

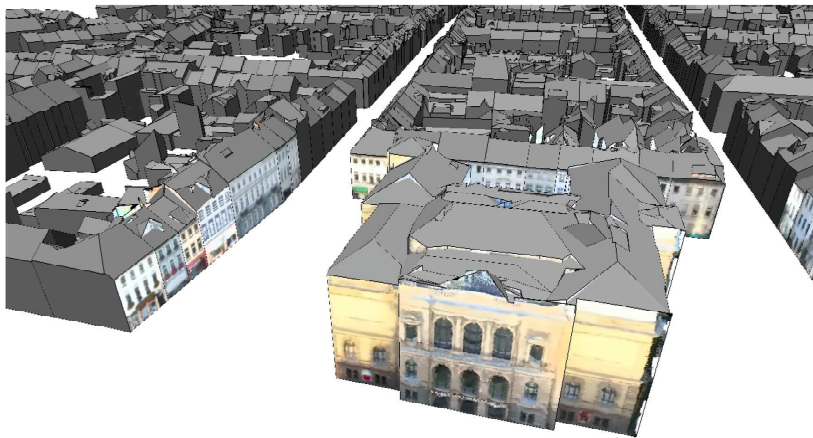
# Iterative Closest Point Algorithm for Accurate Registration of Coarsely Registered Point Clouds with CityGML Models

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# CityGML model, textured with an aligned photogrammetric point cloud



Our aim: Extend LoD2 CityGML models to LoD3.<sup>1</sup>

<sup>1</sup>S. Hensel, S. Goebels, M. Kada: Facade Reconstruction for Textured LoD2 CityGML Models based on Deep Learning and Mixed Integer Linear Programming, ISPRS GSW 2019

# Iterative Closest Point Algorithm (ICP)

Align source point cloud  $S$  to target point cloud  $D$ .

**procedure** ICP(point cloud  $S$ , point cloud  $D$ , convergence criteria)

**while** convergence criteria are not fulfilled **do**

        clear correspondences

**for**  $p \in S$  **do**

            find nearest neighbor  $q \in D$  of  $p$

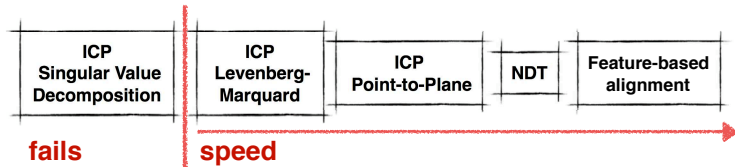
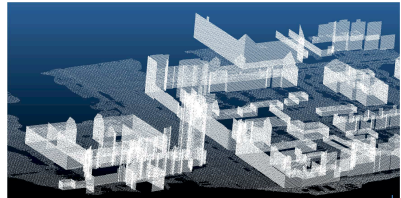
**if** neighbor is within threshold distance **then**

                store correspondence  $(p, q)$

        compute affine transform  $T$  that maps  $p$  to  $q$  as close as possible, simultaneously for all pairs  $(p, q)$   
        (least squares minimization)

        apply  $T$  to all points in  $S$ .

# Tests with Point Cloud Library and sampled city models



# Point-to-Model ICP



**procedure** ICP(point cloud  $S$ , city model  $D$ , convergence criteria)

**while** convergence criteria are not fulfilled **do**

clear correspondences

**for**  $p \in S$  **do**

project  $p$  to all wall and roof polygons of  $D$

select nearest projection  $q$  of  $p$

**if** projection is within threshold distance **then**

store correspondence  $(p, q)$

compute affine transform  $T$  that maps  $p$  to  $q$  as close as possible, simultaneously for all pairs  $(p, q)$

apply  $T$  to all points in  $S$ .

# Residuum of affine transform (homogenous coordinates)

Transformation matrix  $T = T_{\vec{a}, \sigma}$  depends on a scaling factor  $\sigma$  and parameters  $\vec{a} := (\alpha, \beta, \gamma, \Delta x, \Delta y, \Delta z)$ .

