Automatic registration of terrestrial laser scans for geological deformation monitoring

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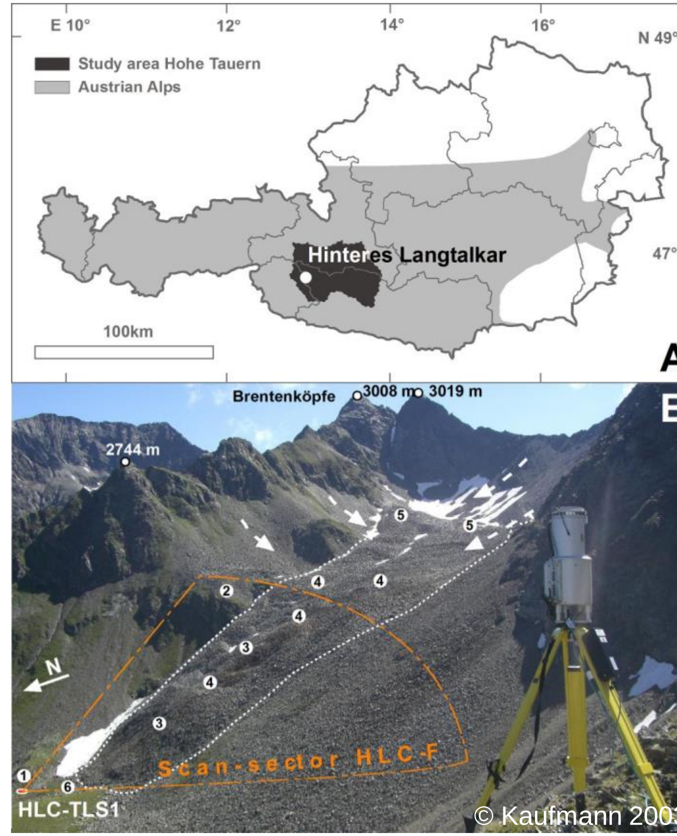
Area under investigation

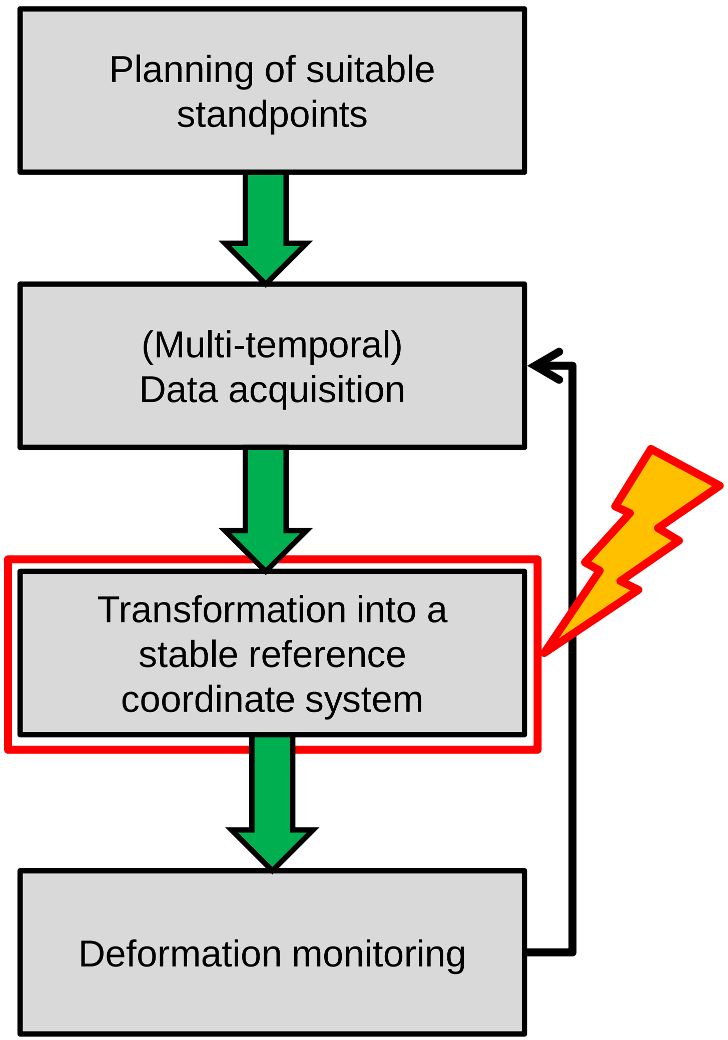
TLS-based monitoring of a rock glacier

- Rock glacier “Hinteres Langtalkar” located in “Hohe Tauern” national park
- Altitude: 2455-2720 m a.s.l.
- Extends over 300 m in width and 900 m in length
- According to DELALOYE *et al.* (2008) one of the fastest moving glaciers in Europe:
  - Annual horizontal movement on average (entire glacier): 10 – 20 cm
  - Maximum annual displacement: 3.6 m
- Annual monitoring with TLS since 2000

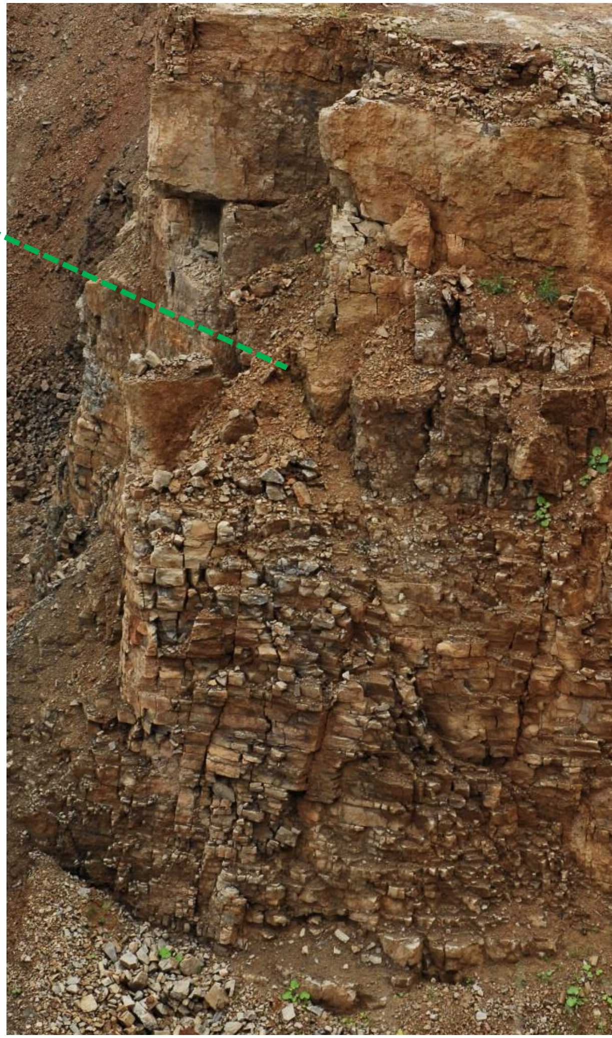
1. Scanner‘s position
2. Prominent bedrock ridge
3. rock glacier boundary (dashed line)
4. Several transversal crevasses on rock glacier surface indicating high strain rates
5. Latero-terminal moraine ridges (Little Ice Age, ~1850 AD)
6. Recently deposited boulders spreading over alpine meadows



