Pixel coverage segmentation for improved feature estimation

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Work together with Dr. Nataša Sladoje

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Introducing myself

Joakim Lindblad

Assistant Professor at the Centre for Image Analysis (CBA)
Swedish University of Agricultural Sciences and Uppsala University
Uppsala, Sweden

M.Sc. in Engineering Physics, Uppsala University, Sweden
Ph.D. in Image Analysis, Centre for Image Analysis, Uppsala, Sweden
Post Doc at British Columbia Cancer Research Center, Vancouver, Canada

Centre for Image Analysis
Swedish University of Agricultural Sciences
Uppsala University

Centre for Image Analysis

http://cb.uu.se

SLU

UPPSALA UNIVERSITET

The Centre for Image Analysis (CBA)

Founded 1988 as a joint research centre between

The Swedish University of Agricultural Sciences

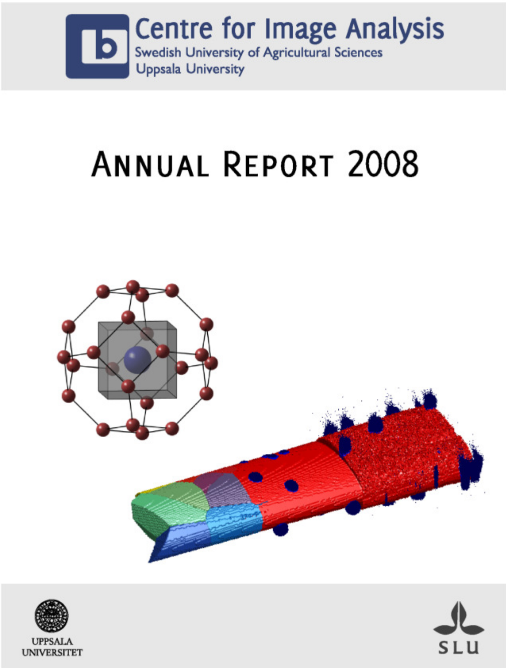
and

Uppsala University

"...to develop theory, methods, algorithms and systems for applications primarily within biomedicine, forestry and the environmental sciences."

Centre for Image Analysis

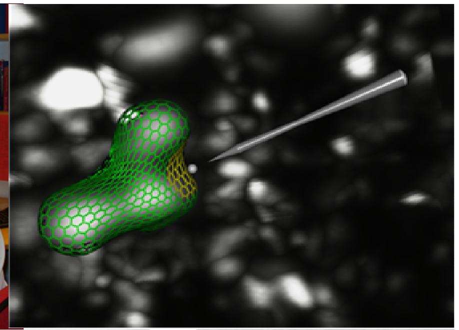
http://cb.uu.se

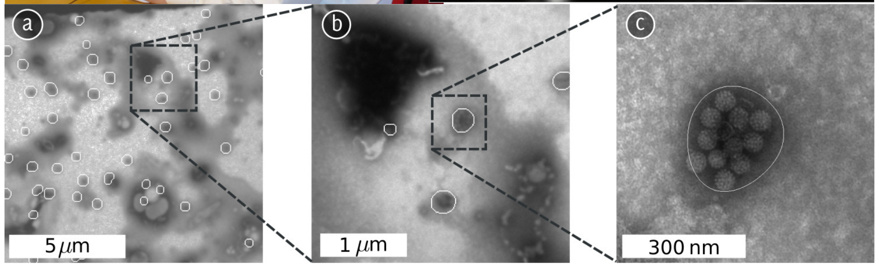


- Graduate education and research in Image Analysis and Visualization, both theoretic and applied.

