# Automatic Registration of Laser Scanner Point Clouds with Genetic Algorithms

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**Abstract**

During a terrestrial laser scan, usually different scanning positions are necessary to avoid hidden parts on the object. The resulting scans are then merged into one single point cloud in a registration procedure. Usually artificial targets or approximate values are required to initiate the spatial transformation. We illustrate the theoretical background of a robust as well as automated registration approach without any prior knowledge of the scanner's position and attitude by using Genetic Algorithms. Then we discuss the results using the example of a cave survey, where the registration using artificial targets reached the limit of practicability.

**Keywords:** automatic registration, point clouds, Genetic Algorithms

**Kurzfassung**

Im Zuge der Erfassung eines Objekts mittels terrestrischer Laserscanner sind im Allgemeinen mehrere Standpunkte notwendig, um Lücken in verdeckten Bereichen zu vermeiden. Die so erfassten Scans werden erst über eine gegenseitige Registrierung zu einer gemeinsamen Punktwolke vereinigt. Häufig werden zu diesem Zweck künstliche Passmarken / Passobjekte oder manuell erzeugte Näherungswerte für die räumliche Transformation verwendet. Die Autoren zeigen den theoretischen Hintergrund eines Ansatzes zur Registrierung von Scans mit Genetischen Algorithmen, der ohne Vorwissen über Standpunkt und räumliche Lage des Scanners auskommt und gleichzeitig zu robusten Ergebnissen führt. Der praktische Einsatz wird anhand der 3D-Erfassung eines bronzezeitlichen Bergbaustollens diskutiert, bei dem die Verwendung künstlicher Ziele an ihre Grenzen gestoßen war.

**Schlüsselwörter:** automatische Registrierung, Punktwolken, Genetische Algorithmen

## 1. Introduction

Surveying is an indispensable companion of every archaeological excavation (fig. 1). Modern documentation techniques allow for complete and precise data acquisition with laser scanners leading to full textured 3D models of the excavation and its artefacts [1]. As the recording and representation of such complex structures and surfaces needs scanning from several scan positions (for results see fig. 2), the single point clouds have to be registered to each other to be transformed into a common coordinate framework. Only after determining and applying the transformation parameters, the merging and final modelling of the point clouds can take place.

*Fig. 1: Typical point cloud acquisition with a terrestrial laser scanner and artificial target spheres*

Generally the registration problem is solved by scanning additional spherical or cylindrical marks, at least three of which have to be visible also from other positions to guarantee a six parameter (relative) spatial transformation. These tie-features should be well distributed in space around the object and lead to a high effort for additional measurements. Figure 1 shows the complicated positioning of target spheres in a narrow pre-historic Bronze Age mining gallery. This gives an idea of the method's limit of practicability. Absolute orientation using control-features was not adopted in this case as the artificial marks were positioned as needed "on-the-fly" and the project did not require any georeferencing.

Another possibility to establish the registration is based on the manual assignment of assumed coincident points in the point clouds. However it is often hard to identify such points. Due to the fact that point clouds are discrete representa-

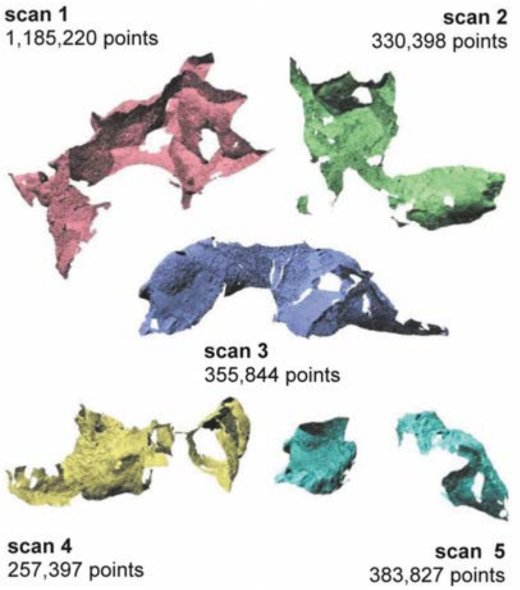


*Fig. 2: Single scans of a prehistoric cave*

tions of the original object's surface only, one can imagine that in most cases there won't even be any exact point-to-point correspondences.