The deformation monitoring processing chain



Leica-geosystems.com



Common practice – Use of targets

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Advantage

- Direct connection to geodetic network feasible

Downsides

- Access of the area under investigation required
  - Dangerous
  - Impossible
  - Prohibited
- Targets need to remain stable between epochs
- High temporal effort required
- Geometrical distribution of targets influences the outcome
- High redundance of TLS is not used

Motivation: Fully automatic deformation monitoring <u>without</u> usage of targets

In this talk…

Registration through usage of the point clouds itself

- Functional principle of the Iterative Closest Point Algorithm (ICP)
- What happens, if „deformed“ point clouds are registered?

Detection of deformation in point clouds

- A novel approach for identification of deformation:
  - The iterative closest proximity-algorithm (ICProx)
- Demonstration of the proposed algorithm based on a prototypical implementation
  → GFaI Final Surface
- Application on two epochs of the „Hinteres Langkartal“ glacier captured in 2011 and 2013

Iterative Closest Point (ICP) Algorithm

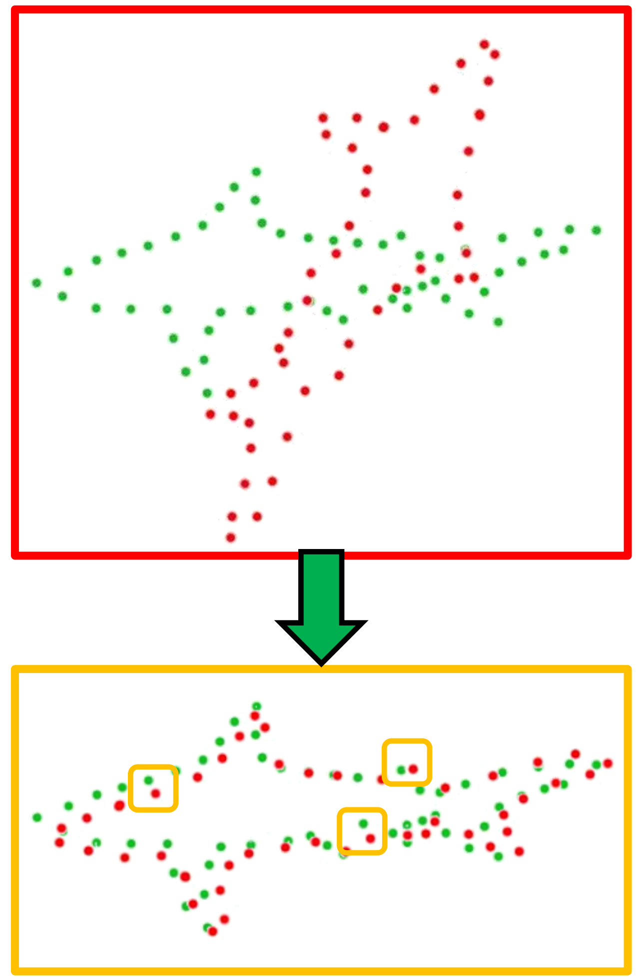
Pre-alignment – avoidance of local minima

↓

Correspondence search – shortest distance

↓

Computation / application of transformation parameters
$t_x, t_y, t_z, r_x, r_y, r_z$



Iterative Closest Point (ICP) Algorithm

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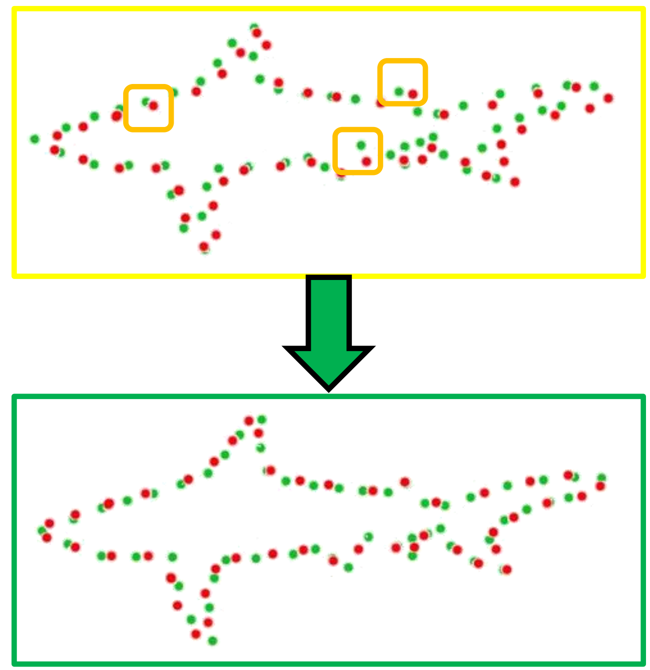
Convergence criterion fulfilled

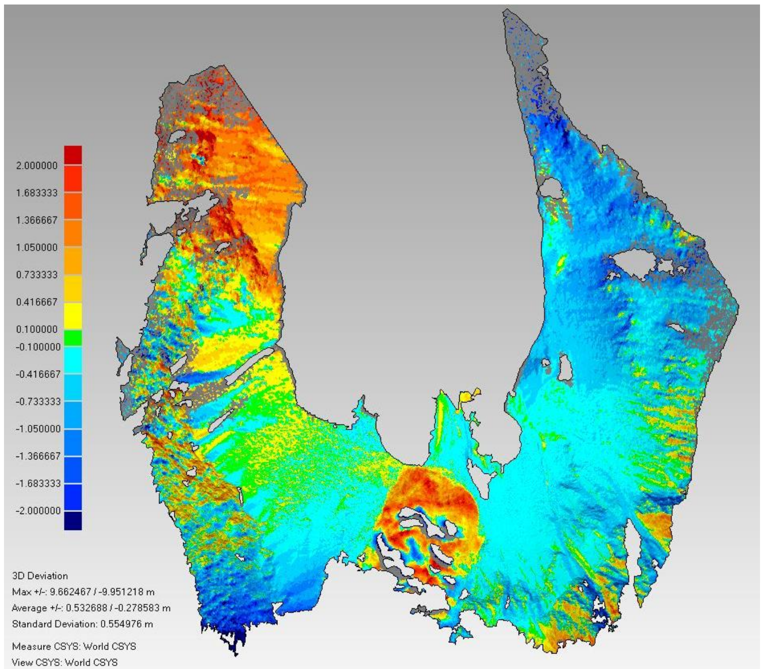


Question:

