Software tool for cranial orthosis design

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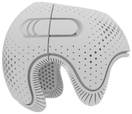
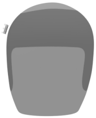
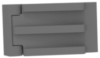
- Contractual research HS7831610 conducted in collaboration with ING corporation spol. s.r.o..

Cranial orthosis model

- The model itself is composed of two parts: a helmet and a locking mechanism. Each part is represented by high-resolution mesh.

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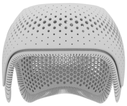
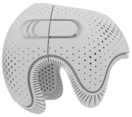
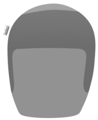
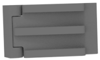

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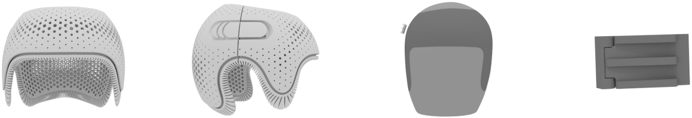
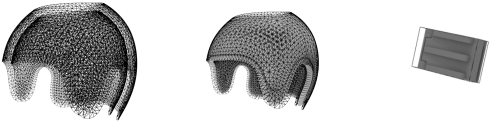


- Beside that, we also need auxiliary meshes, so-called cages.



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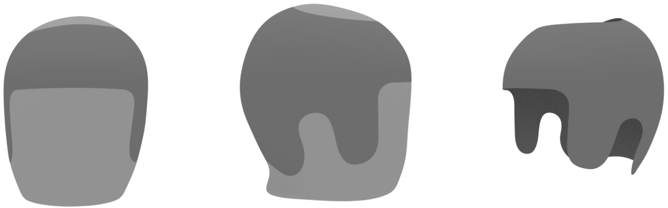

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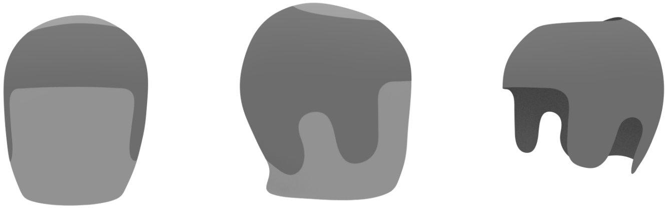
- The goal of the transformation is a non-rigid deformation of the orthosis body to fit the cropped scan and a rigid transformation of the locking mechanism to its specified position.



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4. Transformation by RBF also allows easy incorporation of the rigid parts, which MeshDeform modifier cannot implicitly do.

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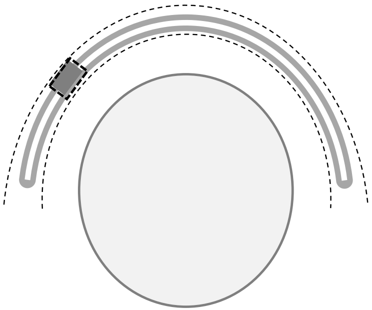

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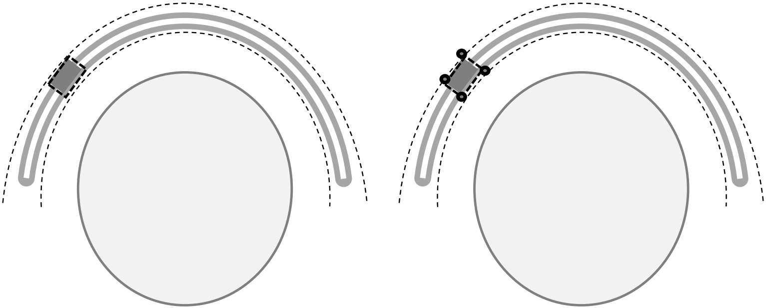