As this procedure is, with a high number of single point clouds, very time-consuming and also fairly error-prone, we tried to develop a robust and automatic approach avoiding any manual interaction. Hereby we combine already well-established registration strategies such as coarse registration using features, the application of Genetic Algorithms as well as ICP-algorithms for fine registration.

Contrary to other popular approaches, however, we do not try to identify the position of the global optimum already after coarse registration. This is reasonable as, due to the necessary approximations during coarse registration, the correct solution may appear worse than those that are actually wrong. Thus we propose to introduce a Genetic Algorithm in between coarse and fine registration to both optimize and reduce the number of possible solutions at the same time.

Further we use imperfect and subdivided features to enhance the robustness of the registration of point clouds which are partially occluded and/or characterized by a significant noise level or imperfect geometry.

Summarized we elaborate the positive aspects of different approaches and try to minimize their drawbacks.

## 2. Related previous work

Mathematically, the process of point cloud registration can be seen as search for an optimal alignment between two point clouds $X = (x_1, \ldots, x_N)$ and $Y = (y_1, \ldots, y_N)$. Sometimes point-to-point correspondences are already known or were manually established. Hereby $X$ and $Y$ do not contain the whole point clouds, but only the corresponding point pairs, meaning that each point $x_i \in X$ has a corresponding point $y_i \in Y$ with the same index. As stated in [2], the rigid-body transformation can be expressed as

$$m(\boldsymbol{x}) := \boldsymbol{x}' = \mathbf{t} + R \cdot \boldsymbol{x} \tag{1}$$

whereby each point $\boldsymbol{x}$ is transformed to a new position $\boldsymbol{x}'$ by applying a rotation $R$ and a translation $\mathbf{t}$, such that the sum of the squared Euclidean distances between $X$ and $Y$ is minimized:

$$\sum_{i=1}^{N} \left\| \boldsymbol{x}_i' - \boldsymbol{y}_i \right\|^2 \to \min \tag{2}$$

If at least three correspondences in two point clouds are known, the registration task can for instance be solved by using the closed-form solution presented in [3].

Similar to the manual identification of point correspondences, also automatic methods use the object's properties itself for the registration and typically also split the registration process into coarse and fine registration. For each of these steps a number of methods can be found in literature [4].

One of the main challenges during coarse registration is the efficient search of correspondences. Especially when registering bigger objects or outdoor scenes, point clouds contain a certain noise level, resulting from the limited instrument precision and/or the discretisation of rough or in small parts occluded object surfaces. In those cases some authors, e.g. [5] and [6], propose the use of features such as planes or also more complex geometric elements such as cylinders [7].

After roughly orientating the point clouds, fine registration improves their alignment further. Most popular approaches are based on the ICP (Iterative Closest Point) algorithm presented by [8] and [9]. [10] list different variations of the ICP-algorithm and evaluate their speed and solution quality.

As alternative to the already mentioned approaches, Genetic Algorithms (GAs) can be adapted for both coarse and fine registration. They prove more robust as they are better in detecting the global optimum and are able to find solutions where other algorithms may fail. They are fairly well suited for the registration of free-form objects as shown for example in [11], [12] or [13]. Nevertheless, their major drawback is that they are computationally expensive.

## 3. Background information

In the following chapter we give some brief background information about basic principles used in this work.

### 3.1 Genetic Algorithms

Genetic Algorithms (GAs) are adaptive heuristic search algorithms which are inspired by the principles of natural evolution. They are able to find solutions in large and complex search spaces where other algorithms may fail due to local optima. Genetic Algorithms are however known to be computationally expensive, which is especially true for the registration f point clouds. By using a Genetic Algorithm in between coarse and fine registration, the algorithm does not need to search the whole solution space and thus we cantake advantage of its robustness and at the same time increase its practicability.

