

Skuller: A volumetric shape registration algorithm for modeling skull deformities



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Problem Statement

- ✓ Medical objective
 - ✓ Quantify the deviation of given skull from a healthy one.
- ✓ Geometric objective:
 - ✓ Develop an algorithm for *volumetric* registration of 3D shapes.

Applications

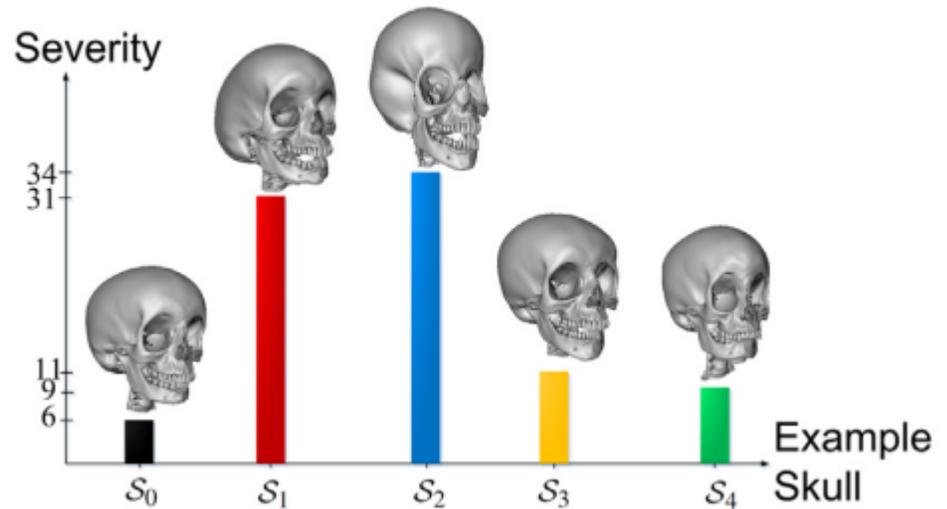
✓ Shape registration:



✓ Statistical shape analysis:



✓ Objective quantification of medical condition(s):



Contributions

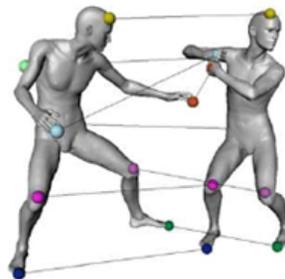
- ✓ A fast and robust solution to a new version of the well-known shape registration problem, namely the registration of two volumetric shapes.
 - ✓ Source: volumetric tetrahedral mesh.
 - ✓ Target: volumetric shape defined by voxels.
- ✓ In contrast to point- and surface-based registration techniques, our method better captures volumetric nature of the data, such as bone thickness.
- ✓ ICP with adaptive scaling.
- ✓ Multi-initialization ICP.

Scope

- ✓ Input: A tetrahedral mesh & A voxelized object (CT scan).



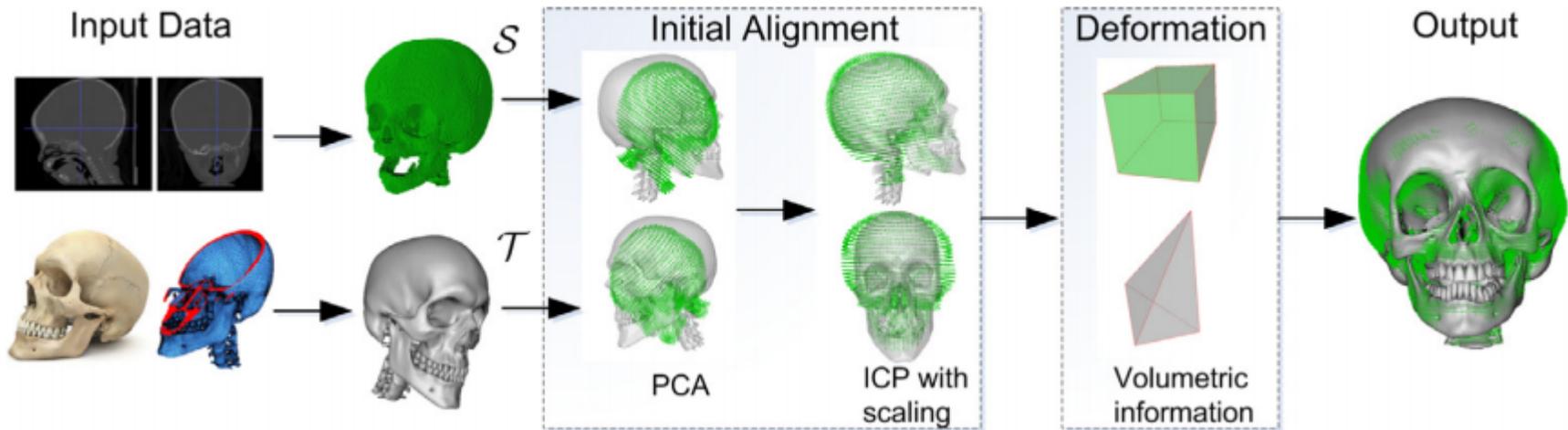
- ✓ Input pair differs by non-isometric/non-rigid transformation.