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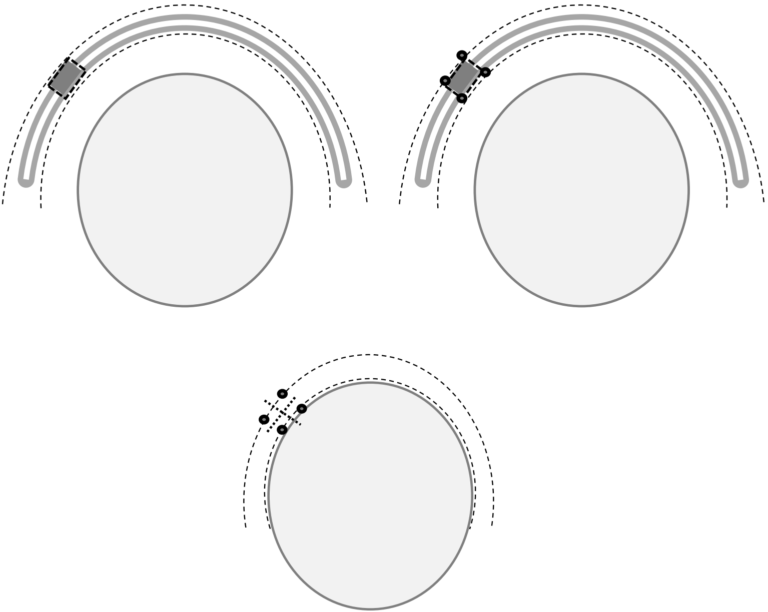

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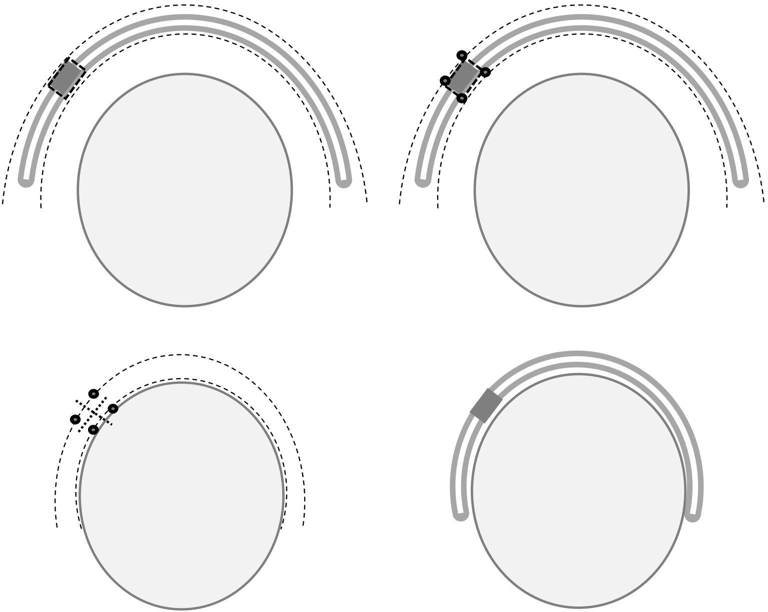

Radial basis function

- Function $\varphi : \mathbb{R}^3 \to \mathbb{R}^3$ that
  - exactly interpolates the displacement $u_j \in \mathbb{R}^3$ of given control points $x_j \in \mathbb{R}^3$, $j = 1, ..., m$,
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$$\varphi_l(x) = \sum_{i=1}^{n_p} \beta_{l,i} p_i(x) + \sum_{j=1}^{m} \theta_{l,j} \rho_{x_j}(x),$$

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$$\begin{pmatrix} K & B^\top \\ B & 0 \end{pmatrix} \begin{pmatrix} \theta_l \\ \beta_l \end{pmatrix} = \begin{pmatrix} u_l \\ 0 \end{pmatrix},$$

where

$$K := (\rho(\|x_j - x_k\|_{\mathbb{R}^3}))_{j,k=1,\ldots,m} \in \mathbb{R}^{m \times m},$$

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- We use triharmonic or thin plate spline (TPS)

$$\rho(r) = r^3, \quad \rho(r) := \frac{\Gamma(3/2-q)}{2^{2q}\pi^{3/2}(q-1)!} r^{2q-3}.$$

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- These functions ensure that the non-linear part of the transformation and the linear transformations $L_q,\ q \neq r$ tends to zero as we move towards the r-th rigid object.