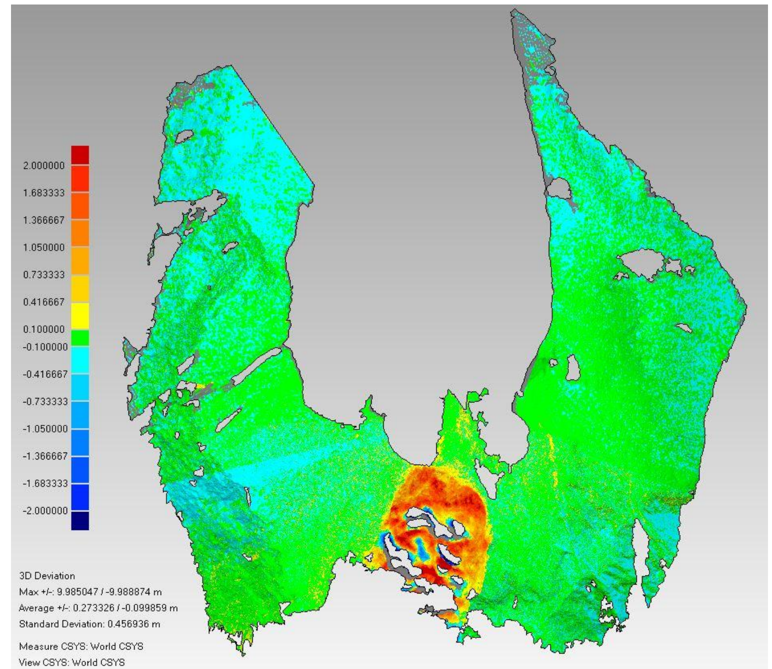
Is the ICP capable to compute correct results despite the existence of deformation?

ICP-registration of a rock glacier

Inspection maps – epoch 2011 vs. 2013



Deformation monitoring based on the ICP



Deformation monitoring (geo-referenced version)

A statement by the authors

*„The algorithm requires no extracted features, no curve or surface derivatives, and no pre-processing of 3D-data, **except for the removal of statistical outliers**…“*

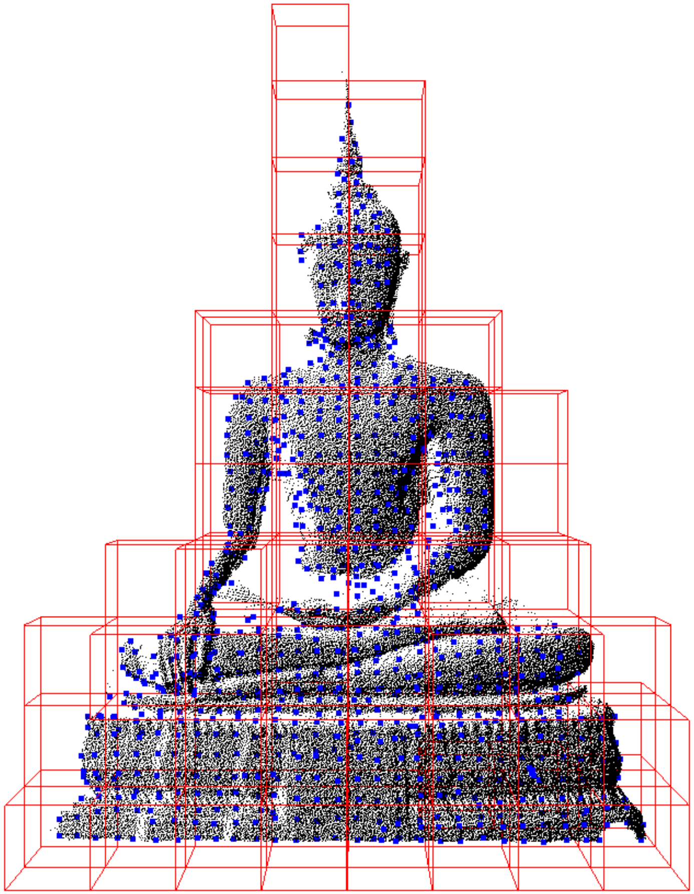
[Besl & McKay 1992]

Our solution:
Identification and rejection of deformation before computation of transformation parameters by segmentation of the object space

Identification of deformation

Basic concept

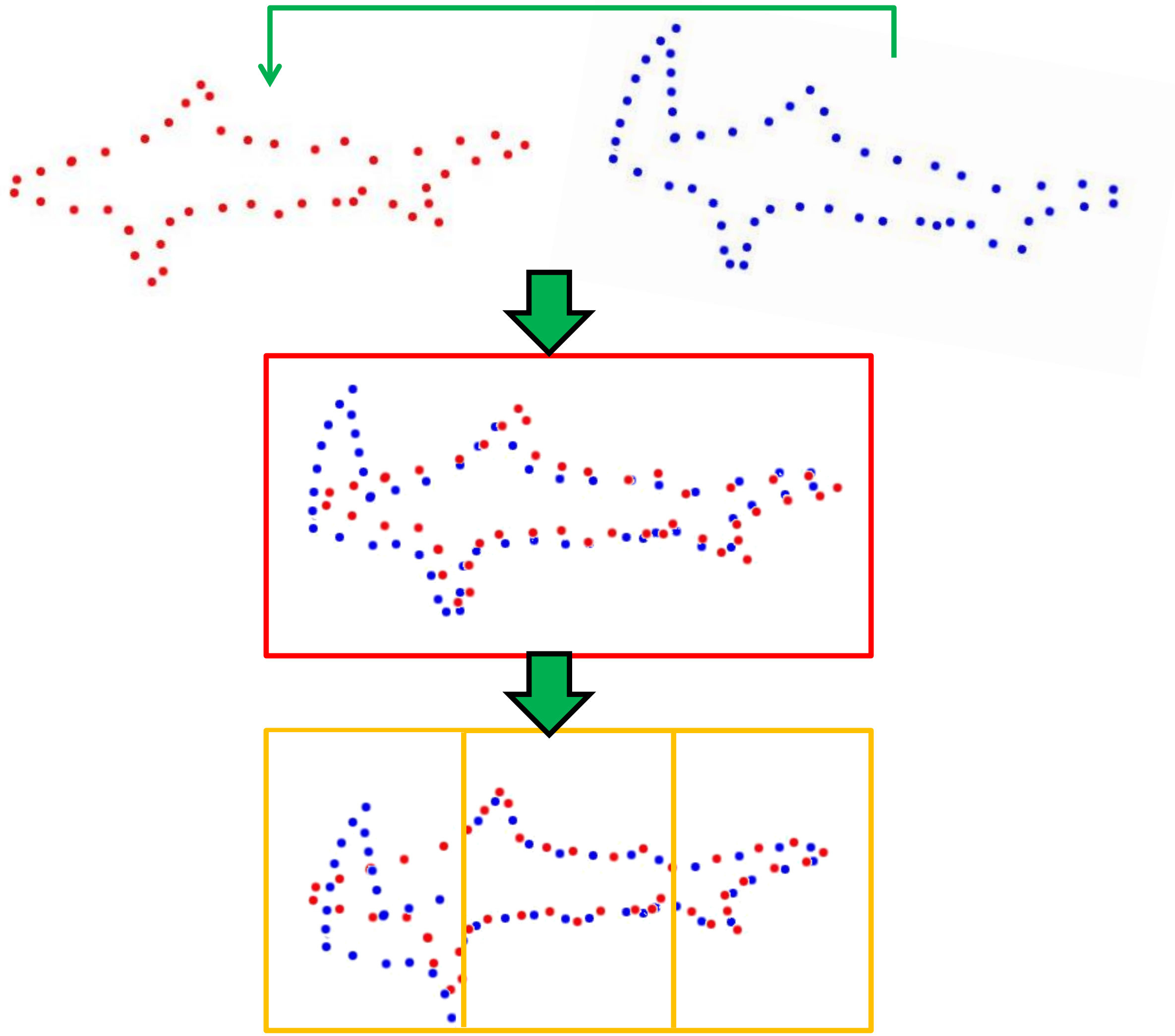
- Segmentation of data sets into spatially equal large and topologically coherent units
  → Usage of metric octrees
- Effect: Percentaged amount of outliers will be locally increased / decreased
  → Identification should simplify
- Preferably even distribution of “candidates” within object space
  → determination of corresponding points (respectively transformation parameters) via ICP within all octree cells