//an isometric pair

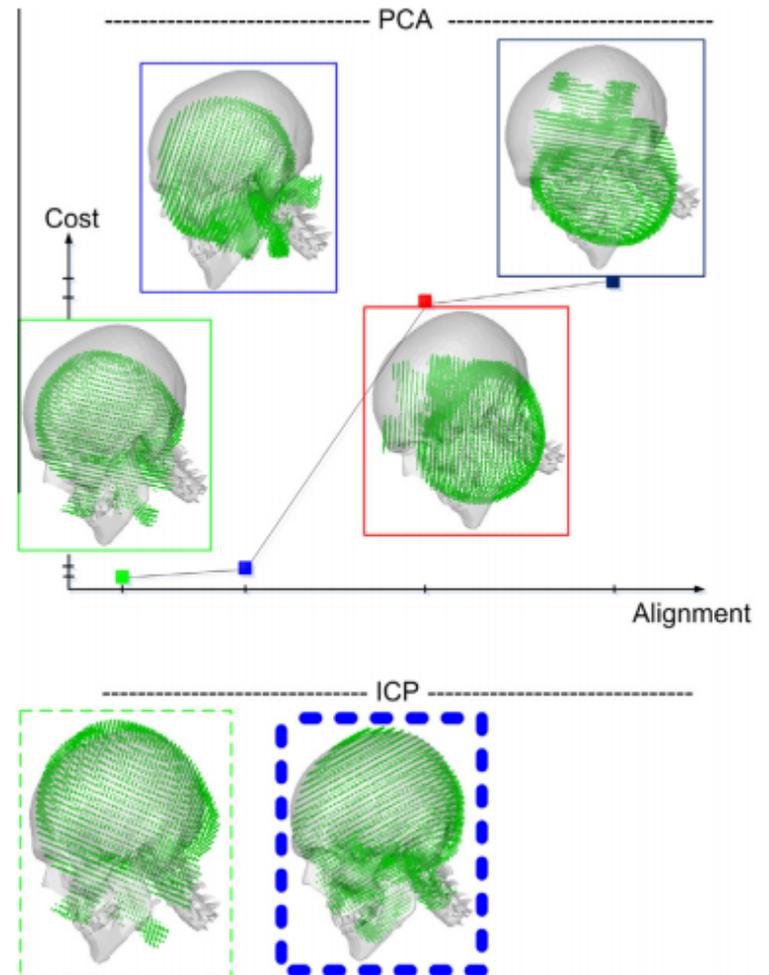
Algorithm

✓ Overview.



Algorithm

- ✓ Initial alignment.
- ✓ A global rigid alignment.
 - ✓ Rotation, translation, uniform scale.
- ✓ Treat input pair as 3D point clouds.
- ✓ PCA-based alignment for multiple ICP initialization.

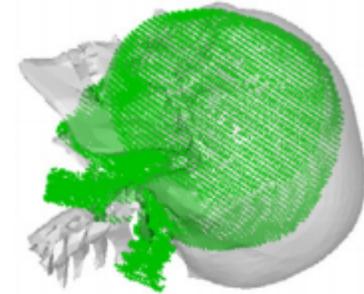


Algorithm

- ✓ Initial alignment.
- ✓ A global rigid alignment.
 - ✓ Rotation, translation, uniform scale.
- ✓ Treat input pair as 3D point clouds.
- ✓ Solve for uniform scale u in addition to the translation d once you have the ICP-rotated points \mathbf{p} .

$$f(\mathbf{p}) = \sum_i \|u\mathbf{p}_i + \mathbf{d} - \mathbf{q}_i\|^2$$

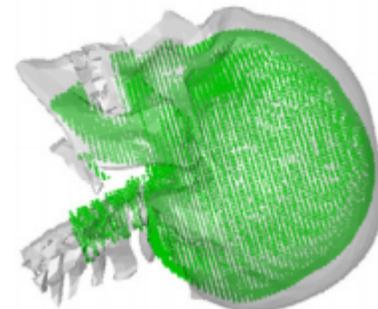
ICP input



ICP with adaptive uniform scaling



Classical ICP



Algorithm

- ✓ Volumetric registration.
- ✓ A non-rigid alignment.
 - ✓ Bending/warping allowed.
- ✓ Seek \mathbf{t} that minimizes the following energy:
 - ✓ $E_{\text{def}}(\mathbf{t}) = E_{\text{corr}}(\mathbf{t}) + \alpha E_{\text{Dirichlet}}(\mathbf{t}) + \beta E_{\text{Tikhonov}}(\mathbf{t})$