- 16 professors (assistant, associate and full)
- 16 PhD students
  - On average 3-4 PhD dissertations/year
- 36 different research projects
- 6 Master thesis projects

Application areas



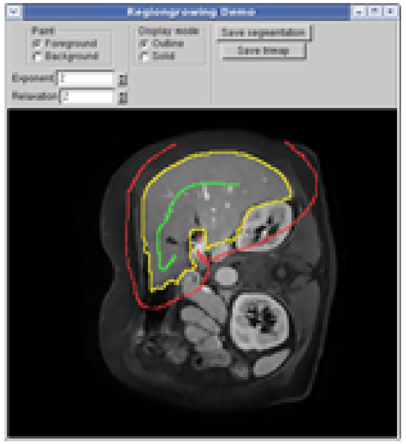


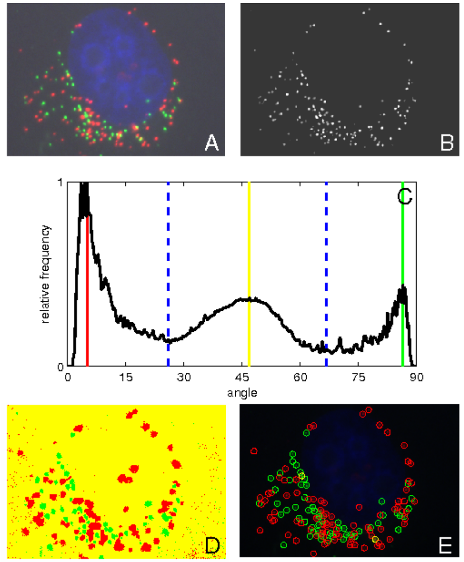
<u>MEDICAL IMAGE ANALYSIS</u>
- PROTEIN STRUCTUE ANALYSIS
- VIRUS (shape, maturation)
- SUB-CELLULAR STRUCTURES (fluorescence)
- CELL ANALYSIS (histopathology, ...)
- MALIGNANCY DETECTION (organs, cells)
- ORGAN ANALYSIS (brain, blood vessels, ...)

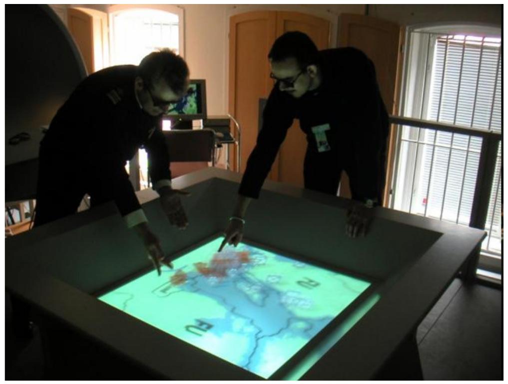
<u>ENVIRONMENT ANALYSIS</u> (from satellite, radar, plane…)
- FOREST INVENTORY
- AGRICULTURAL (field segmentation, analysis)
- WATER MONITORING (lake and coastal)
- CORAL REEF BLEACHING
- UNDER WATER SPECTRAL IMAGERY

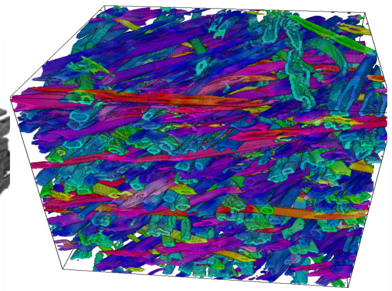
<u>OTHER (INDUSTRIAL)</u>
- WOOD FIBRE ANALYSIS
- 3D PAPER STRUCTURE
- FOOD QUALITY

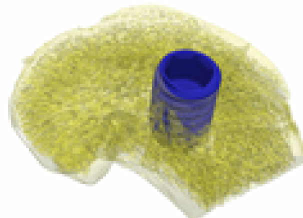
<u>VISUALIZATION</u> (interactive
- MEDICAL
- SCIENTIFIC
- CITY PLANNING

