A CORRESPONDENCE FRAMEWORK FOR ALS STRIP ADJUSTMENTS BASED ON VARIANTS OF THE ICP ALGORITHM

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ABSTRACT:

In order to minimize discrepancies within the overlap area of Airborne Laser Scanning (ALS) strips, a strip adjustment can be performed. Apart from the transformation model, the quality of a strip adjustment is strongly affected by the correspondences used. In order to exploit the full resolution of the data, the correspondences should be established on the basis of the original point cloud instead of interpolated surfaces or rasters. A surface matching method, in which correspondences are based on the original point cloud, is the Iterative Closest Point (ICP) algorithm. Thus, in this study, several ICP variants (suitable for large data amounts), which differ in terms of selection of correspondences, their weighting and the error metric to be minimized are investigated. As a result, a combination of variants, forming a baseline optimized for most ALS data, is presented. The investigated variants provide a correspondence framework for ALS strip adjustments. The benefit of specific variants is demonstrated in an example.

1. INTRODUCTION

Airborne laser scanning (ALS) is the prime data acquisition method for digital terrain models (DTM), especially in forested areas or areas with surfaces with little texture. In order to georeference the scanner raw measurements, the following information is required (Skaloud & Lichti, 2006, Ressl et al., 2009):

1. The position and orientation of the acquisition platform. They are measured by a position and orientation system (POS), consisting of a GNSS system (Global Navigation Satellite System) and an INS (Inertial Navigation System).
2. The relative orientation of the scanner to the POS, consisting of a rotational and a translational part (mounting calibration).
3. The time synchronization between scanner and the POS system.
4. Internal scanner parameters (e.g. zero point and scale of range and angle).

The basic input for a strip adjustment are corresponding geometric elements (e.g. points or planes) within the overlap area of the strips. To exploit the full potential of ALS, these correspondences should be established on the highest data resolution level, i.e. on the basis of the original point cloud, as interpolation potentially introduces additional errors (Toth, 2010). A surface matching method, in which correspondences are based on the original point cloud, is the iterative closest point (ICP) algorithm (Besl & McKay, 1992, Chen & Medioni, 1991).

The aim of the ICP algorithm is to optimize iteratively the alignment of two overlapping point clouds. The geometric transformation applied within the ICP algorithm is typically a rigid body transformation. In ALS strip adjustment with trajectory the transformation model is more complex (Skaloud & Lichti, 2006). However, we are interested in the correspondence problem primarily. We therefore consider only a single strip pair, for which the alignment is an inherent part of ICP. The topic of the strip adjustment model is only briefly addressed in the next section.

We study the effect of different ICP variants on convergence speed and accuracy. A few variants are newly developed to meet the special requirements in ALS. The investigated variants are suitable for large data amounts, as they typically occur in ALS. Real-time processing is not intended. However, the alignment process of two typical ALS strips should be possible in less than one minute (without import and export of points).

After a review of related literature, the basic ICP concept is described introducing a taxonomy of the algorithm in six main steps (derived from Rusinkiewicz & Levoy (2001)). Next, the investigated variants for each of these steps are presented. In this context, a combination of variants forming a baseline optimized for most ALS data is introduced. We conclude by demonstrating the benefit of specific variants in an example.

2. RELATED WORK

In the rich body of literature on ICP algorithms, a huge number of modifications were derived from the original work of Besl & McKay (1992) and Chen & Medioni (1991). They refer to the selection of points, the weighting of correspondences, the metric for measuring the distance, and other aspects. A summary has been given by Rusinkiewicz & Levoy (2001), who suggest that a better expansion of the acronym ICP would be iterative corresponding point instead of the original iterative closest point. Planitz et al. (2005) summarize methods based on intrinsic surface parameters for solving the correspondence problem. References to ICP variants adopted for this study are given in section 3.2.