Algorithm

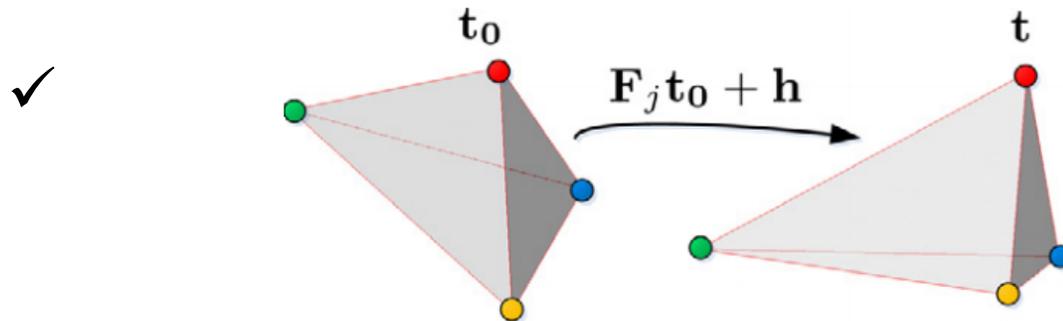
- ✓ Volumetric registration.
- ✓ A non-rigid alignment.
 - ✓ Bending/warping allowed.
- ✓ Correspondence/matching term.
 - ✓ $E_{\text{corr}}(\mathbf{t}) = \|\mathbf{t} - \mathbf{P}\mathbf{s}\|^2$
 - ✓ Brings transformed vertices \mathbf{t} to the scan voxels \mathbf{s} as close as possible.
 - ✓ Permutation matrix \mathbf{P} defines closest-point correspondences.

Algorithm

- ✓ Volumetric registration.
- ✓ A non-rigid alignment.
 - ✓ Bending/warping allowed.
- ✓ Regularization term: Volumetric Dirichlet energy.
 - ✓ $E_{\text{Dirichlet}}(\mathbf{t}) = (\mathbf{t} - \mathbf{t}_0)^T \mathbf{L}(\mathbf{t} - \mathbf{t}_0)$
 - ✓ Preserves rest-pose coordinates \mathbf{t}_0 , hence the good shape, as much as possible.

Algorithm

- ✓ Volumetric registration.
- ✓ A non-rigid alignment.
 - ✓ Bending/warping allowed.
- ✓ Regularization term: Volumetric Dirichlet energy.
 - ✓ $E_{\text{Dirichlet}}(\mathbf{t}) = (\mathbf{t} - \mathbf{t}_0)^T \mathbf{L}(\mathbf{t} - \mathbf{t}_0)$
 - ✓ Measures deviation of tetrahedra's deformation gradients \mathbf{F} from \mathbf{I} using the mesh Laplacian \mathbf{L} .



Algorithm

- ✓ Volumetric registration.
- ✓ A non-rigid alignment.
 - ✓ Bending/warping allowed.
- ✓ Regularization term: Volumetric Dirichlet energy.
 - ✓ $E_{\text{Dirichlet}}(\mathbf{t}) = (\mathbf{t} - \mathbf{t}_0)^T \mathbf{L}(\mathbf{t} - \mathbf{t}_0)$
 - ✓ Measures deviation of tetrahedra's deformation gradients \mathbf{F} from \mathbf{I} using the mesh Laplacian \mathbf{L} .
 - ✓ $\mathbf{L} = \sum_{j \in T} \lambda_j \mathbf{G}_j^T \mathbf{G}_j$, where \mathbf{G}_j extracts vectorized gradient \mathbf{F}_j
when multiplied with all vertices, i.e., $\text{vec}(\mathbf{F}_j) = \mathbf{G}_j(\mathbf{t} - \mathbf{t}_0)$

Algorithm

- ✓ Volumetric registration.
- ✓ A non-rigid alignment.
 - ✓ Bending/warping allowed.
- ✓ Regularization term: Tikhonov energy.
 - ✓ $E_{\text{Tikhonov}}(\mathbf{t}) = \|\mathbf{t} - \mathbf{t}_{\text{prev}}\|^2$
 - ✓ Keeps the amount of displacement from the previous step's coordinates \mathbf{t}_{prev} as small as possible, i.e., no jumps.