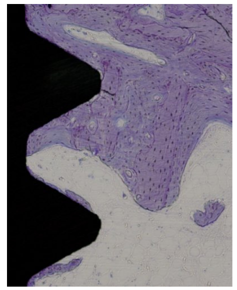






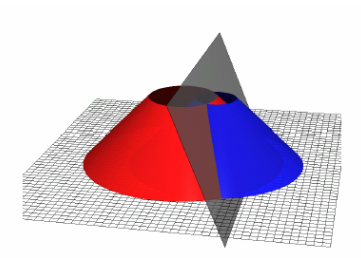


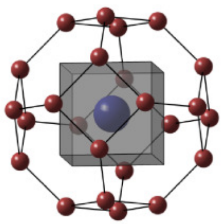


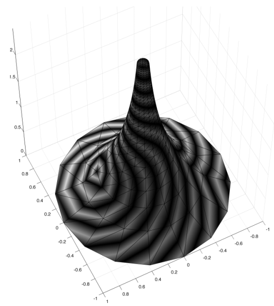


Research interests

- PROPERTIES OF DIGITAL & FUZZY SPATIAL SETS
  - SHAPE, GEOMETRY, MORPHOLOGY, TOPOLOGY,
  - DIFFERENT REPRESENTATIONS (moments, skeletons, etc.)
- SEGMENTATION
- VISUALIZATION
- MULTI- & HYPERSPECTRAL ANALYSIS
- REMOTE SENSING
- INTERACTIVE SYSTEM DESIGN
- ... FOR TWO, THREE, AND MORE DIMENSIONS







Introducing the topic

- The task of **Image Analysis** is to **extract relevant information from images**.
- **Numerical descriptors**, such as area, perimeter, moments of the objects are often of interest, for the tasks of shape analysis, classification, etc.

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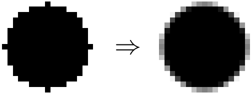
The standard image analysis task (and its solution)

1. Sample preparation and Imaging
2. Pre-processing (optional)
3. Segmentation
    - Usually crisp
4. Feature extraction
    - Discrete representation problematic
5. Classification

There is more information available!



Pixel coverage digitization
Let the value of a pixel be equal to the part of it being covered by the object.

- A useful representation that stays close to the original image data.
- Is based on very weak assumptions about the imaged objects.
- Utilizing the coverage information, significant improvement in precision of extracted feature values can be reached.

Some features that benefit from a pixel coverage representation.

Area and other geometric moments

- N. Sladoje and J. Lindblad. Estimation of Moments of Digitized Objects with Fuzzy Borders. ICIAP'05, LNCS-3617, pp. 188-195, Cagliari, Italy, Sept. 2005.

$$m_{p,q}(S) = \frac{1}{r^{p+q+2}}\,\tilde{m}(rS) + \mathcal{O}\left(\frac{1}{r\sqrt{n}}\right)$$

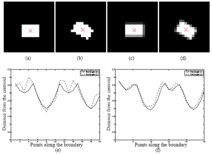
Perimeter and boundary length

- N. Sladoje and J. Lindblad. High Precision Boundary Length Estimation by Utilizing Gray-Level Information. IEEE Trans. on PAMI, Vol. 31, No. 2, pp. 357-363, 2009.

$$\gamma_n^{(0,q)} = \frac{2q}{q + \sqrt{(\sqrt{n^2+q^2} - n)^2 + q^2}}\,, \quad |\varepsilon_n| = \mathcal{O}(n^{-2})$$

Signature

- J. Chanussot, I. Nyström and N. Sladoje, Shape signatures of fuzzy star-shaped sets based on distance from the centroid, Pattern Recognition Letters, vol. 26(6), pp. 735-746, 2005.



Pixel coverage representations

We have nice theory ☺

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Application = Real (noisy) data

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How to go from image to pixel coverage representation?

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Pixel coverage segmentation

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To use the perimeter estimation method we need pixel coverage images.

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To use the perimeter estimation method we need pixel coverage images.

We have proposed three segmentation methods which provide (approximate) pixel coverage images:

1. Direct assignment of area coverage values from a continuous segmentation model.
   - A. Tanács, C. Domokos, N. Sladoje, J. Lindblad, and Z. Kato. Recovering affine deformations of fuzzy shapes. SCIA 2009. LNCS-5575, pp. 735–744, 2009.
2. A method based on mathematical morphology and a dual thresholding scheme.
   - N. Sladoje and J. Lindblad. High Precision Boundary Length Estimation by Utilizing Gray-Level Information. IEEE Trans. on PAMI, Vol. 31, No. 2, pp. 357–363, 2009.
3. A method providing local sub-pixel classification extending any existing crisp segmentation.
   - N. Sladoje and J. Lindblad. Pixel coverage segmentation for improved feature estimation. Accepted for ICIAP 2009.