Identification of deformation

Automatic pre-alignment – Four-Points Congruent Sets algorithm (AIGER et al. 2008)

ICP within all octree cells



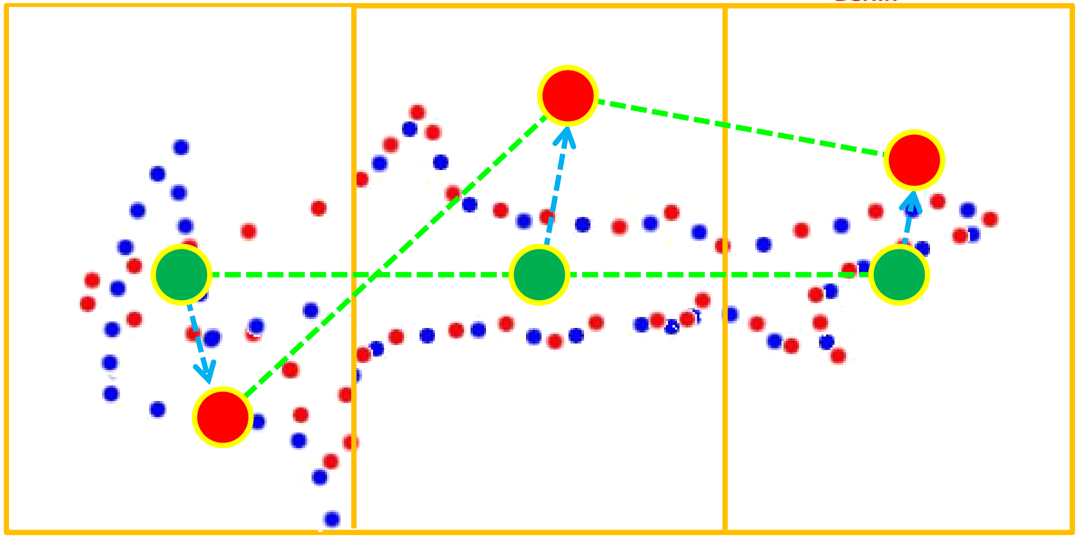
Identification of deformation

Automatic pre-alignment – Four-Points Congruent Sets algorithm (AIGER et al. 2008)

ICP within all octree cells

Identification of deformation

Computation of final transformation parameters based on the biggest congruent cluster



1. Comparable quantities:
   Transformation vectors **ARE** datum dependent
   → but **NOT** the distance between transformed points
2. Congruency analysis:
   → Use of the combinatorial maximum subset method
3. Derivation of stochastic measures

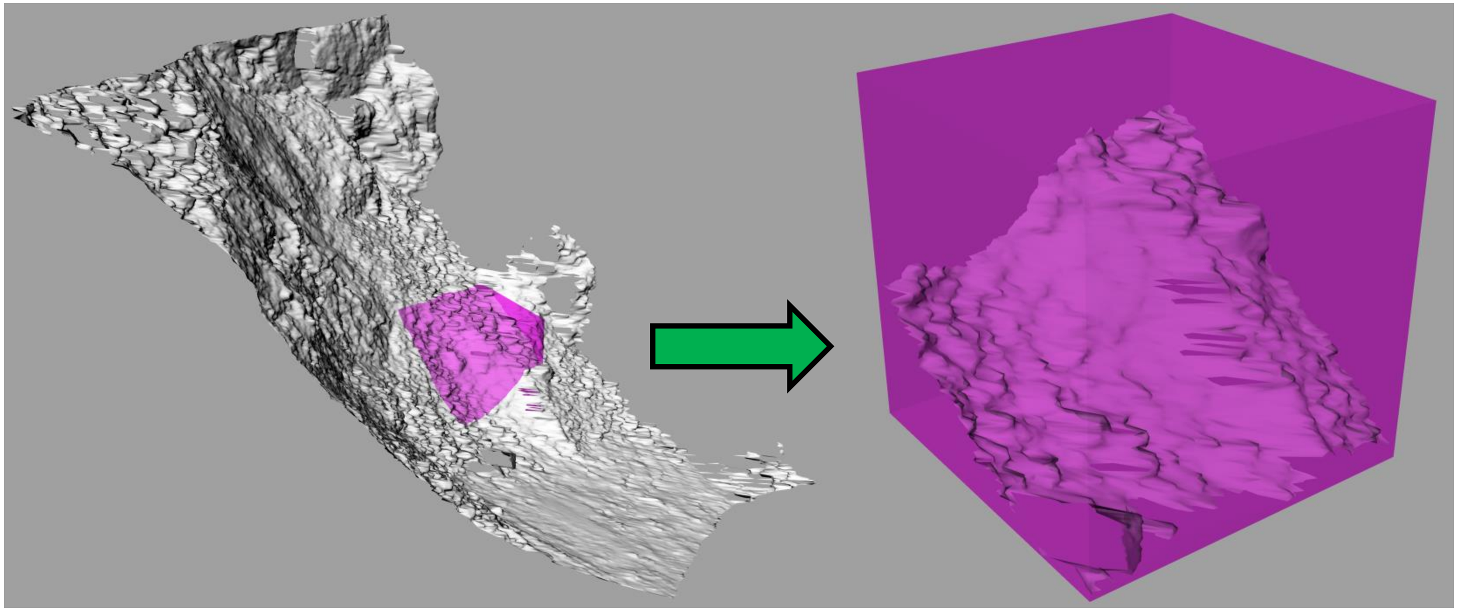
TLS does not measure discrete points!
How can meaningful thresholds be determined?