Algorithm

- ✓ Volumetric registration.
- ✓ A non-rigid alignment.
 - ✓ Bending/warping allowed.
- ✓ Differentiating overall energy w.r.t. \mathbf{t} gives:

$$\begin{aligned}\checkmark \quad \frac{\partial E_{\text{def}}}{\partial \mathbf{t}} &= \frac{\partial E_{\text{corr}}}{\partial \mathbf{t}} + \alpha \frac{\partial E_{\text{Dirichlet}}}{\partial \mathbf{t}} + \beta \frac{\partial E_{\text{Tikhonov}}}{\partial \mathbf{t}} \\ &= 2(\mathbf{t} - \mathbf{Ps} + \alpha \mathbf{L}(\mathbf{t} - \mathbf{t}_0) + \beta(\mathbf{t} - \mathbf{t}_{\text{prev}}))\end{aligned}$$

- ✓ Setting this derivative to 0 gives a sparse linear sys to solve:

$$\checkmark \quad (\alpha \mathbf{L} + (\beta + 1)\mathbf{I})\mathbf{t} = \mathbf{Ps} + \alpha \mathbf{L}\mathbf{t}_0 + \beta \mathbf{t}_{\text{prev}}$$

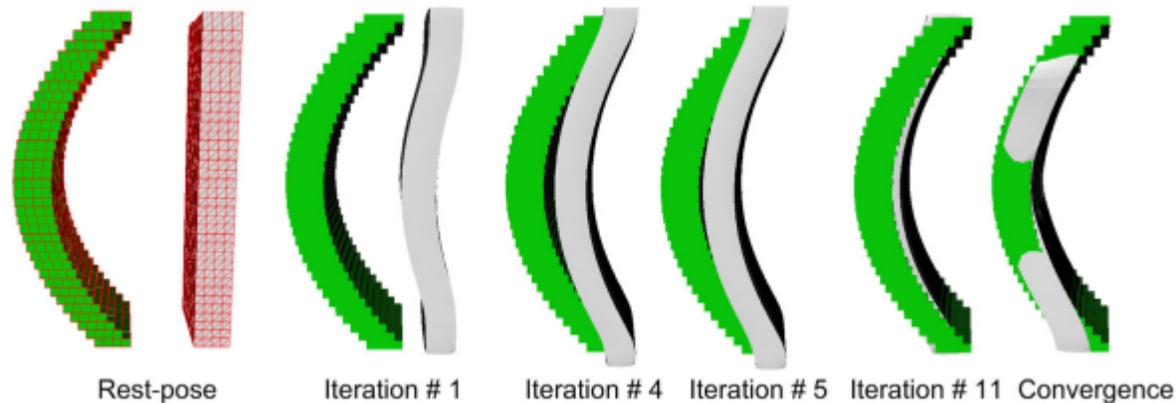
Algorithm

- ✓ Volumetric registration.
- ✓ A non-rigid alignment.
 - ✓ Bending/warping allowed.

- ✓ Tricks to make this process work well.
 - ✓ Adaptive weighting.
 - ✓ Initially high α β as the closest-point correspondences in **P** are not so reliable.
 - ✓ Regularization (α β) prevents a potential damage from \mathbf{E}_{corr} .
 - ✓ Reduce regularization strength when \mathbf{t} is very close to \mathbf{t}_{prev} , i.e., little/no progress.
 - ✓ \mathbf{E}_{corr} becomes more reliable thanks to better correspondences.

Algorithm

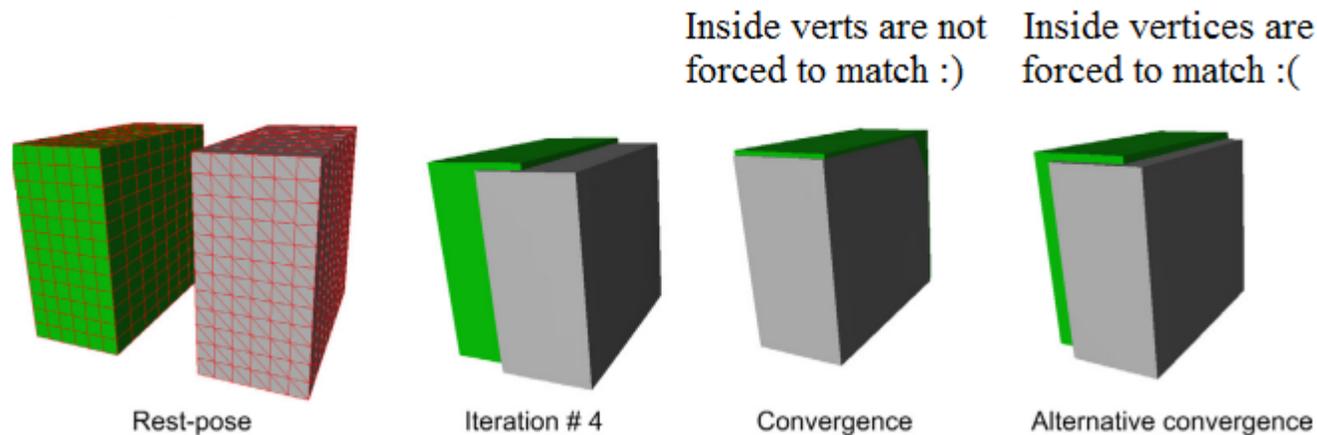
- ✓ Volumetric registration.
- ✓ A non-rigid alignment.
 - ✓ Bending/warping allowed.
- ✓ Tricks to make this process work well.
 - ✓ Adaptive weighting.