Some background

We are not first ones to work with mixed/partially covered image elements.

- “Mixed pixels” - satellite imaging
- “Partial volume effects” - tomographic imaging

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- Fuzzy segmentation techniques

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We are not first ones to work with mixed/partially covered image elements.

- “Mixed pixels” - satellite imaging
- “Partial volume effects” - tomographic imaging

- Fuzzy segmentation techniques

- The presented pixel coverage model assumes **crisp** objects.
  - The membership of a pixel has a precisely defined meaning.

Pixel coverage segmentation

Definition (pixel coverage segmentation)

A *pixel coverage segmentation* of an image I into m components $c_k, k \in \{1, 2, \dots, m\}$ is

$$\mathcal{S}(I) = \left\{ \left((i,j), \alpha_{(i,j)}\right) \,\middle|\, (i,j) \in I_D \right\} \,,$$

where

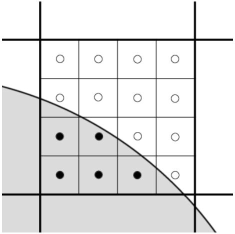
$$\alpha_{(i,j)} = (\alpha_1, \dots, \alpha_m)\,, \quad \sum_{k=1}^{m} \alpha_k = 1\,, \qquad \alpha_k = \frac{A(p_{(i,j)} \cap S_k)}{A(p_{(i,j)})}\,,$$

and where $S_k \in \mathbb{R}^2$ is the extent of the component c_k and $I_D \subseteq \mathbb{Z}^2$ is the image domain.

The sets S_k are, in general, not known, and the values α_k have to be estimated from the image.

1. Use of a continuous segmentation model

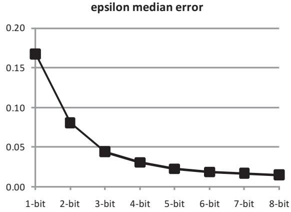
From a continuous (crisp) representation it is fairly straightforward to compute pixel coverage values, either analytically or numerically, e.g. based on supersampling.

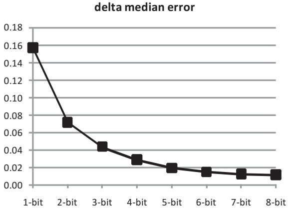


Application 1

Affine registration of digital X-ray images of hip-prosthesis implants for follow up examinations

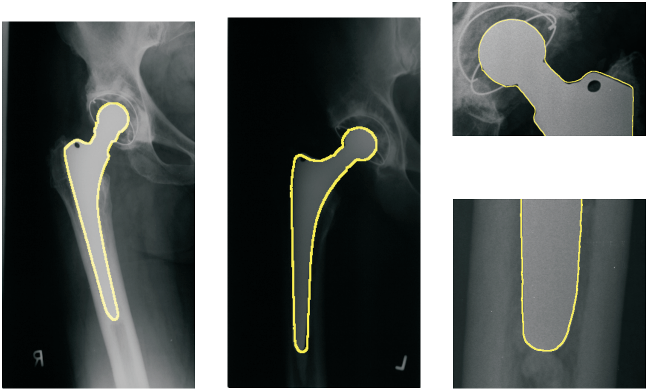
Segmentation using active contours (snakes), modified to provide pixel coverage values utilized for improved moments' estimation in the registration process.





Registration results of 2000 synthetic images using different quantization levels of the fuzzy boundaries.

Application 1



$\delta = 2.17\%$ $\delta = 4.81\%$ $\delta = 1.2\%$

Figure: Real X-ray registration results. (a) and (b) show full X-ray observation images and the outlines of the registered template shapes. (c) shows a close up view of a third study around the top and bottom part of the implant.

2. Image intensities + mathematical morphology

In many imaging situation, acquired pixel intensities correspond almost directly to pixel coverage values.

For example: Integration of photons over finite sized sensor elements, such as those of a digital camera.

