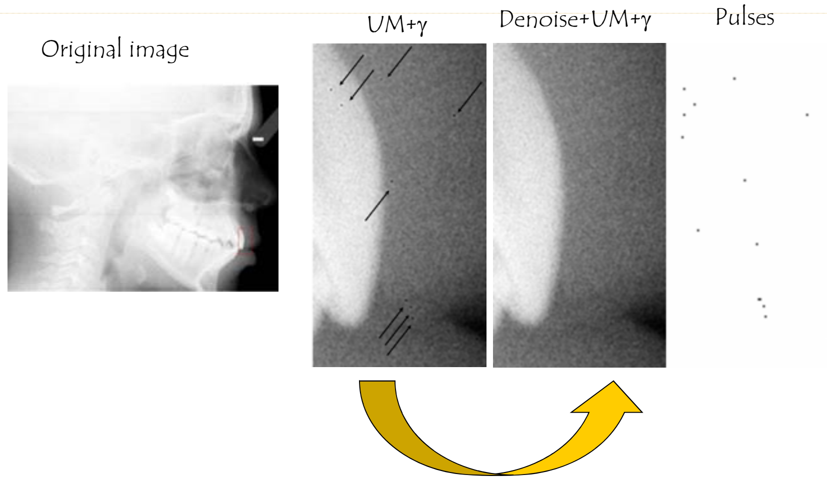
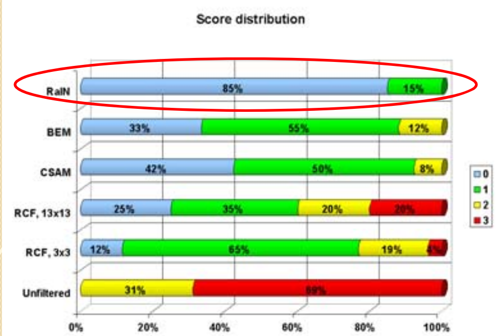
Impulsive noise: results



Impulsive noise: results

- 156 images images unfiltered / treated with the proposed filter / with other impulsive noise filters;
- 15 experts for evaluation;
- Scores:
  - 0 => image with no pulses
  - 1 => no more than two pulses identified in no more than two analyzed areas
  - 2 => many (>2) pulses visible in a few (≤ 2) areas of the image or few pulses (≤ 2 pulses) visible in several (>2) areas of the image (> 2)
  - 3 => more than 2 pulses were visible in many (>2) areas of the image.

Impulsive noise: results



- How many pixels are modified by the filter?

- Prop. method: 0.14%
- BEM: 0.80%
- CSAM: 1.67%
- RCF 13x13: 0.23%
- RCF 3x3: 4.73%

Impulsive noise removal: summary

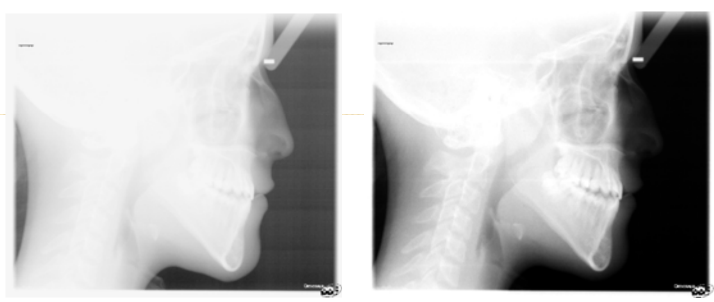
- Mixture of noise: an accurate description of the statistical properties of the noise to accurately classify the pulses;

- Less pixels modified by the filter, but…
- … Less pulses left on the image.

Overview

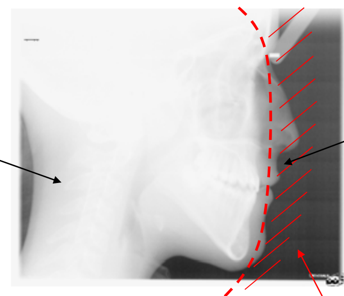
- Statistical models and digital radiography
- Impulsive noise removal filter
- Soft tissue filter
- Conclusion

Soft tissue filter: exposure issue



- Underexposed radiographies: bone cannot be distinguished from soft tissue
- Overexposed radiographies: soft tissue tends to mix with background
- In any case, soft and bone tissue are hard to be optimally exposed at the same time.
- Digital radiographies are acquired on 12 bpp, displayed at 8 bpp.

Soft tissue filter: exposure issue

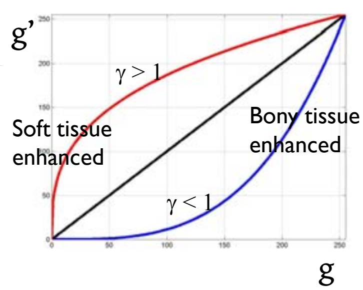


- A raw solution, not so effective..

Soft tissue filter: γ correction

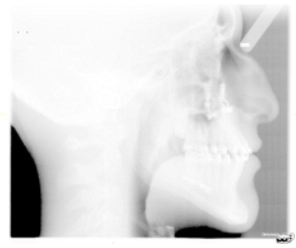
- Gray level correction (NB images are negative images, white = low signal);
- Used for global exposure correction;
- For 8 bit image, gray level g is corrected to g′ as:

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



$\gamma > 1 \rightarrow$ Stretching of the low levels, compression of the high levels.
$\gamma < 1 \rightarrow$ Compression of the low levels, stretching of the high levels.