The registration concept discussed in this paper is not bound to a very specific Genetic Algorithm. A variety of algorithms was successfully tested; we found however that the Genetic Algorithm and parameters described in [12] behave quite well on our datasets. Thus our actual implementation is mainly based on [12] and works with randomly chosen subsets of single points from the point clouds.

Figure 3 shows a typical structure of a Genetic Algorithm. At the beginning a pool of random solutions is created, forming the so-called initial population. Note that these solutions can also be supplied by a preceding algorithm (e.g. an algorithm for coarse registration).

Each solution is represented as vector of parameters. Contrary to [12] we do not store it

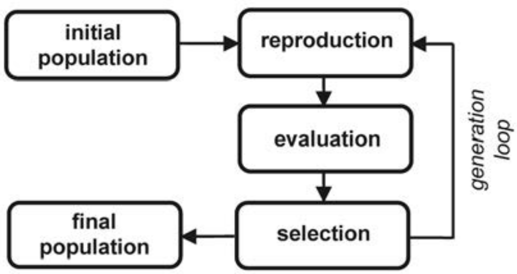


**Fig. 3:** *Typical structure of a Genetic Algorithm*

in the six-dimensional form $[\alpha, \beta, \gamma, t_x, t_y, t_z]$ with the three Euler-angles $\alpha$, $\beta$, $\gamma$ and $t_x$, $t_y$, $t_z$ as the three elements of the translation vector $\mathbf{t}$, but follow the advice in [13] and use a unit quaternion $\mathbf{q}$ for the homogenous representation of the rotation.

In the so called reproduction additional solutions are created by randomly applying the principles of mutation and crossover. Regarding mutation one already given solution is taken and altered by adding a small arbitrary rotation and translation. Crossover is adopted by selecting two existing solutions and interpolating them. For quaternions this can be done for example by applying a spherical linear interpolation (SLERP). The needed interpolation factor $t$ is chosen randomly between 0 and 1.

After the number of solutions in the population was increased (typically doubled), the actual quality (fitness) of the single solutions is evaluated by a so-called fitness function. We are using the one stated in [12] which is based on the sum of the squared distances between corresponding points. To accelerate this step a kd-tree is used.

Based on their quality, a certain number of solutions is then selected for the next iteration (generation) adopting a binary tournament. Hereby solutions with higher quality have a better chance to be selected.

Due to the continuous repetition of reproduction, evaluation and selection, an optimization of the population can be achieved until a specified termination criterion is met (for instance a maximum number of iterations).

By reusing the fitness function, at the end the best solution can be identified within the final population.

### 3.2 Imperfect features

When trying to identify features (e.g. edges, borders or planar patches) in point clouds, one may observe that the selection of detection thresholds can be decisive for the results. If point clouds are characterized by a significant noise level or imperfect geometry (such as rough surfaces or round borders and edges) or contain occluded parts (e.g. due to trees (see fig. 4)), features may emerge differently when applying feature detection to other point clouds also due to the different point of view.

In this sense the term “imperfect features” does not refer to a special feature type as such, but implies that features may be only approxi-

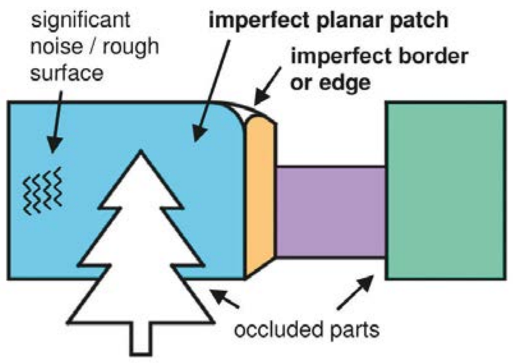


*Fig.4: Imperfect features*

mated, "partly correct" or even misrepresent the original object.