Strip adjustment methods are either formulated in a rigorous way (i.e. with trajectory and calibration parameters) (Kager, 2004, Skaloud et al., 2006) or in an approximate way (i.e. without trajectory) (Ressl et al., 2009). The strip discrepancies can be minimized pairwise or simultaneously for all strip pairs. Correspondences are either generated on the basis of the original point cloud or a derivate of it (e.g. grid or triangulation) (Maas, 2002). Most approaches use planes as corresponding features. They can be of fixed or variable size determined by segmentation (Pfeifer et al., 2005, Filin & Vosselman, 2004). In Akca (2010) reflectance, color and temperature are considered as additional input for the matching of point clouds. An overview of strip adjustment methods is given by Toth (2010).

3. CORRESPONDENCE FRAMEWORK

In this section, a framework for the determination of correspondences is presented. This framework is intended for the integration into an ALS strip adjustment.

3.1 ICP concept and taxonomy

The ICP algorithm refines the alignment of two point clouds by minimizing the sum of squared distances within the overlap area of these point clouds. The alignment is optimized by transforming iteratively the so called loose point cloud, whereas the position of the other point cloud remains fixed. To apply the algorithm, a good estimate of the initial relative orientation of the point clouds is necessary. This main requirement is typically fulfilled in direct georeferenced ALS data sets.

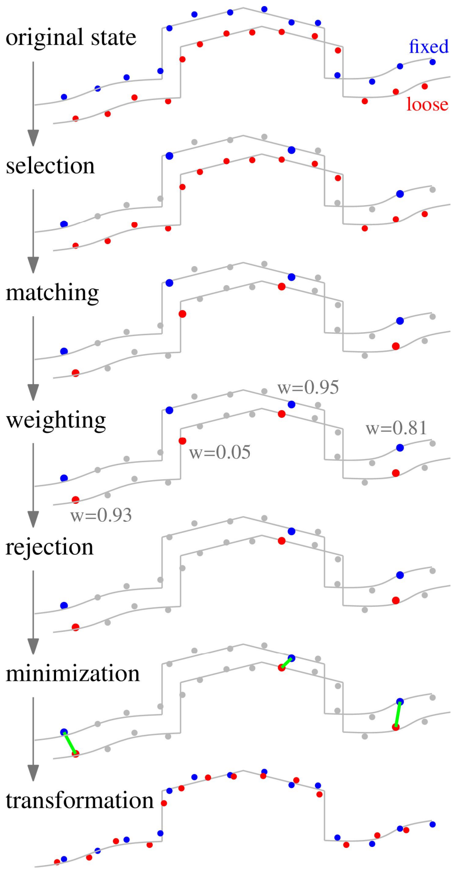

Figure 1: Visualization of the basis ICP steps.

Basically, the ICP algorithm can be classified into six main steps (see Figure 1):

1. **Selection**
   Selection of a subset of points within the overlap area in one point cloud.
2. **Matching**
   Find the corresponding points of the selected subset in the other point cloud.
3. **Weighting**
   Weighting of the found correspondences based on the compatibility of points.
4. **Rejection**
   Rejection of false correspondences (outliers) based on the compatibility of points.
5. **Minimization**
   Estimation of transformation parameters (for the loose point cloud) by minimizing the sum of squared distances.
6. **Transformation**
   Transformation of the loose point cloud with the estimated parameters.

Finally, a suitable convergence criteria is tested. If it is not met, the process restarts from step 1 (rarely from step 2).

As can be seen, steps 1, 3 and 4 are correlated to some extent. For example, if a wrong point was selected in step 1, deactivating this point can be achieved by assigning a zero weight in step 3 or by rejecting it in step 4. Generally, steps 3 and 4 can be considered as a refinement of step 1.

In the next section we will discuss some variants for each of these six steps.

3.2 Suitable ICP variants for ALS data

In a preprocessing step the normal vector and a roughness value were derived for each point of the two ALS strips. As demonstrated later, these two attributes are of great importance for finding the best alignment. Variants forming a baseline optimized for most ALS scenes are marked with an asterisk (*).