The ICProx-algorithm

Iterative closest proximity algorithm explained on one octree cell:

→ Application only on the reference points cloud

1. Sort point cloud into octree

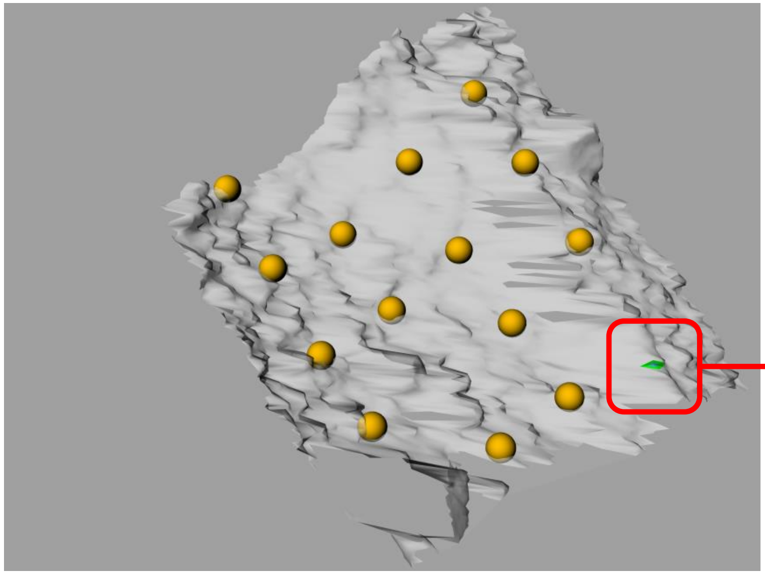


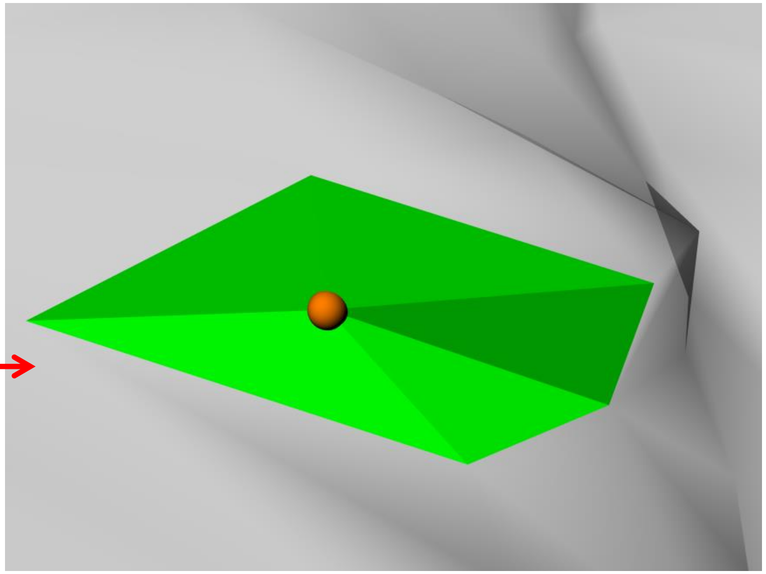
The ICProx-algorithm

Iterative closest proximity algorithm explained on one octree cell:

→ Application only on the reference points cloud

1. Sort point cloud into octree
2. Equal distribution of candidates
3. Determination of a „habitat“
   – Where can a corresponding point be located within a successively measured epoch?





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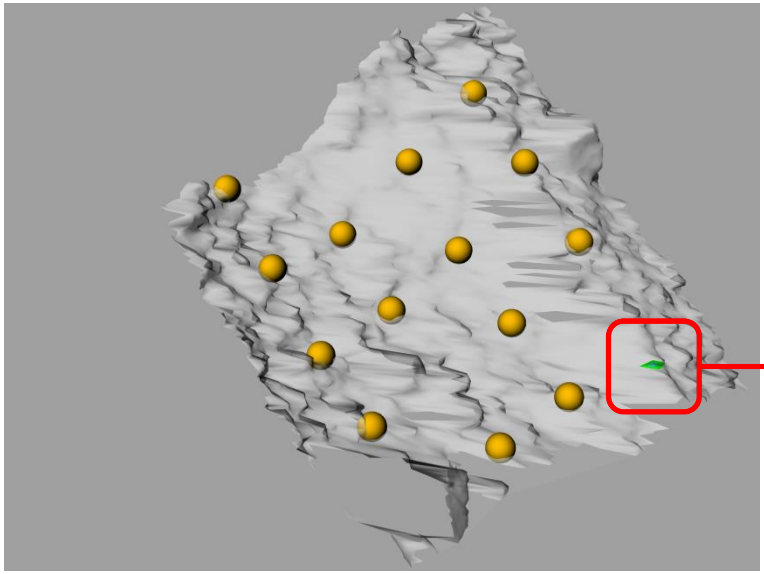
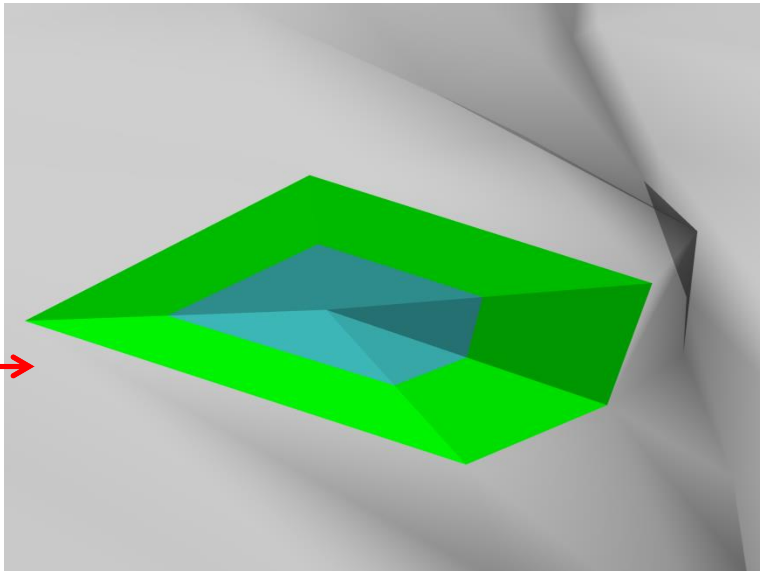