### 3.3 Subdivided features

Sometimes it may happen that due to unfavourable circumstances the needed feature correspondences can get rather poor for a "correct" registration. This is especially true with datasets where we can't deny the presence of imperfect features. To overcome this we propose to subdivide larger features into smaller parts (see fig. 5) and work only with those which are not influenced by occlusion or other effects anymore.

In [5] the concept of subdividing point clouds into regular raster cells for fast plane detection was introduced. We evolve this idea not by subdividing the point clouds itself, but its features. Note that in this paper we mainly refer to subdivided planar patches, but the concept is applicable to other feature types as well.

By calculating the barycentre and principal axis of each planar patch we can establish an individual local coordinate system and useit for subdividing features into a regular grid (see fig. 5). For some features this will lead to similar grids (and therefore similar subdivided features) also in other point clouds. Our algorithm is, however, able to handle also the other cases, where subdivision results in a differing grid. For more information about imperfect and subdivided features consult [14] or [15].

## 4. Automatic registration

One of the biggest challenges in point cloud registration is the huge amount of data, which is typically given as unsorted list of point-coordinates. Due to this, efficient strategies have to be used to achieve practically acceptable running times also for bigger objects.

Figure 6 shows the three main steps of the here presented registration strategy GAReg-ISF (Genetic Algorithm Registration with Imperfect and Subdivided Features) [14], exemplarily using coloured puzzle pieces to represent the single point clouds.

In a first step the point clouds are individually analysed and for all of them additional information such as normal vectors and features are identified. This is followed by the pair-wise registration of the possible point cloud combinations.

Afterwards a multi-view registration is employed where the results of the pair-wise registrations are used to align the point clouds to a globally consistent digital representation of the original object.

### 4.1 Scan-analysis

The so-called scan-analysis is the first step in GAReg-ISF. The main aim of scan-analysis is to reduce the millions of single points to distinctive areas (features) to increase the overall robustness of the registration process. Hereby geometrical features are identified out of the single point clouds; planes for instance proved to be rather robust against noise, outliers and small occlusions.

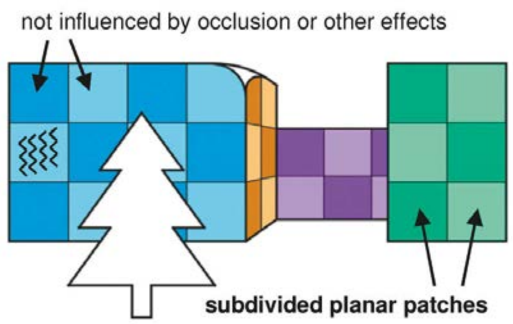


*Fig. 5: Subdivided features*

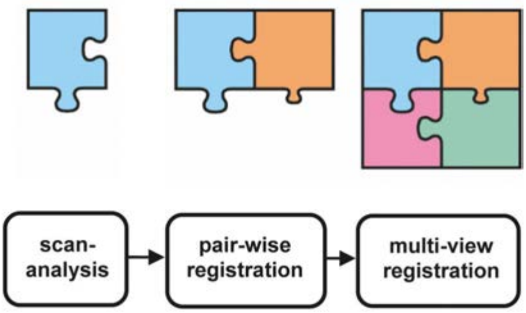


*Fig. 6: Automatic registration strategy*

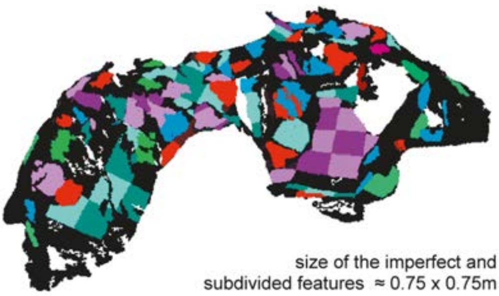


*Fig. 7: Imperfect and subdivided planar patches*

The results of a scan-analysis using imperfect and subdivided features can be seen in figure 7, illustrating scan 3 of a cave in Mauken near Brixlegg, Tyrol, Austria.