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For each pair  $(\vec{s}, \vec{d})$  we discuss local residuum

$$\vec{r}(\vec{a}, \sigma) = (r_1, r_2, r_3, 0)^\top := T_{\vec{a}, \sigma} \cdot \vec{s} - \vec{d} \in \mathbb{R}^4.$$

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We combine all local residua to one vector in  $\mathbb{R}^{3n}$ :

$$\vec{R}(\vec{a}, \sigma) := (\vec{r}_{1,1}, \vec{r}_{1,2}, \vec{r}_{1,3}, \vec{r}_{2,1}, \dots, \vec{r}_{n,3})^\top$$

where  $\vec{r}_{k,j}$  is the  $j$ -th component,  $j \in \{1, 2, 3\}$ , of the local residuum of pair  $(\vec{s}_k, \vec{d}_k)$ .



# Objective function for computing

$$\vec{a} = (\alpha, \beta, \gamma, \Delta x, \Delta y, \Delta z)$$

Subject to a scaling factor  $\sigma = 1$ , we have to minimize an objective function (mean of the squared residua)

$$e(\vec{a}, 1) := \left\| \frac{1}{\sqrt{n}} \vec{R}(\vec{a}, 1) \right\|_2^2 = \frac{1}{n} \sum_{k=1}^{3n} (\vec{R}_k(\vec{a}, 1))^2$$

to find optimal rotation and translation parameters.

Scaling parameter  $\sigma$  will be determined in a second step.

# Gauss-Newton method

Let  $D(\vec{a})$  be the Jacobian of  $\frac{1}{\sqrt{n}}\vec{R}(\vec{a}, 1)$ . This matrix of first derivatives can be composed from Jacobians of local residua. Gauss-Newton iteration are defined via  $\vec{a}_0 := (0, 0, 0, 0, 0, 0)$  and

$$\vec{a}_{l+1} := \vec{a}_l - (D(\vec{a}_l)^\top \cdot D(\vec{a}_l))^{-1} \cdot D(\vec{a}_l)^\top \frac{1}{\sqrt{n}}\vec{R}(\vec{a}_l, 1).$$

# Levenberg-Marquardt method

Let  $I$  be the identity matrix and  $\lambda_l \geq 0$  parameters controlling the search radius  $r$  (step size) for local minima. Initial value:  $\lambda_0$ .

$$\vec{a}_{l+1} := \vec{a}_l - (D(\vec{a}_l)^\top \cdot D(\vec{a}_l) + \lambda_l I)^{-1} \cdot D(\vec{a}_l)^\top \frac{1}{\sqrt{n}} \vec{R}(\vec{a}_l, 1).$$

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Only downhill steps have to be considered:

- If the objective function does not decrease: parameter  $\lambda_l$  is doubled.
- If the objective function directly decreases:  $\lambda_{l+1} := \lambda_l/2$ .

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Remark:

- $\lambda_l = 0$ : Gauss-Newton step
- $\lambda_l$  large: small step of gradient descent.

# Determining a scaling factor $\sigma_0$

For previously computed parameters  $\vec{a}_l$ , minimize

$$e(\sigma) := \sum_{k=1}^{3n} (\vec{R}_k(\vec{a}_l, \sigma))^2.$$

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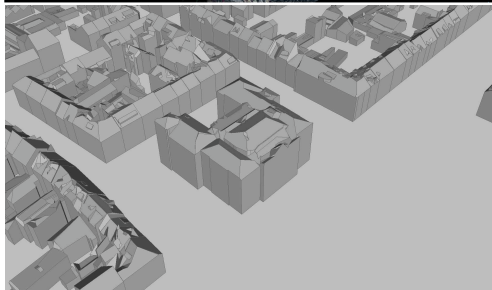
$$e(\sigma) := \sum_{k=1}^{3n} (\vec{R}_k(\vec{a}_l, \sigma))^2.$$

The necessary condition  $\frac{d}{d\sigma} e(\sigma) = 0$  results in

$$\sigma_0 := \frac{\sum_{k=1}^n \sum_{j=1}^3 (T_{\vec{a}_l, 1} \vec{s}_k)_j \cdot (d_k)_j}{\sum_{k=1}^n \sum_{j=1}^3 (T_{\vec{a}_l, 1} \vec{s}_k)_j^2}.$$