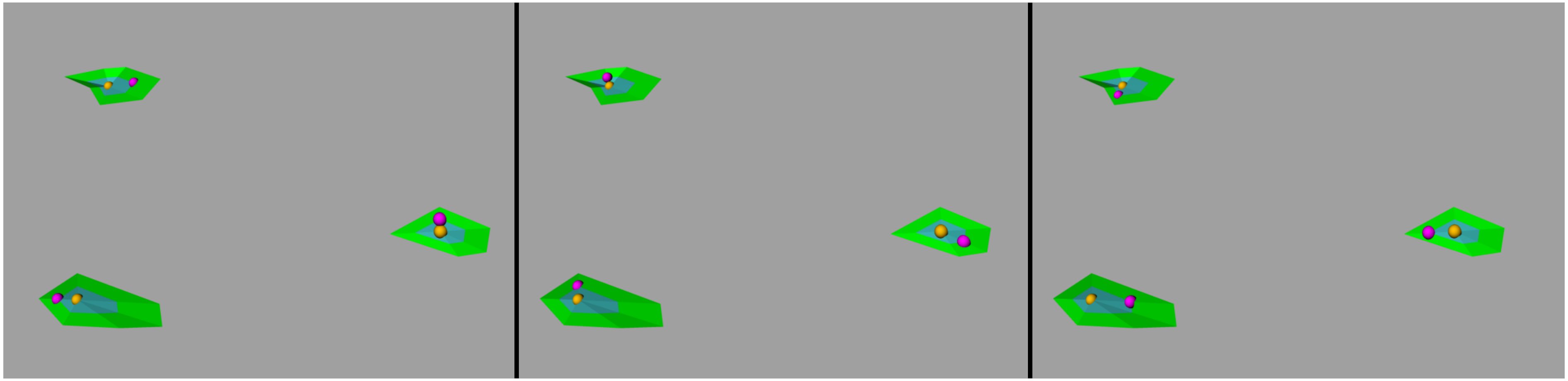


The ICProx-algorithm

Iterative closest proximity algorithm explained on one octree cell:

→ Application only on the reference points cloud

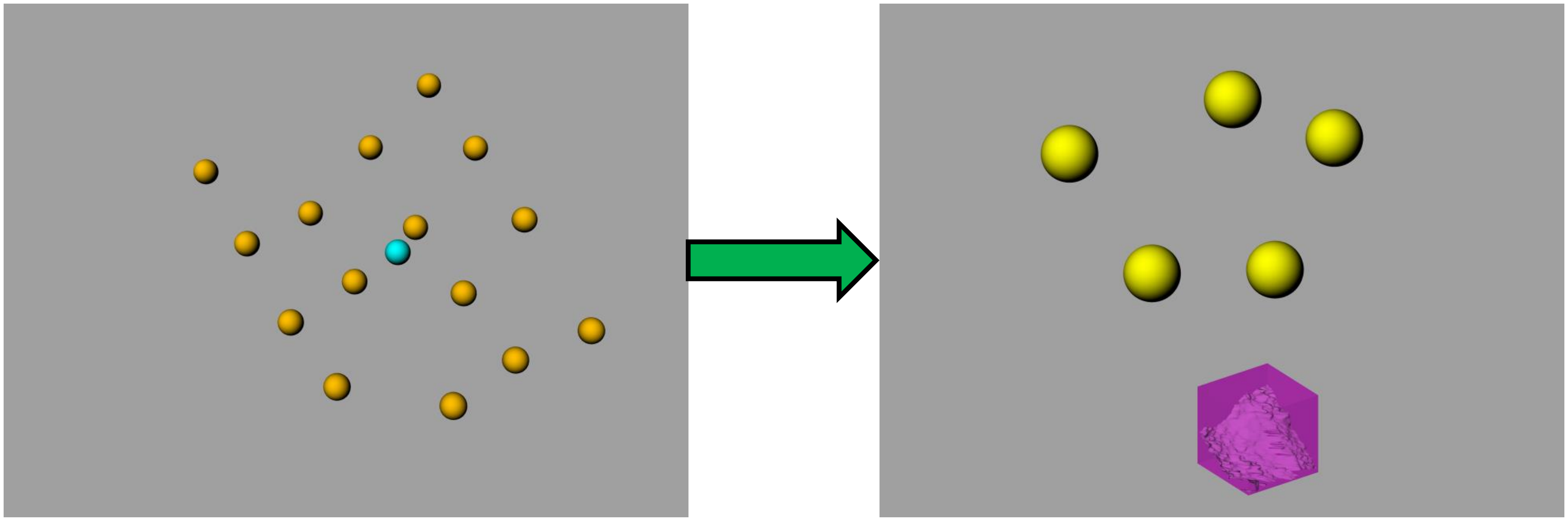
4. Determination of *n* random combinations between candidates and „virtual“ correspondences within a habitat
   → computation of *n* sets of transformation parameters



The ICProx-algorithm

Iterative closest proximity algorithm explained on one octree cell:

5. Application of *n* sets of transformation parameters onto the according centre of gravity of all candidates within a cell
6. Adjustment of the centre of gravity based on previously conducted transformations.
   Determination of <u>uncertainty</u> for TLS in dependence to:
   → local geometric properties,
   → spatial resolution within a cell