### 4.2 Pair-wise registration

The information resulting from scan analysis is processed during pair-wise registration; hereby respectively two point clouds are aligned with each other.

First of all coarse registration using imperfect and subdivided features takes place, traditionally followed by fine registration. Figure 8, however, shows the enhanced approach of GAReg-ISF, where a third step right in between coarse and fine registration is introduced by using a Genetic Algorithm. Hereby, valid solutions resulting from coarse registration mark possible locations (schematically represented as bubbles in fig. 8) of the global optimum in the search space. This is done by taking the solutions of coarse registration as initial population for the Genetic Algorithm. When one or eventually even several solutions have been identified by the algorithm, a pair-wise fine registration can be employed using an accordingly higher degree of details.

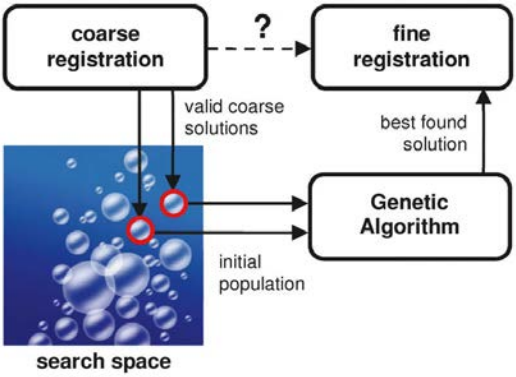


*Fig. 8: Enhanced pair-wise registration*

#### 4.2.1 Coarse registration

The principal target of coarse registration is the approximately correct alignment of two point clouds. The huge data volume and the very often missing information about the spatial relationship between the single point clouds prove particularly challenging in this step.

As stated in [6], three linearly independent planes $\varepsilon_i$, $\varepsilon_j$, $\varepsilon_k$ (see figure 9a) in each point cloud are necessary to form a valid registration. In some cases it is however difficult or simply not possible to gather enough corresponding planes in each point cloud for registration.

An additional consideration is presented in [16]: Hereby also the barycentre of each planar patch is used for the registration process, which means that only two planar patches need to be visible and detectable in each point cloud. The same strategy can be adapted also to imperfect and subdivided features with the barycentres $\mathbf{r}_i$ and $\mathbf{r}_j$ as shown in figure 9b.

To keep computational efforts within an acceptable range, several hierarchical comparisons are carried out.

At the beginning, all possible combinations of (yet not subdivided) planar patch pairs from one point cloud with all of such of the other point cloud have to be considered. A lot of wrong com-

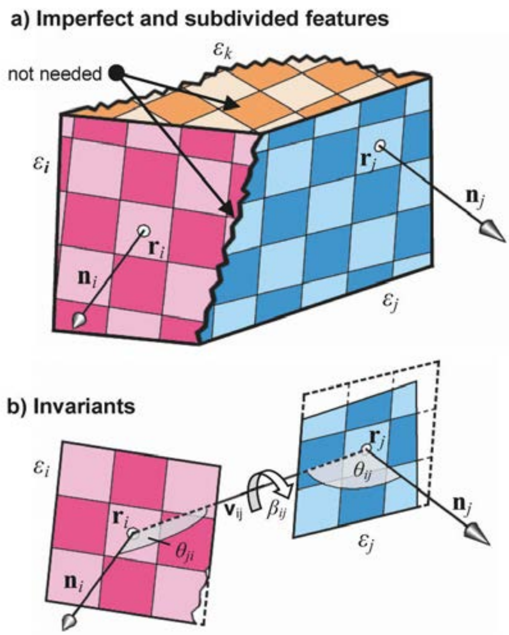


*Fig. 9a-b: Invariants of the imperfect and subdivided features for efficient correspondence detection* binations can however be eliminated by checking the minimal and maximal spatial distance of the (yet not subdivided) planar patch pairs as well as the angle between normal vectors [16] and the difference of mean intensity information.