- A reasonable model for low resolution images, where resolution is decided based on limited means for handling of the data, rather than the optical system. This is often the case for low-resolution video, but also for e.g. CT volumes.

However, noise may provide unreliable measurements. Appropriate pre-processing is recommended.

2. Image intensities + mathematical morphology

Properties of pixel coverage images

- The pixel coverage digitization leads to images where objects have grey edges which are never more than **one pixel thick** (if sampled at high enough resolution).
- The theoretical results of the perimeter estimation method relies on such thin grey boundaries.
- However, it is rarely the case that objects in real images exhibit such thin boundaries.

2. Image intensities + mathematical morphology

A pixel coverage segmentation method based on mathematical morphology in combination with a double thresholding scheme.

The requirement of a one pixel thin grey border is conveniently expressed using **grey-scale mathematical morphology**.

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Given a grey-scale image, we seek a threshold couple, b and f, where pixels darker than b are defined to belong completely to the background, while pixels brighter than f belong completely to the foreground, such that the pixels in between form a one pixel thick separating band.
In addition, we want the contrast between foreground and background, i.e., the difference $f - b$, to be as large as possible.

Algorithm

Input: A grey-scale image I.
Output: An approximates pixel coverage representation J
with n positive grey-levels.

$b = 0; f = 0$
for each grey-level b'
  $F' = \{p \mid [\varepsilon I](p) > b'\}$ /* Foreground */
  if $F' \neq \emptyset$
    $f' = \min_{p \in F'} [\varepsilon\delta I](p)$
    if $f' - b' > f - b$ /* Better than previous */
      $f = f'; b = b'$
    endif
  endif
endfor

$n = f - b$

$$J(p) = \begin{cases} 0 & , \quad [\delta\varepsilon I](p) \leq b, \\ 1 & , \quad [\varepsilon\delta I](p) \geq f, \\ \frac{I(p)-b}{n} & , \quad \text{otherwise.} \end{cases}$$

Digital photos of a straight edge segment

Photos of the straight edge of a white paper on a black background at a number of angles using a Panasonic DMC-FX01 digital camera in grey-scale mode.

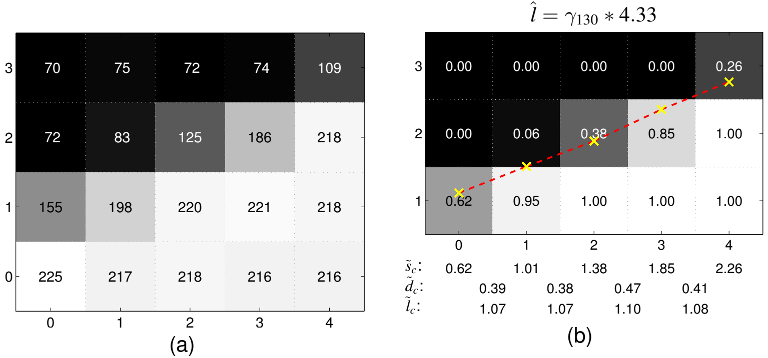


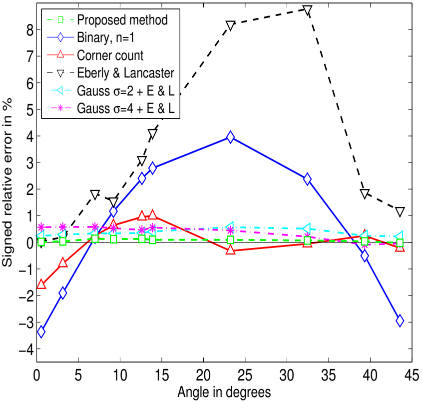
Figure: (a) Close up of the straight edge of a white paper imaged with a digital camera. (b) Segmentation output from Algorithm 2 using 130 positive grey-levels. Approximating edge segments are superimposed.

Results

The observed noise range in the images is between 20 and 50 grey-levels, out of 255, and the found value of n in the segmentation varies from 90 to 140 for the different photos.