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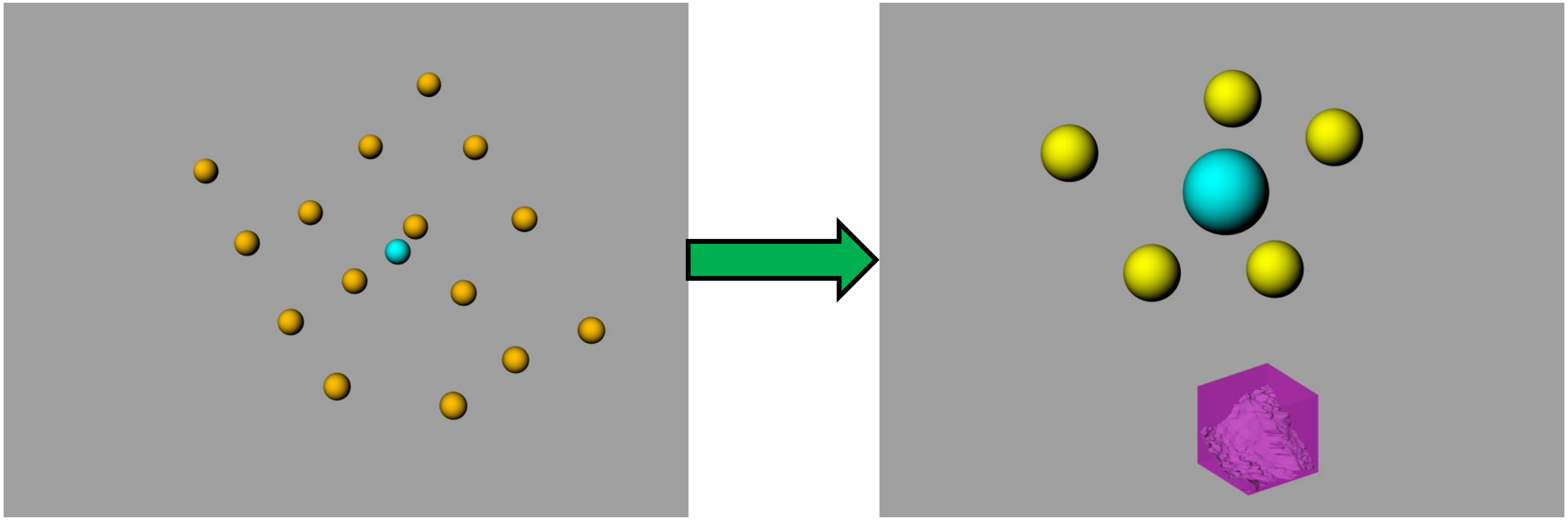
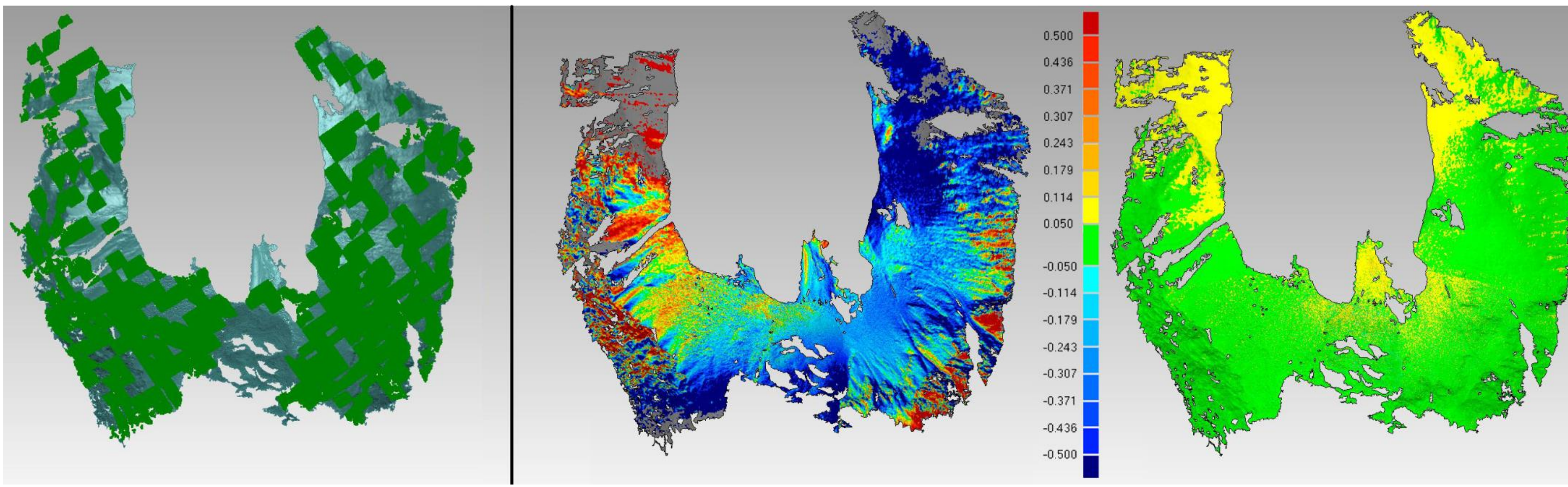


Results ICProx

Outcome of the algorithm:

- Deformation monitoring from two stand points: Octree size 30 m
  → Inspection maps to a reference
- Comparison of results generated by standard ICP vs. georeferenced data of epoch 2011
- Comparison of outcome processed by ICProx vs. georeferenced data of epoch 2011



Identification of stable areas by ICProx | Outcome of ICP vs. reference | Outcome ICProx vs. reference

Conclusion and outlook: The ICProx-algorithm

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Conclusion

- Allows fully automatic and robust deformation monitoring (Coarse: 4PCS; Fine: ICProx)
- Suitable for monitoring of scenarios with high rates of deformation
  - Prerequisite: Sufficient „geometric contrast“ + sufficient pre-alignment
  - Practical datasets have been successfully registered featured ~70% of deformation
- Combinatorial method solves downsides of DefoScan++ (WUJANZ *et al.* 2013)
  → Achievable resolution has been increased

Outlook

- Demands onto coarse-alignment algorithms increases with growing fraction of deformation / outliers within point clouds
  - Development of robust pre-alignment algorithms
  - Direct georeferencing for coarse matching of point clouds: TLS + GNSS + compass
- Analysis of deformed regions
  - Identification of objects e.g. big boulders
  - Object related matching in order to determine change of location AND orientation (TEZA *et al.* 2007, 2008)

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Reasons for this behaviour

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> *„The algorithm requires no extracted features, no curve or surface derivatives, and no pre-processing of 3D-data, **except for the removal of statistical outliers**…“*
>
> [BESL & MCKAY 1992]

Break down point of the method of least squares

- L2-Norm: 0% of outliers within the data
- L2-Norm + data snooping (BAARDA 1968): 3 - 5% of outliers