For the remaining correspondences their subdivided planar patches are now used. Figure 9b shows four invariants, stated in [11] and [4], which enable an efficient search strategy. The invariants between two subdivided features with the barycentres $\mathbf{r}_\mathrm{i}$ and $\mathbf{r}_\mathrm{j}$ correspond to the distance $||v_{ij}||$ between the barycentres, the pair-wise relative orientations $\theta_{ij}$ and $\theta_{ji}$, as well as a twist angle $\beta_{ij}$.

It is quite obvious that in most cases still a lot of wrong correspondences will result from the above mentioned rough comparison. For further limitation, the local neighbourhoods of the features are now included into the search process. This is done by comparing also the eight nearest subdivided planar patches around $\mathbf{r}_\mathrm{i}$ and $\mathbf{r}_\mathrm{j}$ (fig. 9b). The remaining combinations of subdivided planar patch pairs can then be used to create a list of rough pair-wise alignments of the point clouds. After sorting out similar solutions these are supplied as initial population to a Genetic Algorithm.

#### 4.2.2 Genetic Algorithm

The use of a Genetic Algorithm in GAReg-ISF has different reasons. First of all it is able both to optimize and reduce the number of solutions provided by the coarse registration. This way the probability of missing the "correct" solution can be decreased. At the same time the Genetic Algorithm is able to correct the allowed approximations resulting from the concept of imperfect and subdivided features and from coarse registration.

A well balanced optimization carried out with a Genetic Algorithm is most of the times characterized by the convergence of a population towards the global optimum. Such a convergence on the basis of the translation $\mathbf{t}$ of a dataset used in [15] is shown in figure 10 a-c. Note that in this case the translation is dimensionless as the dataset used in this example was temporary scaled to unit size during the registration process. Through the implementation of an additional "taboo-search" also more than one solution can be found by repeating the procedure. This was successfully tested registering two synthetic doubly-symmetric planar patches with two graves (forming an X), where the algorithm was able to find all four solutions[14].

#### 4.2.3 Fine registration

To conclude the pair-wise matching process, an ICP-algorithm (see [8], [9] and [10]) is employed for fine registration. In this step we use an ICP-algorithm for the alignment of only two point clouds, whereas after multi-view registration an algorithms is applied which supports the simultaneous alignment of more than two point clouds.

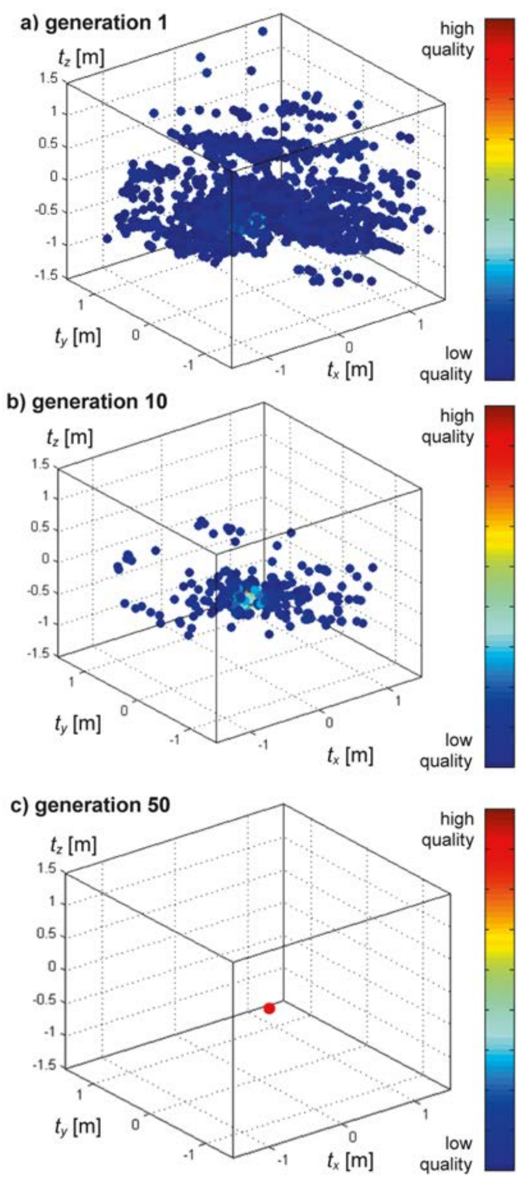


*Fig. 10a-c: Convergence of the solutions*

### 4.3 Multi-view registration

In most cases several point clouds need to be registered in order to create a preferably complete digital representation of an object.