Soft tissue filter: γ correction



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

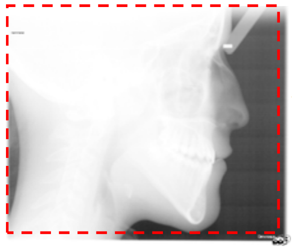
Soft tissue filter: the idea

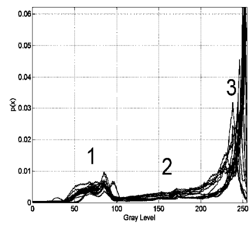
(I. Frosio and N.A. Borghese, IEEE Trans. Med. Imag. 2006)

- Exposure issue: different γ for bony and soft tissue;
- An adaptive γ correction scheme has to be identified;
- How to modulate the value of γ across the image?

- (soft) image clusterization through mixture model

Soft tissue filter: Typical histogram





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

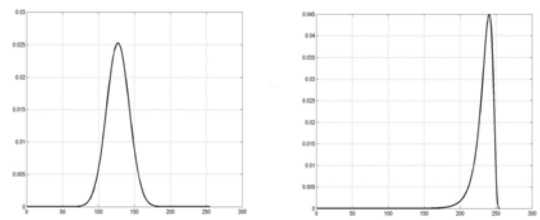
Soft tissue filter: the mixture

- Mixture model: a linear combination of M probability density functions:

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

- The most common mixture: mixture of Gaussians.

Soft tissue filter: the mixture



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

Soft tissue filter: EM

- Parameters: P(j) – mixing parameters and μ_j, σ_j, for each distribution: j=1…3
- n = 1:N, number of pixels
- 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 with respect to the parameters through the EM algorithm

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

Soft tissue filter: EM

Histogram

- 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:

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

Soft tissue filter: hard segmentation

- Threshold *Th(j,j+1)* minimizes

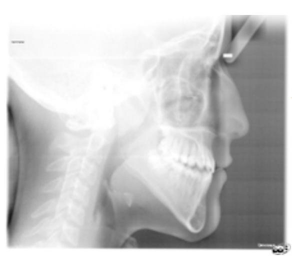
$$\int_0^{Th(j,j+1)} P(j+1)\cdot p(x \mid j+1)dx + \int_{Th(j,j+1)}^{N_{GL}-1} P(j)\cdot p(x \mid j)dx$$

- Three classes: Background, soft tissue, bone tissue

Soft tissue filter: hard segmentation

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

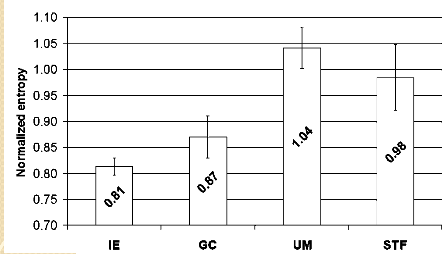
Soft tissue filter: soft segmentation

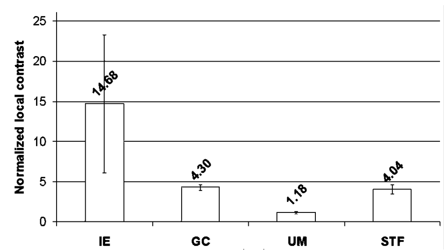


- γ map has to be smoothed
- Down sampling, moving average 3x3 filtering, up sampling using bilinear interpolation (or efficient moving average filter in space domain)
- Two classes: Background & soft tissue, bone tissue

Soft Tissue Filter: results

IE = image equalization
GC = γ correction
UM = Unsharp masking
STF = Soft tissue filter





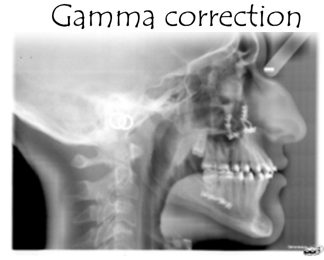
The local contrast (measured between two different anatomical areas) **improves**;
The **image information content** remains **unaltered**.

Soft tissue filter: results

Original

Gamma correction

Unsharp masking



Soft tissue filter

Overview

- Statistical models and digital radiography
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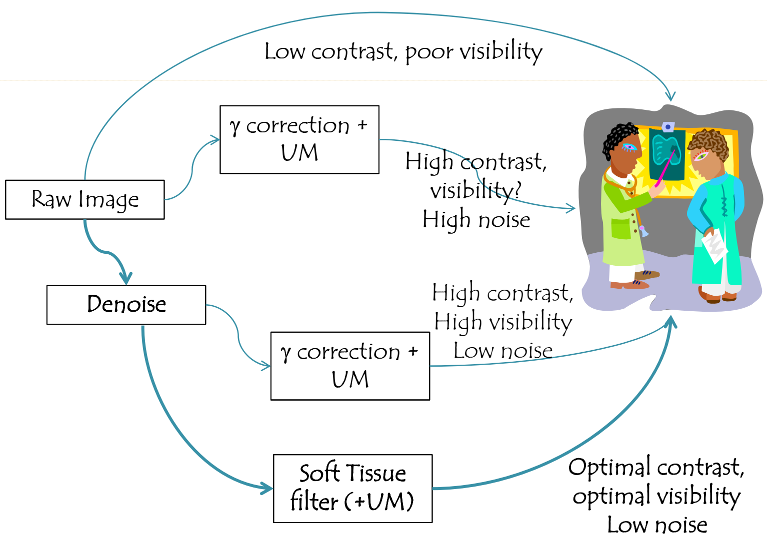
Impulsive noise removal + soft tissue filter

N. A. Borghese, I. Frosio (2010). Denoising and Contrast Enhancement in Dental Radiography. Handbook of Research on Dental Computing and Applications, Ed. A.Daskalaki.



Conclusion

- **Principled statistical models** as an effective alternative to traditional filtering;
- Computational demand is no more an issue. Technology advance promise even faster computation (e.g. CUDA);
- Accurate description of the image statistical properties leads to "optimal" filters (in a likelihood sense);
- Better statistical models can be considered?

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