- ✓ Little displacement b/w iter 4 & 5 triggers adaptive weighting.

Algorithm

- ✓ Volumetric registration.
- ✓ A non-rigid alignment.
 - ✓ Bending/warping allowed.
- ✓ Tricks to make this process work well.
 - ✓ E_{corr} disabling.
 - ✓ A vertex that is already inside the volume should not be affected by E_{corr} as it is not possible to establish meaningful matches now.
 - ✓ Instead it should be free to move as dictated by regularization.



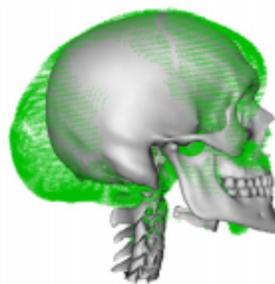
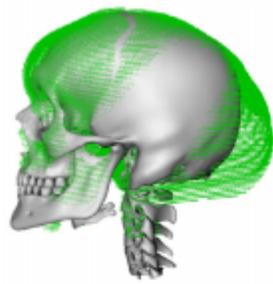
Algorithm

- ✓ Computational complexity.
- ✓ n tetrahedral mesh vertices, m scan voxels.
- ✓ Initial global alignment.
 - ✓ $O(n \log m)$ due to closest-point search.
- ✓ Volumetric registrations.
 - ✓ $O(n \log m)$ due to closest-point search.
 - ✓ $O(n + w)$ Cholesky factorization performed i times, where $i = \#$ deformation iterations is about 20 in our runs. w high constant.

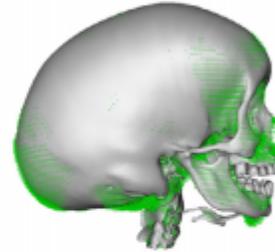
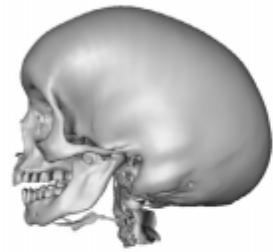
Algorithm

- ✓ Computational complexity.
- ✓ n tetrahedral mesh vertices, m scan voxels.
- ✓ Initial global alignment.
 - ✓ $O(n \log m)$ due to closest-point search.
- ✓ Volumetric registrations.
 - ✓ $O(n \log m)$ due to closest-point search.
 - ✓ $O(n + w)$ Cholesky factorization performed i times, where $i = \#$ deformation iterations is about 20 in our runs. w high constant.
- ✓ Execution time on a 2.2 GHz PC.
 - ✓ Input tetrahedral mesh: 160K vertices, 560K tetrahedra.
 - ✓ Input CT scan: 190K voxels.
 - ✓ 20 minutes.
 - ✓ 133 secs initial alignment, 1 sec (closest-point) + 49 sec (Cholesky) per deformation iteration.

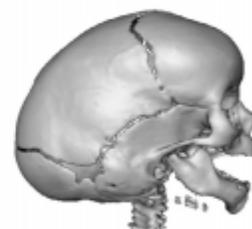
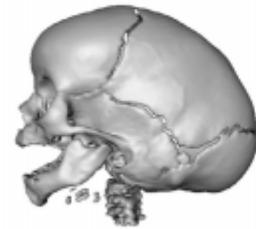
Results



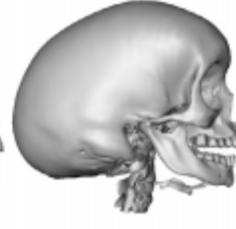
//Initial global alignment.



//Resulting registered model.