3.2.1 Selection

For comparatively small point clouds each point can be selected. However, for ALS data this is not feasible. This is particularly true if the single strip pair problem is generalized to an ALS strip adjustment of a complete data acquisition campaign, in which hundreds of strip pairs have to be processed simultaneously. Thus, compared to the full amount of available data (up to several million points), only a comparatively small number (a few thousands) of points can be selected within the overlap area of each strip pair. As the selected subset can affect the final alignment accuracy, the selection of the relevant points is crucial.

We consider the following three different strategies for the selection of points - they are sorted by increasing computational complexity (see Figure 2):

1. **Random sampling**
   This is the fastest of the investigated options: points are randomly selected within the overlap area (Masuda et al., 1996). Since the point density of ALS is only varying slightly (compared e.g. to typical TLS data sets), this option can be considered as an approximation of uniform sampling.
2. **Uniform sampling (*)**
   We selected uniform sampling in object space as the baseline method, because it gives a homogeneous distribution of the selected points within the overlap area, in which subregions of equal area are assumed to be of equal importance.
   This option was implemented by dividing the overlap area into a voxel structure and selecting the closest point to each voxel center. The minimum distance between two selected points is defined by the edge length of the voxels.
3. **Normal space sampling**
   The aim of this strategy is to select points such that the distribution of their normals in angular space is as large as possible (Rusinkiewicz & Levoy ,2001). This is achieved

by grouping the points into clusters of similar normal direction in angular space (slope vs. aspect). Points are selected as uniformly as possible across these clusters. Basically, this strategy is especially useful when one normal direction is predominating, but the data still includes some valuable features for the alignment.

However, since in ALS the initial alignment is very good and the overlap area of the strips generally is extensive, random and uniform sampling normally perform better, as both methods gather enough points on the relevant features (see Figure 2) and the weighting of the overlap area is typically more homogeneous.

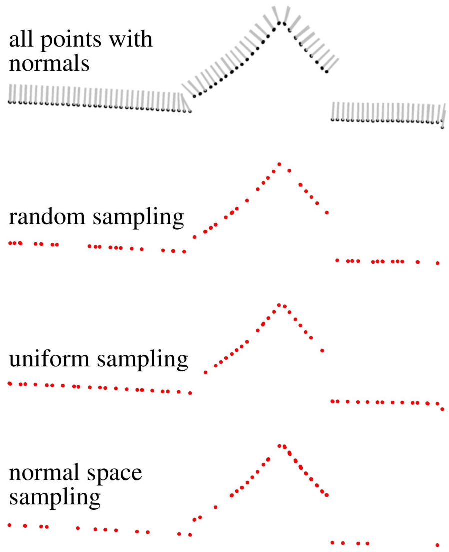

Figure 2: Different sampling methods visualized by the means of a cross section of a house and its surroundings acquired in one ALS strip.

3.2.2 Matching

In this step the correspondences are established, i.e. each selected point of the previous step is paired to one point in the other point cloud.

The simplest strategy is to match the selected points to their **closest point** (*), as proposed by Besl & McKay (1992). We found that for contemporary ALS data this is an adequate choice, mainly due to the good initial relative orientation and the high point density of ALS strips. The search for closest points can be realized efficiently using k-d trees.

Further matching methods are either computationally too expensive (e.g. **normal shooting**, Chen & Medioni, 1991, **reverse calibration**, Blais & Levine, 2005), or not necessary (Planitz et al., 2005) due to the good initial alignment of the strips (e.g. **closest compatible point**, Sharp et al., 2002). Thus, within this study, no other variants were investigated for this step.

3.2.3 Weighting

Weighting is a way to assess the reliability of the established correspondences by comparing the attributes of corresponding points ($\boldsymbol{p}$,$\boldsymbol{q}$).

Five different weighting strategies were examined in this study:

1. **Weighting based on the distance between corresponding points** (Godin et al., 1994)

$$w = 1 - \frac{dist(\boldsymbol{p}, \boldsymbol{q})}{dist_{max}}$$

where $dist_{max}$ is the largest allowed distance between two points defined by the user. This much-cited strategy is especially useful in presence of outliers (false correspondences). If no outliers are present (or are rejected in step 4), this strategy decreases the convergence rate, since small distances are weighted higher than large distances.