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- The coefficients β_l for polynomial corrections are replaced by weighted sum of the individual object linear transformations

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- We are able to determine the axes through the use of eigenvalues and eigenvectors of the covariance matrix consisting of a small group of neighboring points.

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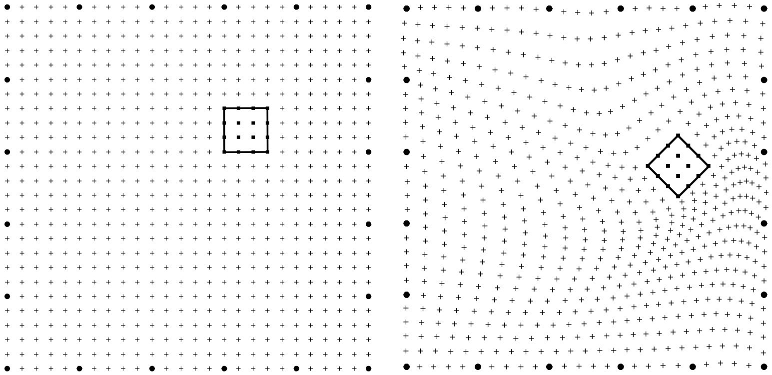

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- OpenMP technology to parallelize transformation.

Results

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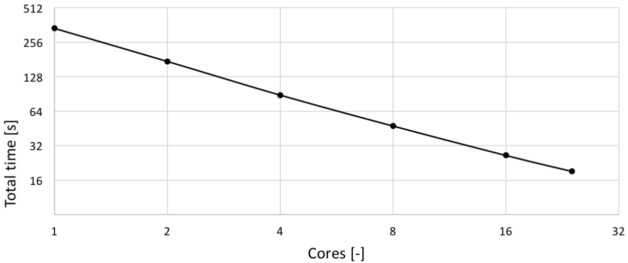
- We have also measured computational demands of the algorithm based on the model size.
- For all the tests, configuration of the RBF and the solver was as follows:
  - Thin plate spline (TPS) as a kernel function $\rho(r)$.
  - Bunch-Kaufman factorization of a symmetric matrix using packed storage has been used as a solver.

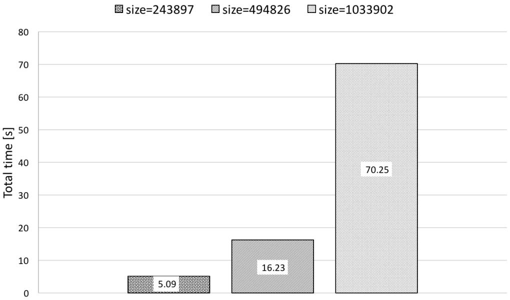
Algorithm speed and possible speed-up by OpenMP on multiple CPU cores

CPU cores [-]	1	2	4	8	16	24
Shrink [s]	0.80	0.75	0.73	0.72	0.73	0.72
Prepare [s]	85.36	46.44	23.32	12.30	7.96	5.63
Solve [s]	3.94	2.65	2.18	1.96	1.88	1.88
Transform [s]	248.07	124.19	62.29	32.56	15.75	10.87
Total [s]	338.16	174.03	88.51	47.54	26.33	19.09



Computation times for different sizes of the model

Model size [vertices] (1d)	243897	494826	1033902
Shrink [s] (2)	0.24	0.72	2.61
Prepare [s] (3)-(4)	1.65	4.83	18.54
Solve [s] (5)	0.44	1.89	10.19
Transform [s] (6)	2.76	8.79	38.91
Total [s] (2)-(6)	5.09	16.23	70.25



Result model