This is particularly challenging as often not only one but several pair-wise registration results can seem feasible. Figure 11 shows different solutions resulting from the pair-wise registration of the same two point clouds (represented as puzzle pieces).

Thereby contradicting solutions (fig. 11a) seem to be detectable more easily as apparently correct (but wrong) solutions (fig. 11b). Both cases are however quite similar, because the actual surface contradictions are limited to areas of direct contact. As proposed in [17], a visibility consistency check can help to identify wrong alignments.

To differentiate between locally (fig. 11c) and globally correct solutions (fig. 11d), solutions showing a larger overlap are preferred. Note that in this case a solution is called "globally correct" if it leads to the result expected by the user (see fig. 12).

According to [18], at the beginning of the multi-view registration the results of the pair-wise registration are sorted according to their quality. The best solution is fixed and iteratively the next pair is added until all point clouds are aligned (fig. 12). After each iteration step the point clouds are realigned so that a globally consistent representation of all views can be ensured.

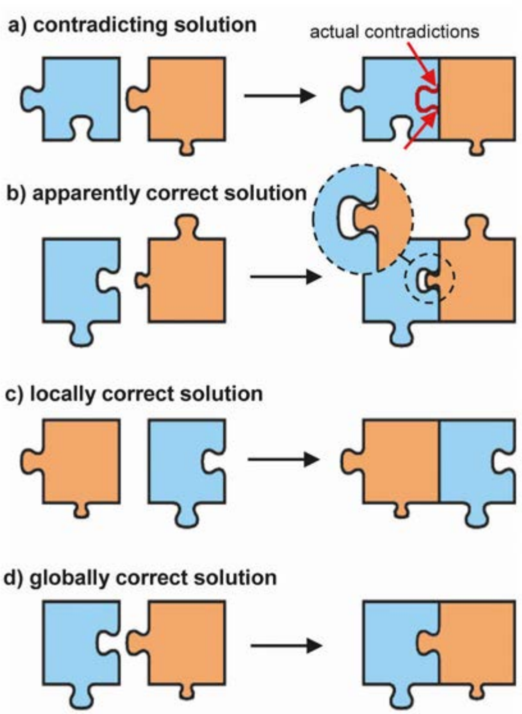


*Fig. 11a-d: Different solutions resulting from pair-wise registration*

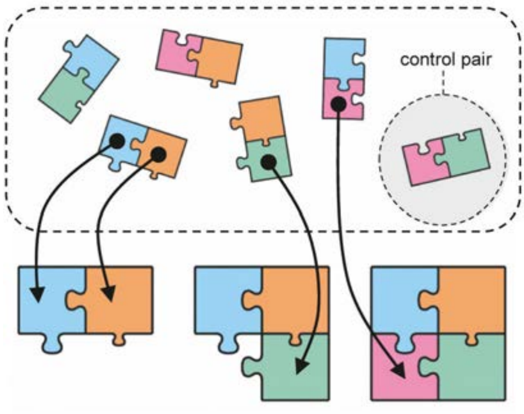


*Fig. 12: Multi-view registration*

### 5. Experimental results

To explore the potentials and limits of GAReg-ISF, a number of experiments have been carried out [15]. The cave in Mauken is definitely among those cases that are not characterized by ideal conditions for a registration method using planes. Nevertheless, we were able to represent even such complex surfaces by using imperfect and subdivided features (fig. 7).

For the feature extraction and for the ICP-algorithm 100,000 randomly chosen points were used, whereas for the Genetic Algorithm 3,000 were taken.