2. **Weighting based on the roughness of corresponding points (*)**

$$w = 1 - \frac{max(r_p\, ,\, r_q)}{r_{max}}$$

where r_p and r_q are roughness values associated to the corresponding points $\boldsymbol{p}$ and $\boldsymbol{q}$ and r_{max} is the largest allowed roughness value defined by the user. This weighting strategy considers the fact that the reliability of ALS data in rough areas (e.g. vegetation) is lower than in flat areas (e.g. roads). Since roughness is very variable in ALS, this strategy shows a large positive effect on the alignment. As roughness value the standard deviations of points within a defined neighborhood regarding a plane fit might be used.

3. **Weighting based on arbitrary invariant attributes of corresponding points**

$$w = 1 - \frac{|a_p - a_q|}{\Delta a_{max}}$$

where a_p and a_q are invariant attributes associated to the corresponding points $\boldsymbol{p}$ and $\boldsymbol{q}$ and Δa_{max} is the largest allowed difference between such attributes defined by the user.

4. **Weighting based on the angle between the normal vectors of corresponding points (*)** (Godin et al., 1994)

$$w = |\boldsymbol{n}_p^T \cdot \boldsymbol{n}_q|$$

Strategies can be used simultaneously and are then combined by:

$$w = w_1 \cdot w_2 \cdot \ldots \cdot w_n$$

3.2.4 Rejection

The aim of this step is the detection and rejection of outliers, as they may have a large effect on the alignment result of the least squares optimization.

We propose the following strategies:

1. **Rejection based on the weight of a correspondence (*)**
If a low weight was assigned to a correspondence in the previous step, it provides no substantial information for solving the alignment problem. In order to reduce the number of equations, correspondences with a weight below a threshold w_{min} should be rejected. Furthermore, it should be noted that the first three discussed weighting strategies can lead to negative weights if the thresholds are

exceeded. Obviously these correspondences should be rejected in any case. We recommend

$$w_{min} = 0.1.$$

2. **Rejection based on the distance between corresponding points (*)**
As a weighting of correspondences based on the distance decreases the convergence rate (see sec. 3.2.3.), a threshold d_{max} should be used for the rejection of outliers. For signed distances[1] we recommend

$$d_{max} = \pm 3\sigma_{mad}$$

and to reject all correspondences outside this range[2].
For unsigned distances[3] a fixed threshold (e.g. 2 m) or a quantile (e.g. 90%) of all distances can be used.

In order to maximize the robustness of the alignment solution, both proposed strategies should be applied in the presented order.

3.2.5 Minimization

At this stage of the algorithm the transformation parameters are estimated by minimizing the sum of squared distances between the established correspondences. Two types of distances are commonly used:

1. Euclidean (unsigned) distance between corresponding points (“**point-to-point” error metric**) (Besl & McKay, 1992):
Basically, this error metric should be avoided in ALS, as no real point correspondences exist and the convergence speed is somewhat slow (Rusinkiewicz & Levoy, 2001). The objective function to be minimized is

$$E = \sum_i w_i \cdot \| T(\boldsymbol{p_i}) - \boldsymbol{q_i} \|^2$$

where $\boldsymbol{p_i}$and $\boldsymbol{q_i}$ are the corresponding points, T denotes a transformation and w_i are the weights. As can be seen, the fixed point cloud is formed by the points $\boldsymbol{q_i}$ and the loose point cloud by the points $\boldsymbol{p_i}$.
If a rigid-body transformation is applied, a closed form solution exists for this error metric (Horn et al., 1998).