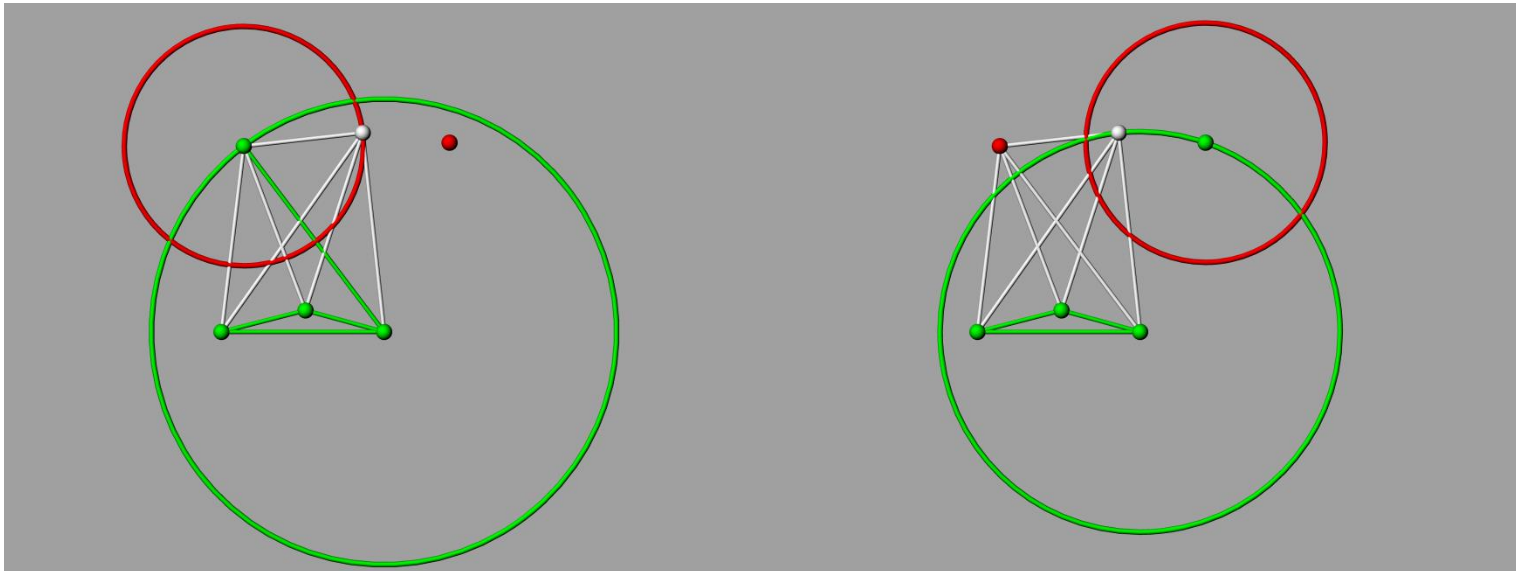
Possible solutions

- Preprocessing with L1-Norm and a theoretical break down point of max. 50% - however as a rule lower in dependence to geometry and functional model of the stated problem
- Use of geometrical considerations (NEITZEL 2004) for outlier identification

Congruency analysis

How can we cluster congruent cells?

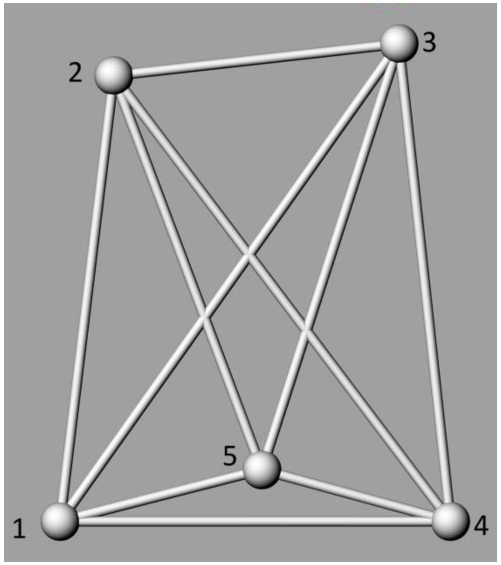
- DefoScan++ (WUJANZ *et al.* 2013): Simple clustering via comparison of distances between corresponding points
  → Sequential solution
- Sequential clustering leads to two essential problems:
  1. A purely scalar perception neglects direction of action
  2. The result is dependent to the order in which the analysis is undertaken



Congruency analysis

How can we cluster congruent cell?

- Usage of the maximum subset method (MSS) by NEITZEL (2004)
  - Determination of distances between points within a network in all combinations
  - Comparison to distances in successive epoch: e.g. signal to noise ratio or statistical test
  - Setting up the incidence matrix
  - Computation of the adjacency matrix
    → Identification of the maximum subset



	Pt. 1	Pt. 2	Pt. 3	Pt. 4	Pt. 5
s1,2	1	-1	0	0	0
s1,3	1	0	-1	0	0
s1,4	1	0	0	-1	0
s1,5	1	0	0	0	-1
s2,3	0	1	-1	0	0
s2,4	0	1	0	-1	0
s2,5	0	1	0	0	-1
s3,4	0	0	1	-1	0
s3,5	0	0	1	0	-1
s4,5	0	0	0	1	-1

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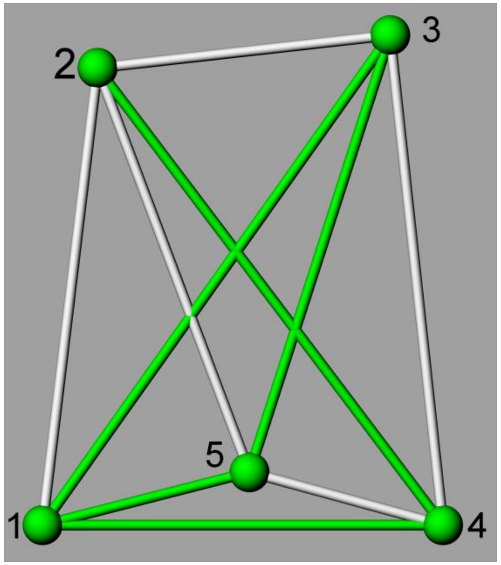

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s2,4	0	1	0	-1	0
s2,5	0	1	0	0	-1
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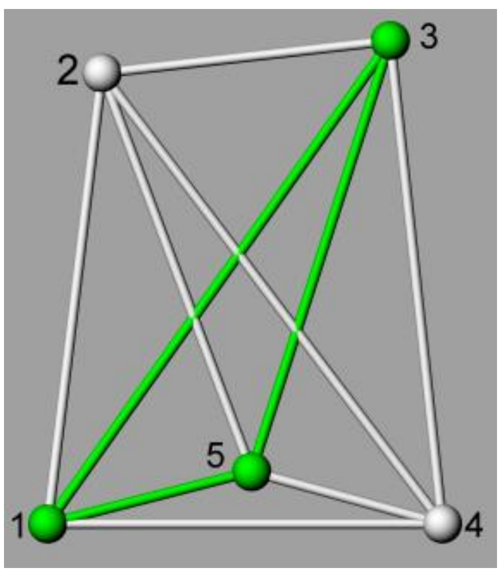

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Pt. 3	-1	0	2	0	-1
Pt. 4	-1	-1	0	2	0
Pt. 5	-1	0	-1	0	2

	Pt. 1	Pt. 3	Pt. 5
Pt. 1	3	-1	-1
Pt. 3	-1	2	-1
Pt. 5	-1	-1	2

The combinatory wall

- Computational effort:
  - Maximum subset of 10 within a dataset consisting of 20 points: 184756
  - Maximum subset of 15 within a dataset consisting of 30 points : $1.551*10^{8}$
  - Maximum subset of 50 within a dataset consisting of 100 points: $1.008*10^{29}$
- The solution: Spilt & Merge strategy