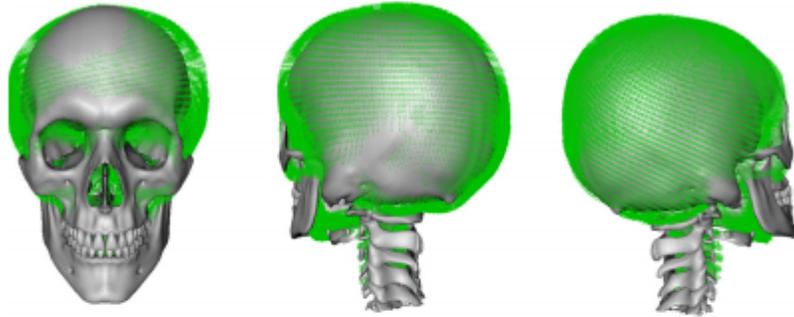


//Underlying ground-truth surf.
//(extracted by Marching Cubes)

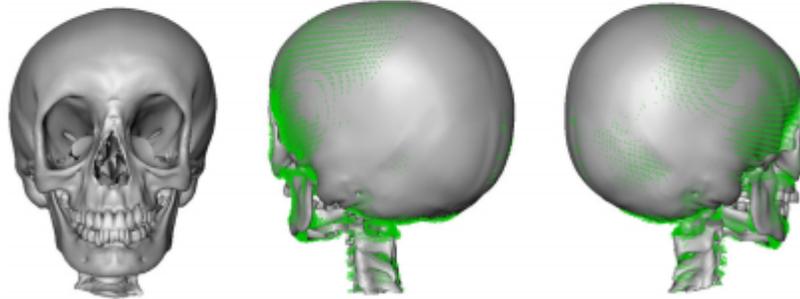


//Deformation process.

Results

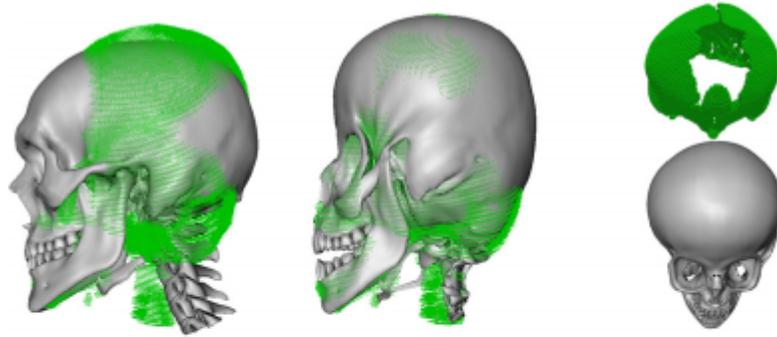


//Initial global alignment.

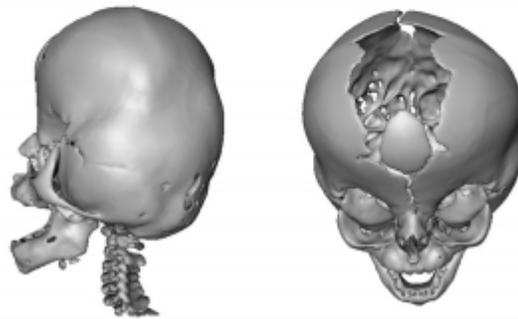


//Resulting registered model.

Results

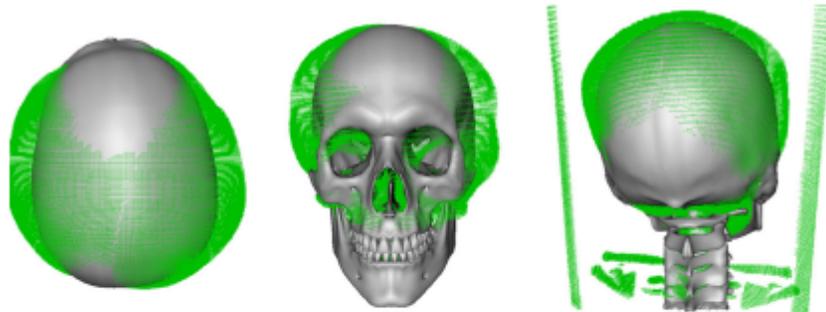


//Initial global alignment and
//resulting registered model.