2. Perpendicular (signed) distance of one point to the tangent plane of the other point (“**point-to-plane” error metric**) **(*)** (Chen & Medioni, 1991):
This error metric is characterized by a high convergence speed, as flat regions can slide along each other without costs. The objective function to be minimized is

$$E = \sum_i w_i \cdot [(T(\boldsymbol{p_i}) - \boldsymbol{q_i})^T \cdot \boldsymbol{n_i}]^2$$

where $\boldsymbol{n_i}$ are the normal vectors of the fixed point cloud. The value inside the square brackets is the point-to-plane distance, hereinafter referred as Δp.
For this error metric a closed form solution exists for the rigid-body transformation only after linearizing the rotation matrix, i.e. for small rotations (*Chen & Medioni, 1991*).

Other error metrics can be imagined. For instance, Masuda & Yokoya (1994) use the Least Median Square (LMS) norm instead of the euclidean norm (L2) above.

We solved this optimization problem by an ordinary least squares adjustment. The closed form solutions were used for verification.

3.2.6 Transformation

Using a rigid body transformation (having 6 parameters: shift and rotation) for improving the relative and absolute georeferencing of ALS strips appears to be a reasonable choice. However, as pointed out in Ressl et al. (2009), if additionally the effects of a wrong mounting calibration shall be reduced without considering the GNSS-INS trajectory data, then it is important to use a 3D affine transformation (having 12 parameters). Thus, we use a 3D **affine transformation (*)** within this study. The objective function to be minimized for the recommended point-to-plane error metric is:

$$E = \sum_i w_i \cdot [(A\boldsymbol{p_i} + \boldsymbol{t} - \boldsymbol{q_i})^T \cdot \boldsymbol{n_i}]^2$$

where A denotes an (3x3) affine matrix and $\boldsymbol{t}$ is a (3x1) shift vector.

As mentioned in the introduction, this contribution focuses in the correspondence problem primarily, no other variants were investigated for this step within this study.

4. EXPERIMENTAL RESULTS

In this section, the introduced correspondence framework is demonstrated on the basis of a typical ALS scene (Cramer, 2010), which includes buildings, vegetation and a slightly changing topography. The presented variants are compared for the **selection**, **weighting**, **rejection** and **minimization** step. Although the problem of finding the best alignment of two entire ALS strips is addressed in this article, we limit the overlap area (without limiting generality) to the extent of some hundred meters for visualization purposes.

4.1 Comparison methodology

Each comparison refers to one single step, e.g. the selection step. For the remaining steps, the recommended baseline method was applied (with a voxel size for uniform sampling = 2.5 m and a maximal roughness value $r_{max} = 0.15$ m).

An objective quality measure is necessary for a fair comparison among the investigated variants. In ALS, a high and homogenous distributed accuracy of points is desired. Thus, we decided to use the σ_{mad} value of uniformly sampled (voxel size = 0.5 m) point-to-plane distances Δp within smooth areas ($r_{max} = 0.15$ m) as a neutral quality measure (denoted as “alignment error” for the remaining part of the section).

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[1] “point-to-plane” distance, see sec. 3.2.5.

[2] σ_{mad} is a robust estimator for the standard deviation of a data set under the assumption that the set has a Gaussian distribution $\sigma_{mad} = 1.4812 \cdot mad$; where mad is the median of the absolute differences (with respect to the median) of the data set.

[3] “point-to-point” distance, see sec. 3.2.5.