The observed maximal errors for the methods are as follows:

- Proposed method **0.14%**;
- Binary 3.95%;
- Corner count 1.61%;
- Eberly & Lancaster 8.78%;
- Gauss $\sigma = 2$ + E & L 0.57%;
- Gauss $\sigma = 4$ + E & L 0.58%.



3. Un-mixing based on local classification

Assumption

Partial pixel coverage exist only at the object boundaries of the existing crisp segmentation.

Approach

Re-assign class belongingness to the boundary pixels based on a local classification using the surrounding non-boundary pixels.

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Re-assign class belongingness to the boundary pixels based on a local classification using the surrounding non-boundary pixels.

To obtain a pixel coverage segmentation, we propose a method composed of the following four steps:

1. Application of a crisp segmentation method, appropriately chosen for the particular task
2. Selection of pixels to be assigned partial coverage
3. Application of a liner mixture model for “de-mixing” of partially covered pixels and assignment of pixel coverage values
4. Ordered thinning of the set of partly covered pixel to provide one pixel thin 4-connected regions of mixed pixels

Pixel coverage segmentation

Definition (pixel coverage segmentation)

A *pixel coverage segmentation* of an image I into m components $c_k, k \in \{1, 2, \ldots, m\}$ is

$$\mathcal{S}(I) = \left\{ \left((i,j), \alpha_{(i,j)} \right) \,\middle|\, (i,j) \in I_D \right\} ,$$

where

$$\alpha_{(i,j)} = (\alpha_1, \ldots, \alpha_m) \,, \; \sum_{k=1}^{m} \alpha_k = 1 \,, \quad \alpha_k = \frac{A(p_{(i,j)} \cap S_k)}{A(p_{(i,j)})} \,,$$

and where $S_k \in \mathbb{R}^2$ is the extent of the component c_k and $I_D \subseteq \mathbb{Z}^2$ is the image domain.

The sets S_k are, in general, not known, and the values α_k have to be estimated from the image.

Steps 1 and 2.

1. **Any** crisp segmentation model.
   - For the example to come, we used Linear Discriminant Analysis in combination with Iterative Relative Fuzzy Connectedness[1]

[1] J. Lindblad, N. Sladoje, V. Ćurić, H. Sarve, C.B. Johansson, and G. Borgefors. Improved quantification of bone remodelling by utilizing fuzzy based segmentation. SCIA 2009

Steps 1 and 2.

1. **Any** crisp segmentation model.
   - For the example to come, we used Linear Discriminant Analysis in combination with Iterative Relative Fuzzy Connectedness[1]
2. **Selection of pixels to re-evaluate**
   - All pixel which are 4-connected to a pixel with a different label.

[1] J. Lindblad, N. Sladoje, V. Ćurić, H. Sarve, C.B. Johansson, and G. Borgefors. Improved quantification of bone remodelling by utilizing fuzzy based segmentation. SCIA 2009

3. Computation of partial pixel coverage values

3.1 Estimate the spectral properties c_k of the pure classes locally.

- The mean values of the respective classes present in the assumed completely covered pixels in a local Gaussian neighbourhood.

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- The mean values of the respective classes present in the assumed completely covered pixels in a local Gaussian neighbourhood.

3.2 Compute the mixture proportions a_k of the pixels selected in step 2.

- The intensity values of a mixed pixel $p = (p_1, p_2, \ldots, p_n)$ (n being the number of channels of the image) are assumed, in a noise-free environment, to be a convex combination of the pure classes c_k:

$$p = \sum_{k=1}^{m} \alpha_k c_k \,, \quad \sum_{i=k}^{m} \alpha_k = 1 \,, \quad \alpha_k \geq 0 \,. \tag{1}$$

where each coefficient α_k corresponds to the coverage of the pixel p by an object of a class c_k.

3. Computation of partial pixel coverage values

In the presence of noise, it is not certain that there exists a (convex) solution to the linear system (1). Therefore we reformulate the problem as follows:

Find a point p^* of the form $p^* = \sum_{k=1}^{m} \alpha_k^* c_k$, such that p^* is a *convex* combination of c_k and the distance $d(p, p^*)$ is minimal. We solve the constrained optimization problem by using Lagrange multipliers, and minimize the function

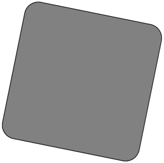
$$F(\alpha_1, \ldots, \alpha_m, \lambda) = \|p - \sum_{k=1}^{m} \alpha_k c_k\|_2^2 + \lambda(\sum_{k=1}^{m} \alpha_k - 1)$$

over all $\alpha_k \geq 0$. This leads to a least squares type of computation.

