ESTIMATION OF SHAPE MODEL PARAMETERS FOR 3D SURFACES

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Problem:

Fit a statistical shape model to new data without the use of point correspondence

Solution:

Apply an optimizer

Introduction

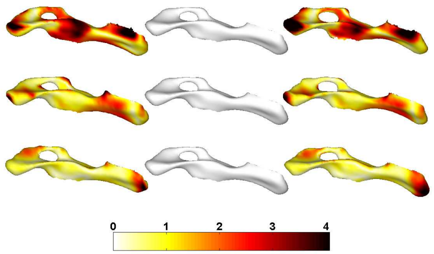
Statistical shape models are a compact way of representing shape variation. Fitting a shape model to unseen data enables characterizing the data in terms of the model parameters, but require full correspondence between points.

A Gauss-Newton optimization scheme is proposed to estimate shape model parameters of 3D surfaces without the requirement of point correspondence.

For applications where speed and cost are issues, this formulation enables fitting a statistical shape model to arbitrarily sampled data. It is applied to 33 3D surfaces (**s**) of porcine bones obtained with CT.

PCA based shape model: $\mathbf{s}(\mathbf{p}) = \mathbf{s}_{mean} + \mathbf{\Phi p}$

-3 std. / Mean shape / +3 std.



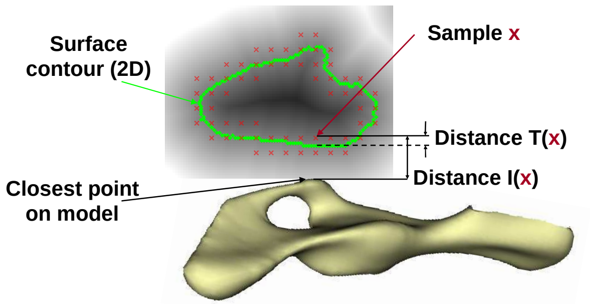
Methodology

- Iterative Gauss-Newton optimization scheme (Lukas-Kanade algorithm)[1]
- Formulation using distance maps of unknown shape (**T**)
- Allows *arbitrary* sampling (**x**) near contours
- Determine closest point in the model (**I**)
- Minimize cost function:

$$\sum_{\mathbf{x}} \big(\mathbf{I}(\underbrace{W(\mathbf{x};\mathbf{p})}_{\textit{Warp of } \mathbf{x} \textit{ with } \mathbf{p}}) - \mathbf{T}(\mathbf{x}) \big)^2$$

- Update shape model parameters **p** until convergence
- Simple derivatives: Vertex normals
- Simple Jacobian: Given by eigenvectors (**Φ**) of shape model

Distance map of template T



Input I (Shape model)

Validation

- **x** = surface vertices
- Initialize mean shape using ICP
- Compare 3 schemes to "true" parameters
  - "**Comb.**" - parameters estimated simultaneously.
  - "**Seq-est**" - parameters estimated sequentially.
  - "**Seq-true**" – parameters estimated seq. with previous parameters fixed to true value (for comparison).
- Leave-one-out validation

Results

- Most cases have a mean difference <0.1 std.
- Similar performance when estimating 1-2 modes
- The combined scheme (**comb.**) has a max. std. of 0.76 for the first 5 modes, compared to 0.53 af the **seq-est** scheme.
- **For the first 3 modes the max. std. of the seq-est scheme is 0.34 and the mean is within [-0.01,0.02] std.**
- The rms error is within 0.01mm of that obtained using true parameter values

Parameter estimates

difference from "true" values

Modes	Comb.	Seq-est	Seq-true
1	0.01 (0.33)	0.01 (0.33)	0.01 (0.33)
2	-0.07 (0.34)	-0.01 (0.34)	0.02 (0.35)
3	-0.04 (0.56)	0.02 (0.32)	-0.01 (0.32)
4	-0.07 (0.76)	0.03 (0.53)	0.04 (0.52)
5	0.07 (0.58)	0.04 (0.49)	0.01 (0.43)
6	-0.21 (0.97)	-0.07 (0.42)	-0.06 (0.47)
7	-0.55 (1.08)	-0.17 (0.98)	-0.16 (0.76)

Fig. 1 -Mean

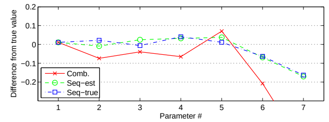


Fig. 2 - Rms error

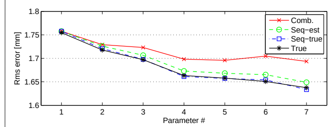
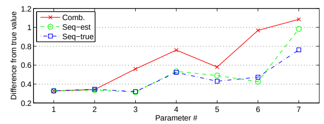


Fig. 3 - Std.



Conclusion

The first 3 parameters of a statistical shape model are estimated reasonably well using an optimizer, compared to parameters obtained using point correspondence. The method enables fitting shape models to sparse or incomplete data, e.g. in applications where cost and speed are issues.

References

(1) Baker, S., Matthews I., "Lucas-Kanade 20 Years On: A Unifying Framework", Int. Journal of Computer Vision 56(3), 221–255, 2004.

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