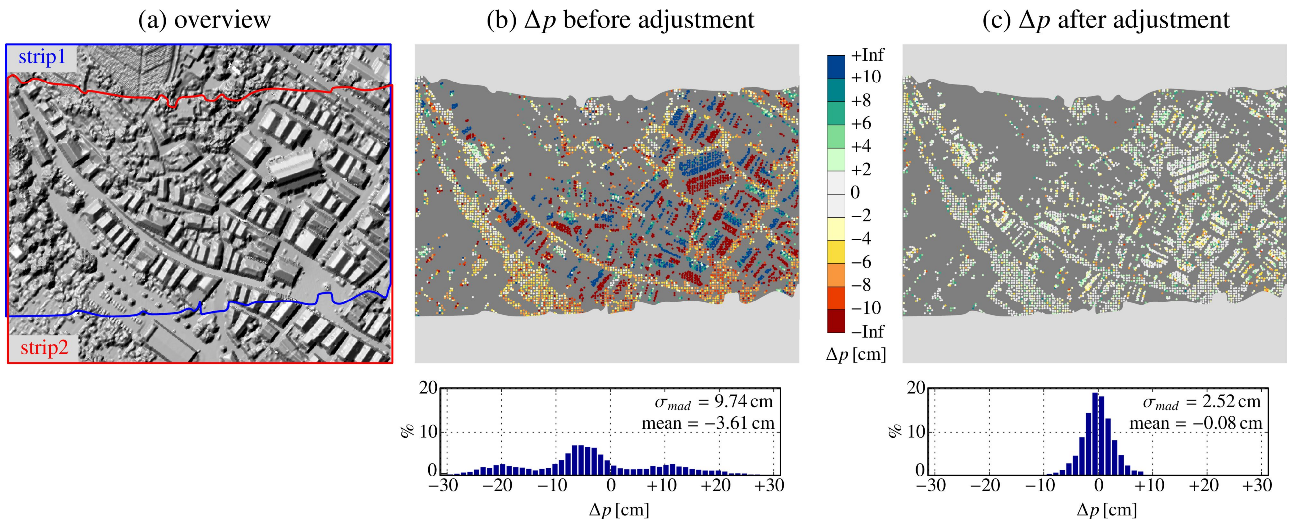

Figure 3: Alignment result with the baseline method for a typical ALS scene. In the overlap area of the two ALS strips 8600 correspondences are established (Δp denotes the point-to-plane distance).

4.2 Baseline method result

The result obtained applying the recommended baseline method is shown in Figure 3. In sum, 8600 correspondences are established within smooth areas (mainly building roofs and roads) of the scene. In (b) the point-to-plane distances in the original state are shown; here a clear planar misalignment of the ALS strips can be recognized as a change of sign within the building roofs. After the adjustment (c), systematics are widely eliminated and the alignment error is reduced to 2.52 cm.

The convergence rate of different **selection** strategies (see sec. 3.2.1) is compared in Figure 4. To be fair, for all three sampling methods the same number of points (8600) was selected. However, for the "no sampling" variant all 20700 points were selected. The results show that:

- Due to the relative good initial alignment of the strips, all strategies converge within two iterations to their global minima.
- Differences among variants are minimal (only up to 1 mm after one iteration). However, uniform sampling converges slightly faster than random and normal space sampling in this case.

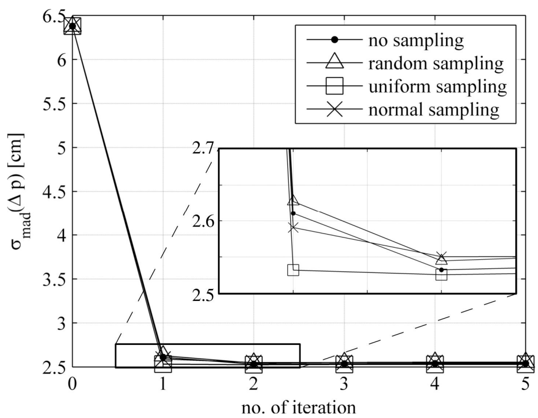

Figure 4: Comparison of selection strategies.

In Figure 5 the effect of different **weighting** strategies (see sec. 3.2.3) is shown. Since in rough areas ALS points don't provide a reliable description of the underlying object, the biggest effect is achieved by weighting the correspondences on the basis of roughness values. Generally, this is particularly important if the strip contains much vegetation. The weighting based on the angle between corresponding normal vectors, leads in comparison to the alignment without weights (w = 1), only to small improvements. However, as it increases the overall robustness of the alignment, this weighting strategy is recommended to be applied together with the roughness weighting. As already stated in sec. 3.2.3., the weighting based on the distances between corresponding points, significantly slows down the alignment process and thus, is not recommended (in this case d_{max} was set to 1 m).

