

Image analysis with subpixel precision - The Coverage model

Some application examples

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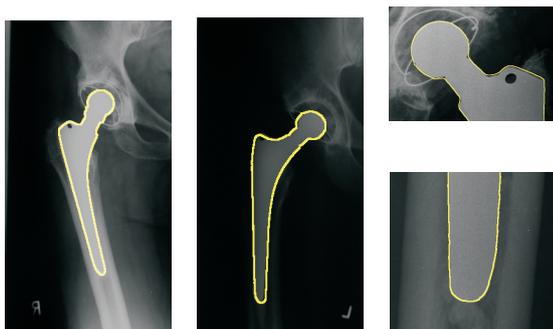
2012, Uppsala

Some applications

- Affine registration of digital X-ray and CT images utilizing improved moments estimation**
 - 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.
 - A. Tanács, J. Lindblad, N. Sladoje, and Z. Kato. Estimation of linear deformations of 3D objects. ICIP 2010, IEEE, pp. 153-156, Hong Kong, 2010.
- Histomorphometrical study from microscopy images, using coverage representation and feature estimates.**
 - N. Sladoje, J. Lindblad. Pixel coverage segmentation for improved feature estimation. ICIAP 2009. LNCS-5716, pp. 929-938 Vietri sul Mare, Italy, 2009.
- Coverage segmentation of a CT image, followed by precise feature estimates**
 - F. Malmberg, J. Lindblad, I. Nyström. Sub-pixel segmentation with the image foresting transform, IWCI 2009, LNCS- 5852, pp. 201-211, 2009.
 - F. Malmberg, J. Lindblad, N. Sladoje, and I. Nyström. A Graph-based Framework for Sub-pixel Image Segmentation. Theoretical Computer Science, Vol. 412, No. 15, pp. 1338-1349, 2011

Application 1 – Registration from moments

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

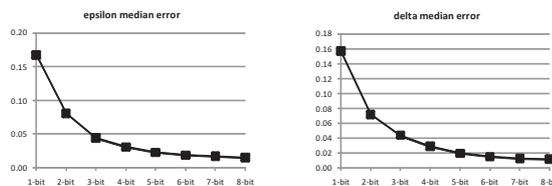


Real X-ray registration results. (a) and (b) show full X-ray observation images and the outlines of the registered template shapes. (c) shows a close up view of a third study around the top and bottom part of the implant.

Application 1 – Registration from moments

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

Coverage values used for improved moments' estimation in a registration process.

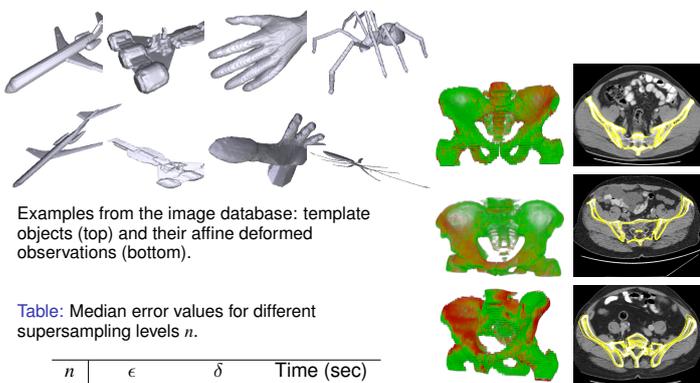


Registration results of 2000 synthetic images using different quantization levels of the coverage representation.

$$\epsilon = \frac{1}{m} \sum_{p \in T} \left\| (A - \hat{A})p \right\|, \quad \text{and} \quad \delta = \frac{|R \Delta O|}{|R| + |O|}$$

Application 1 – Registration from moments

Same thing in 3D



Examples from the image database: template objects (top) and their affine deformed observations (bottom).

Table: Median error values for different supersampling levels n .

n	ϵ	δ	Time (sec)
1	0.0361	0.1555	1.54
2	0.0108	0.0627	1.56
4	0.0069	0.0470	1.54
8	0.0065	0.0402	1.52

Registration of pelvic CT data

Application 2 – Contact length estimation

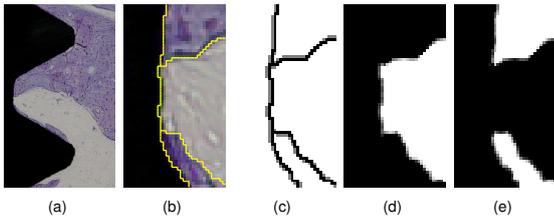
Histomorphometrical study from microscopy images

Measure bone implant integration for the purpose of evaluating new surface coatings which are stimulating bone regrowth around the implant. Local unmixing segmentation followed by area and boundary estimates.



Application 2 – Contact length estimation

Histomorphometrical study from microscopy images



(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** on average, as compared to when using estimates from the crisp starting segmentation.

Application 3 – Precise volume estimation

Coverage segmentation of a CT image, followed by feature estimates
User assisted graph based segmentation of the spleen, for medical diagnosis based on accurate feature estimates.



Fig. 3. Segmentation of the spleen in a slice from a CT volume. (Left) Seed-point regions used in the experiment. The green pixels define all object seeds, while the red pixels define background seeds. Single pixels from the green region were used to define object seeds. (Middle) Example result of crisp IFT. (Right) Example result of the proposed sub-pixel IFT.

Table 1. Statistics on the measured area for the 41 segmentations in the experiment. (Areas are given in number of pixels.)

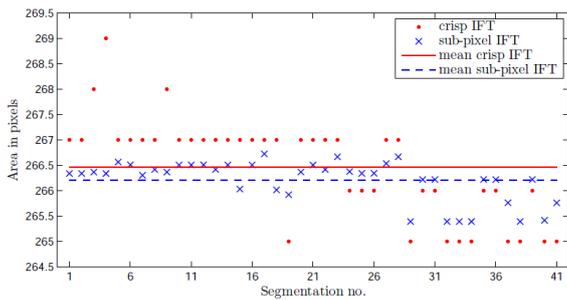
Method	Mean area	Min area	Max area	σ
Crisp IFT	266.5	265	269	0.98
Sub-Pixel IFT	266.2	265.4	266.7	0.40

Result: **50% reduction of standard deviation** of estimates, as compared to when using estimates from the crisp starting segmentation.

Application 3 – Precise volume estimation

Coverage segmentation of a CT image, followed by feature estimates

User assisted graph based segmentation of the spleen, for medical diagnosis based on accurate feature estimates.



Result: Assuming that the mean result is correct, **more than 3 times reduction of the maximal error**, as compared to when using estimates from the crisp starting segmentation.

Application 4 – Subpixel precise tracking