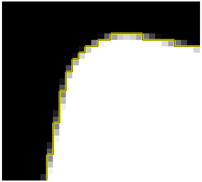
The obtained solution provides estimated partial coverage of the pixel p by each of the observed classes c_k.

4. Ordered thinning

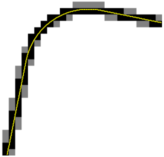
To ensure one pixel thick boundaries, the “least” mixed pixels are one at a time assigned to their most prominent class, until only one pixel thick mixed boundaries remain.



(a) Test object



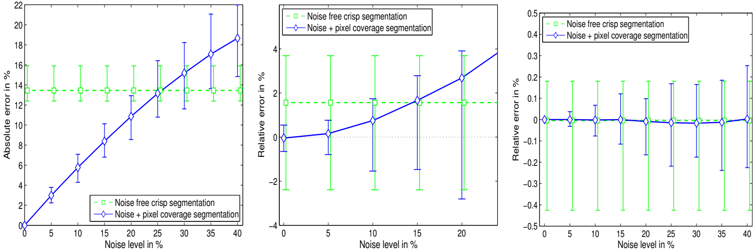
(b) Part of pixel coverage segm.



(c) Part of re-evaluated set

Evaluation

How does this work in a noisy environment?

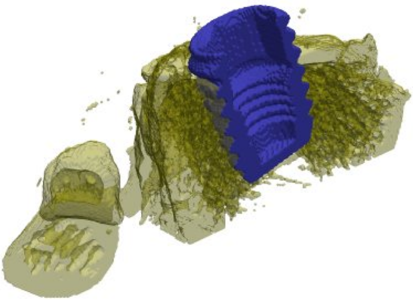


(d) Coverage values (e) Perimeter estimate (f) Area estimate

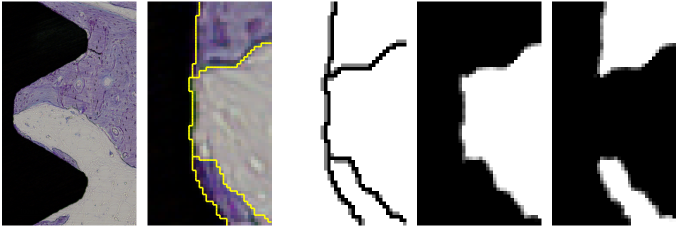
Figure: Estimation errors for increasing levels of noise. Green is noise free crisp reference. Bars represent max and min.

Application 2

Measure bone implant integration for the purpose of evaluating new surface coatings which are stimulating bone regrowth around the implant.



Application 2



(a) (b) (c) (d) (e)

Figure: (a): The screw-shaped implant (black), bone (purple) and soft tissue (light grey). (b) Part of a crisp (manual) segmentation of (a). (c) The set of re-evaluated pixels. (d) and (e) Pixel coverage segmentations of the soft tissue and the bone region, respectively.

Result:

Approximately a **30% reduction of errors** as compared to when using estimates from the crisp starting segmentation.

Summary

- Pixel coverage representations are shown to be superior to crisp image object representations for many reasons.
- By suitably utilizing information available in images it is possible to perform a **Pixel coverage segmentation**.
- We observe that even for moderate amount of noise, the achieved pixel coverage representation provides a more accurate representation of image objects than a perfect, noise free, crisp representation.

Thanks to the people involved

- Dr. Nataša Sladoje
- Prof. Gunilla Borgefors
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- Hamid Sarve
- Vladimir Ćurić
- Prof. Jocelyn Chanussot
- Dr. Ingela Nyström
- Dr. Attila Tanács
- Csaba Domokos
- Prof. Zoltan Kato
- Prof. Joviša Žunić