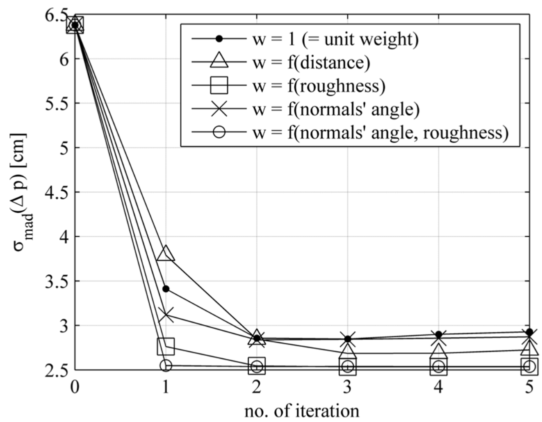

Figure 5: Comparison of weighting strategies.

In Figure 6 the benefit of the distance based **rejection** (see sec. 3.4.2) of correspondences is shown. Although both variants converge quickly to a minima, the alignment error is reduced by approx. 1 cm by the rejection of potentially wrong correspondences.

In Figure 7 a comparison between the point-to-point and the point-to-plane **minimization** (see sec. 3.2.5) is visualized. With the point-to-plane metric the global minima is already reached after the first iteration, whereas the "point to point" metric converges non monotonously to a local minima in this case.

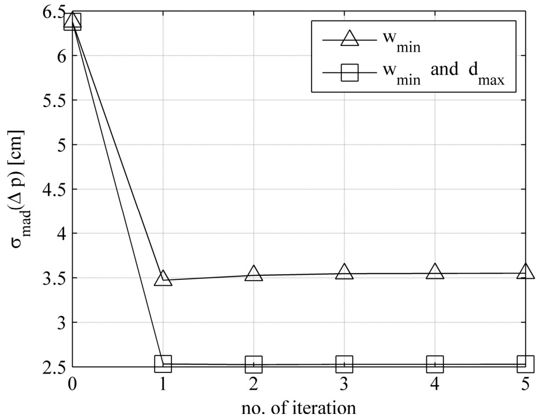

Figure 6: Comparison of rejection strategies.

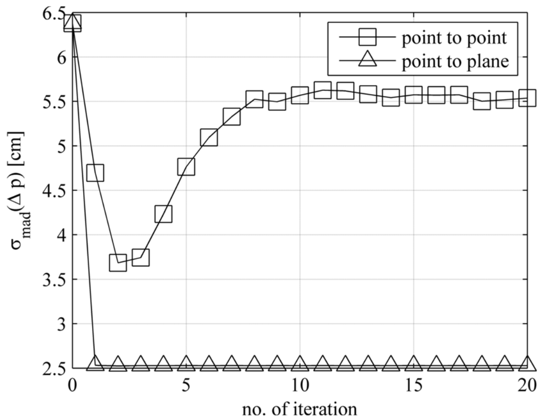

Figure 7: Comparison of matching strategies

5. CONCLUSION AND OUTLOOK

This article presents a study of different correspondence options for ALS strip adjustments. A baseline of variants optimized for most typical ALS data sets was found by the comparison of several variants. The main findings of this work are:

1. Since the initial relative orientation of point clouds in ALS is very good, for most of the cases only two iterations of the alignment process are necessary.
2. The consideration of roughness within the alignment process is crucial, since in rough areas (e.g. vegetation) the ALS points don't provide a reliable description of the underlying object. Thus, only flat areas are recommended for the alignment of ALS data.
3. Since the ground sampling of two ALS strips is always different, no real point to point correspondences exist in ALS. This fact has to be considered by minimizing the distances between points and their corresponding tangent plane (instead of minimizing point-to-point distances).
4. A homogeneous distribution of correspondences in object space is recommended, since then subregions of equal area are weighted equally. This leads to a homogenous distributed accuracy of the aligned points.
5. In order to increase the robustness of the alignment, a rejection of correspondences based on the a priori distribution of distances is necessary.

Currently we are working on the integration of the correspondence framework presented herein into a rigorous formulation of the strip adjustment problem (i.e. with the consideration of the trajectory information) (Skaloud & Lichti, 2006).

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