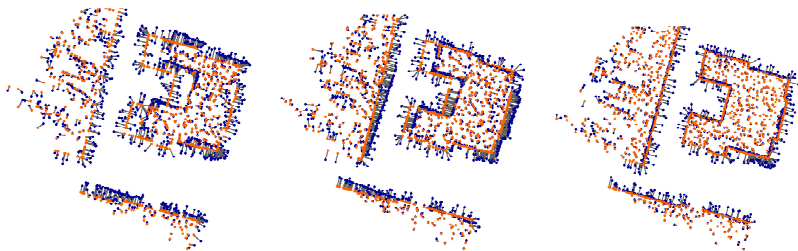
Scaling has to be restricted to factors near 1 to avoid contraction of the cloud to one point.

# Example: Kaiser Wilhelm museum point cloud





# Correspondences at start, after 10, and after 25 iterations



(One Gauss-Newton step, projection to bounding rectangles)

# Levenberg Marquardt optimization (LM) compared with one Gauss-Newton (GN) step

Kaiser Wilhelm museum point cloud: All runs reduce an error of 6.10032 to the same final error 1.976.			
method	number of outer iterations	number of inner iterations	running time
GN	61	limited to 1	326 s
LM $\lambda_0 = 1$	91	limited to 1	488 s
LM $\lambda_0 = 1$	61	average: 4.5	816 s
LM $\lambda_0 = 1/16$	61	average: 2	483 s
LM $\lambda_0 = 1/64$	61	average: 2	484 s

# Projection to roof and wall polygons with gradient descent

- Project point to bounding rectangle.
- If projected point is outside the polygon then move point to polygon's border using gradient descent on a distance transform.

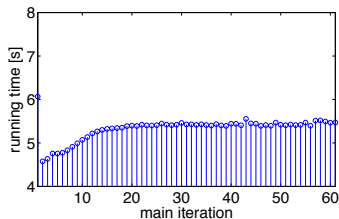
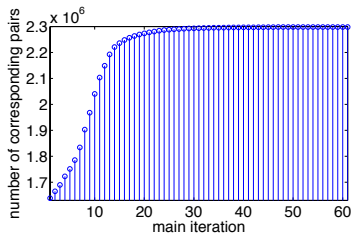
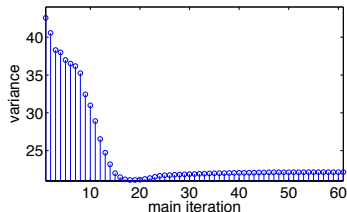
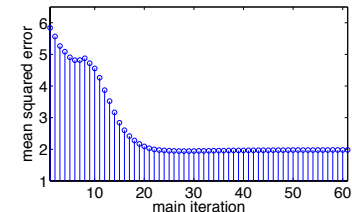


black: section of a polygon



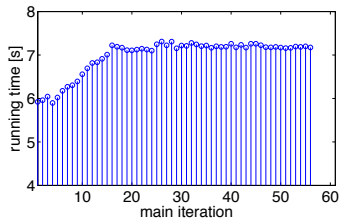
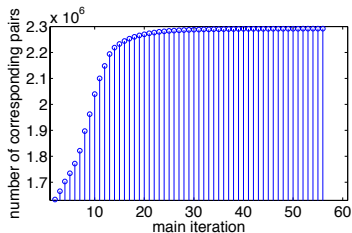
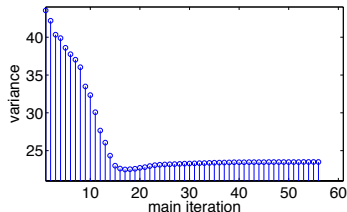
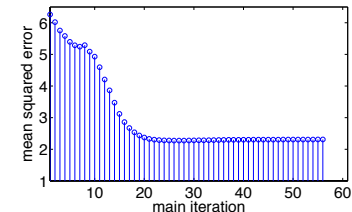
grey value indicates distance

# Computational results for projection to rectangles



projection to bounding rectangles (using one Gauss-Newton step,  
61 iterations, running time: 326 s)

# Computational results for projection to polygons



projection to wall and roof polygons (using one Gauss-Newton step, 56 iterations, running time: 392 s)