The point clouds were registered twice using two independent methods: the classical registration with artificial spheres (as tie-features) and the automatic registration approach GAReg-ISF. As the local coordinates of the sphere centres were already gathered for each station during the classical approach, they can also be transformed according to the transformation parameters calculated with GAReg-ISF. This makes it possible to compare the resulting coordinates of the sphere centres for both approaches. Table 1 illustrates the standard deviations of the sphere centres as well as the spatial distances between the averaged centres.

As noticed even the classical registration using artificial spheresshows certain deviations. This is probably due to the scanner's limited accuracy

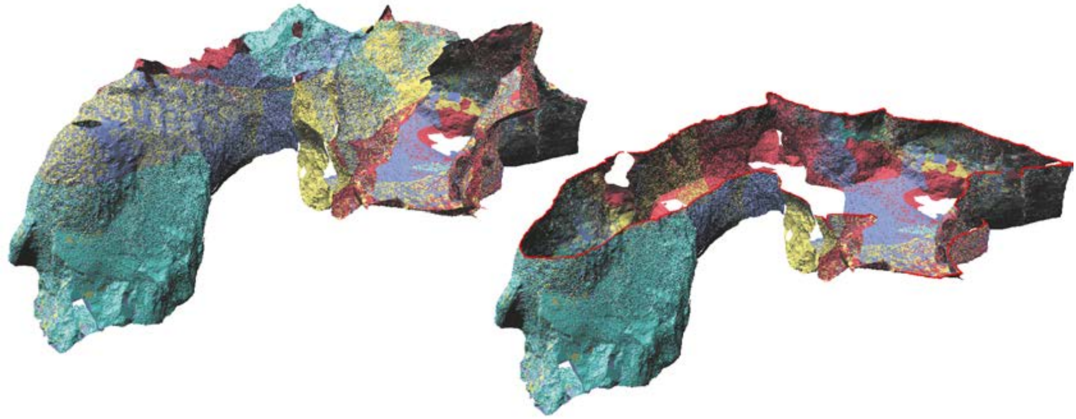

*Fig. 13a-b: Exterior view and horizontal section of the registered scans*

and minor displacements of the spheres in the course of the measuring. The same displacements also influence the results of GAReg-ISF, though actually working without spheres.

For both methods the maximal standard deviation can be found in x-direction of sphere 3 as well as the maximal spatial distance with 1.6 mm. Overall these results are absolutely satisfying. Figure 13 shows different views of the five registered point clouds of the Mauken cave.

| sphere | station | std. dev. of sphere centres | | | | | | spatial distance [mm] |
|---|---|---|---|---|---|---|---|---|
| | | target spheres | | | GAReg-ISF | | | |
| | | X mm | Y mm | Z mm | X mm | Y mm | Z mm | |
| 1 | 1,3, 4,5 | 0.9 | 0.6 | 0.4 | 0.3 | 0.8 | 0.5 | **1.0** |
| 2 | 1,2, 3,4 | 1.6 | 2.1 | 0.1 | 0.8 | 2.8 | 1.1 | **0.6** |
| 3 | 1,2, 5 | 2.6 | 0.7 | 0.1 | 3.7 | 2.0 | 1.2 | **1.6** |
| 4 | 1,2, 3,4, 5 | 0.6 | 1.7 | 0.3 | 1.5 | 1.1 | 0.6 | **1.5** |

*Tab. 1: Comparison of the sphere centres resulting from the registration with artificial spheres and GAReg-ISF*

## 6. Conclusion

In the mentioned cave project, the classical registration approach using artificial spheres has reached its limits as it was hard to select useful positions for the single spheres. Thus we used the fully automatic registration approach GAReg-ISF and evaluated the spatial difference of the results by applying the calculated transformation parameters to locally known target sphere coordinates. We showed that GAReg-ISF is able to reach results of comparable accuracy as the classical registration using artificial spheres in complex surroundings by rendering at the same time the overall registration workflow more efficient.

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