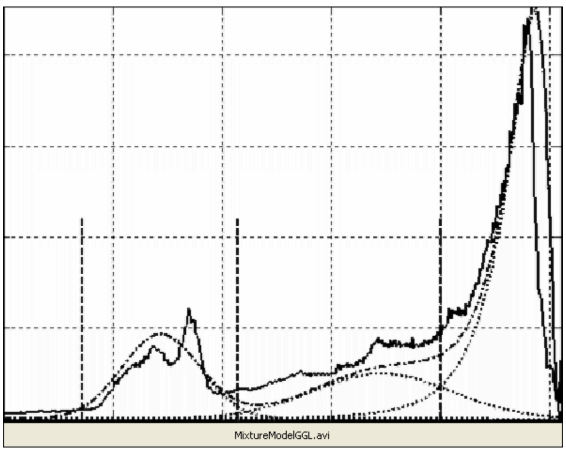

Clustering

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- Thresholds *Th(j,j+1)* minimize

$$\int_0^{Th(j,j+1)} P(j+1)\cdot p(x \mid j+1)dx + \int_{Th(j,j+1)}^{N_{GL}-1} P(j)\cdot p(x \mid j)dx$$

- Three classes: Background, soft tissue, bone tissue

Local γ Correction

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- γ = 1 background
- γ = 0.25 bone tissue
- γ = 1.5 soft tissue
- Artifacts, patient profile not clearly visible!

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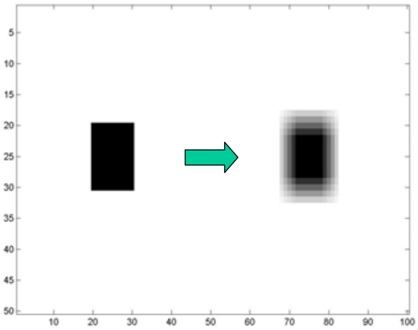
γ smoothing: low pass filtering

- Low pass filtering of γ …

Filter (5x5):

$$\begin{pmatrix} 1/25 & 1/25 & 1/25 & 1/25 & 1/25 \\ 1/25 & \dots & & & \\ \dots & & & & \\ \dots & & & & 1/25 \end{pmatrix}$$



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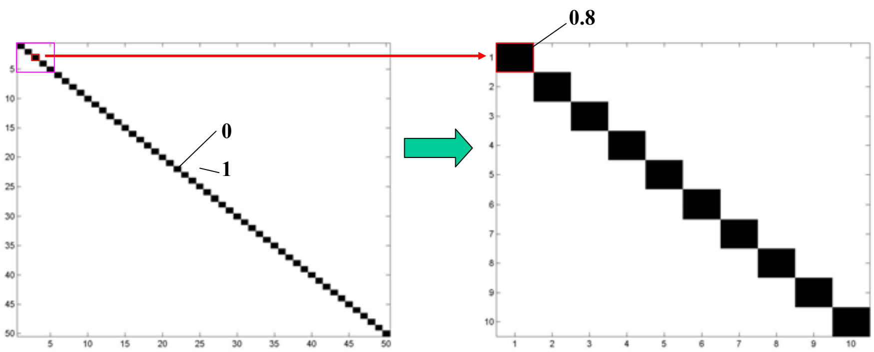
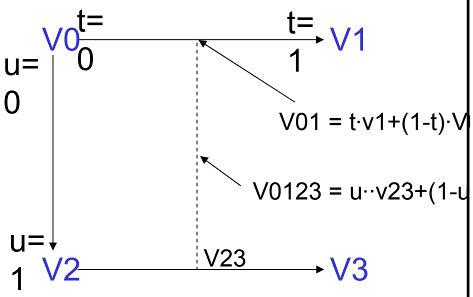
γ smoothing: downsampling + upsampling

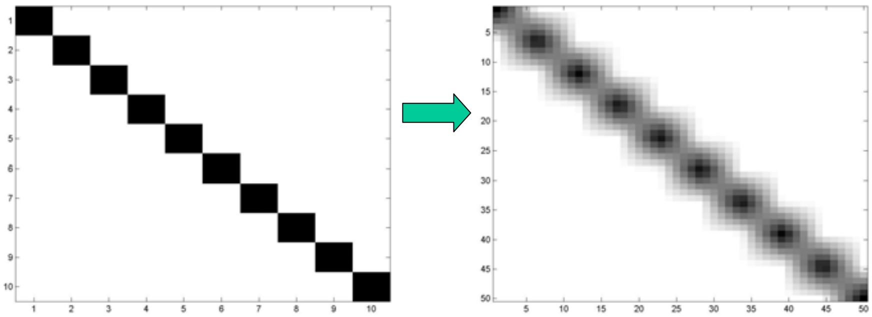
- Image downsampling…
  - For the pixel (x,y), compute the mean value around (x,y)…



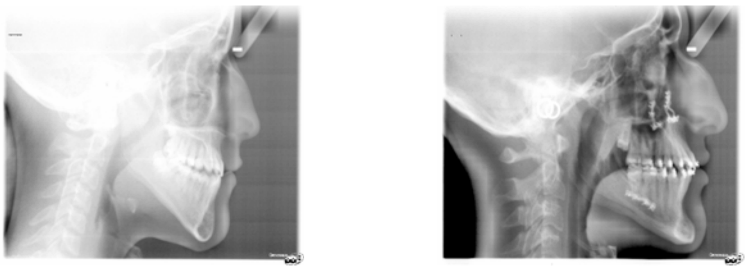
γ smoothing: downsampling + upsampling

- Image upsampling…
  - Bilinear interpolation…





γ smoothing



- γ map has to be smoothed
- Down sampling, moving average 3x3 filtering, up sampling using bilinear interpolation (or efficient moving average filter in space domain)
- Two classes: Background & soft tissue, bone tissue

Results

Original

Gamma correction

Unsharp masking

Soft tissue filter

Notes

- The filter is nowadays commonly used in clinical practice.
- Patent pending at EPO.

Thank you for your attention !!