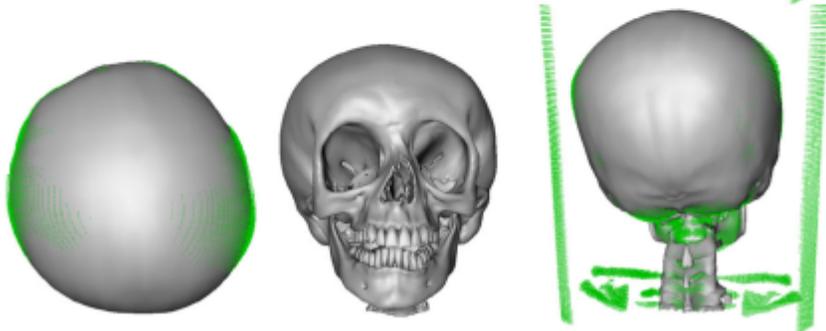


//Underlying ground-truth surf.

Results



//Initial global alignment.

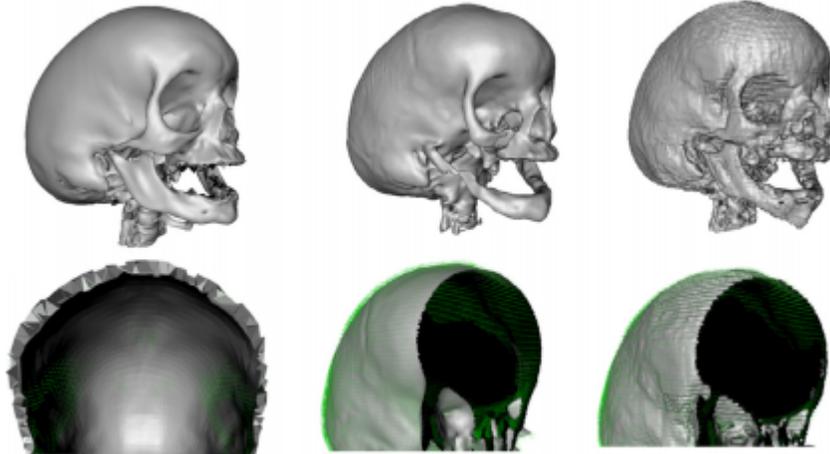


//Resulting registered model.



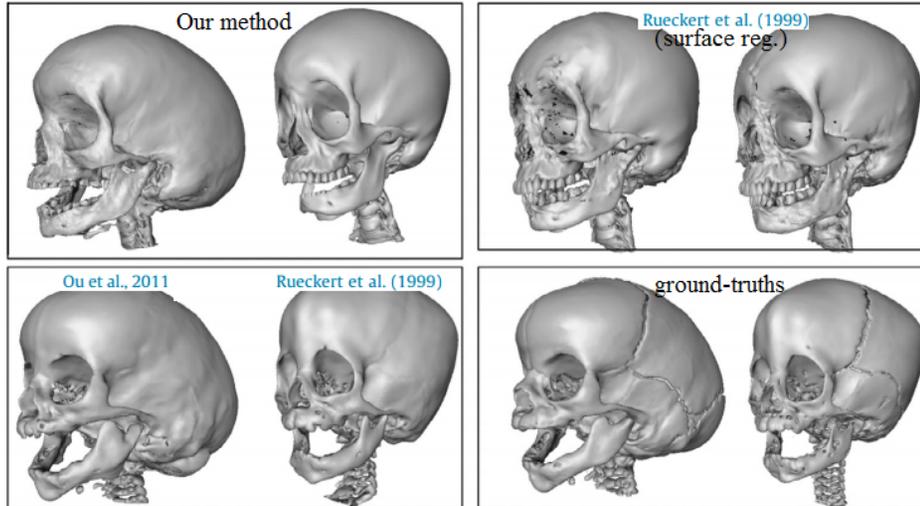
//Underlying ground-truth surf.

Results



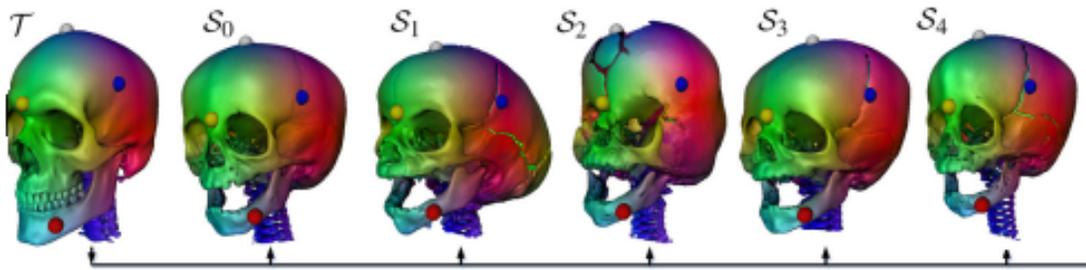
//Our *volumetric* registration
//that respects bone thickness
//(left column) is favorable over
//unscreened and screened
//Poisson *surface* registrations.

Results



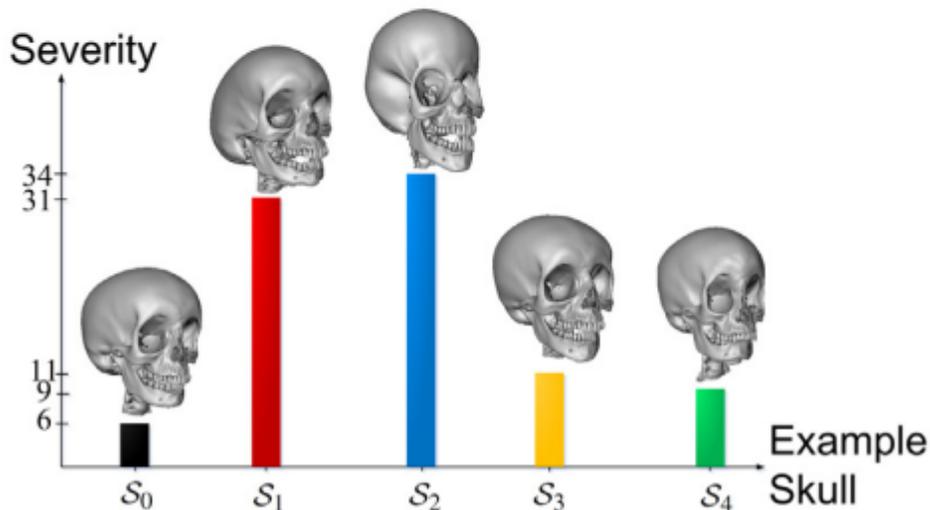
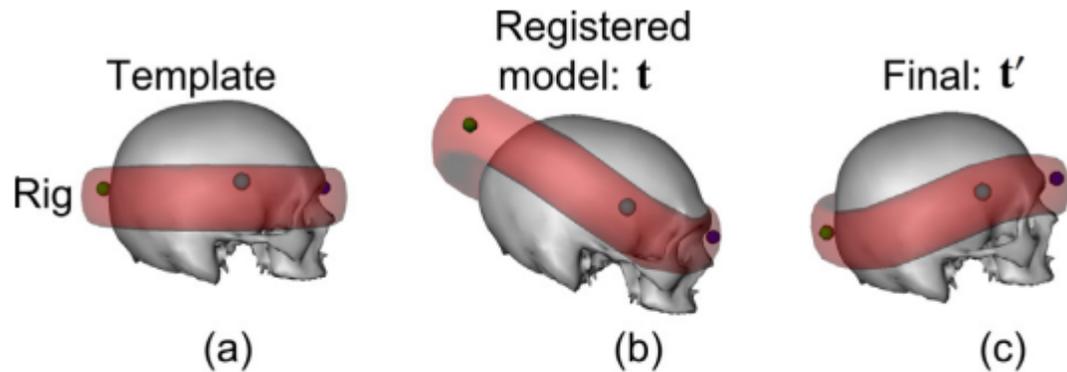
//Our volumetric registration
//in comparison with volumetric
//image registration techniques.

Applications



//Transfer of colors (or any
//other attributes) through the
//*dense correspondence*
//achieved b/w the template and
//deformed/registered pose, and
//effectively between ground-
//truth geometries of all the
//example skulls

Applications

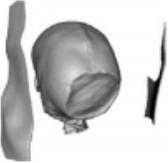


//Objective quantification of
//severity of skull deformities.
//Rig designed specifically for
//the template mesh (top)
//enables interactive
//deformation of the registered
//model using ARAP energy.
//The effort of the doctor during
//this session, i.e., the
//deformation energy, is used as
//the objective quantification
//(bottom).

Future Work

- ✓ Identify most efficient user interfaces for quantification.
- ✓ Data-driven statistical models for quantification.
- ✓ Remeshing algorithms to handle the missing data (teeth) or the finest details (cracks) in the CT scans.

Conclusion

- ✓ Fast and robust solution to volumetric registration of 3D solid shapes.
- ✓ Volumetric deformation energy plus additional tricks such as disabling of correspondence term and adaptive weighting.
- ✓ Faster than registering volume images as mostly done in the medical imaging community.
 - ✓ Also using a template mesh makes it robust to outliers. 
- ✓ More accurate than surface registration as mostly done in computer graphics community.
- ✓ Side contributions for ICP (uniform scale, multi-init).
- ✓ Cool apps.
 - ✓ Dense correspondence and objective quantification.

People

✓ Asst. Prof. Yusuf Sahillioğlu, METU, Turkey.

✓



✓ Asst. Prof. Ladislav Kavan, UPenn, USA.

✓

