COMBINING GENETIC ALGORITHMS WITH IMPERFECT AND SUBDIVIDED FEATURES FOR THE AUTOMATIC REGISTRATION OF POINT CLOUDS (GAREG-ISF)

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ABSTRACT:

Terrestrial laser scanners have achieved a great popularity in the last decade. Their easy on-site application and the possibility of a flexible and high quality post processing added to their success also in architectural, archaeological and heritage documentation. We present a method for handling the automatic registration of point clouds which are characterized by a significant noise level, generally imperfect geometry and occlusions. Hereby we combine and extend already existing and established methods to facilitate the registration of point clouds without prior pre-processing. Our approach consists - similar to other methods - of three steps which are scan analysis, pair-wise matching and multi-view matching. To handle the above mentioned datasets we propose to use imperfect and subdivided features, and to implement Genetic Algorithms (GAs). At the same time our approach can be seen as extension to already known Genetic Algorithms used for the registration of point clouds. By implementing an adapted version of a Genetic Algorithm in the classical registration process between coarse and fine registration we are able to maintain robustness and computational performance also when registering scans of bigger objects characterised by a notably increased number of points, a significant noise level and occlusions. We show and discuss the successful application of the algorithm also on scenes which do not consist of classical geometric primitives such as planes.

1. INTRODUCTION

Laser scanners are able to capture real-world surroundings in a fairly short amount of time (Hanke et al., 2006). The growing amount of collected data does not only increase the quality of the results and the areas of applications but also the necessary time needed for planning, performing and elaborating the on-site measurements. In order to avoid hidden or missing parts, generally several scanning stations have to be used and the resulting point clouds have to be registered to each other.

The common and robust geodetic way of using artificial (spherical, cylindrical or plain) targets is time-consuming and needs at least three of these targets to be inside the measurement range of the laser scanner. This can be avoided by using robust and automated algorithms for the registration process working with the object's shape itself as long as it is guaranteed that a comparable accuracy of the registration will be achieved. A first study of the here proposed algorithm is found in Schenk and Hanke (2009).

An overview of different registration methods can be found in Salvi et al. (2007). Herein registration methods are classified either as coarse or fine registration; for a complete matching both have to be applied to identify and refine the global optimum.

Several methods exist to perform the coarse registration of point clouds. Bae and Lichti (2004) proposed to use local surface attributes such as normal vectors or geometric curvature, whereas Johnson and Hebert (1997) used spin images for the successful registration of point clouds. Von Hansen (2007) and Brenner et al. (2008) successfully used planar patches for the registration of urban environments, and Rabbani et al. (2007) worked with different objects as targets for the registration of industrial areas.

Fine registration is typically done with the well-known iterative closest point (ICP) algorithm, proposed by Besl and McKay (1992) as well as by Chen and Medioni (1992). An overview of efficient variants of the ICP algorithm can be found in Rusinkiewicz and Levoy (2001).

Genetic Algorithms (GAs) are able to solve problems where search space is large or poorly understood and no simple mathematical analysis of the solution is available. Brunnström and Stoddard (1996) used a GA to find an initial guess for the free-form matching problem that is finding the translation and the rotation between an object and a model surface. An advanced evolutionary algorithm, CHC, was used by Cordón et al. (2003) for 3D image registration. They used both a coding scheme with 7 parameters representing the translational and rotational components and a factor for uniform scaling; they also compared binary coding to real value coding. A comprehensive description of using GAs for the alignment of multi-view range images has been presented in Silva et al. (2005). They also introduced the so-called "Surface Interpenetration Measure" that allows a more precise evaluation of the registration results. Lomonosov et al. (2006) proposed to use a GA for the pre-registration of arbitrarily oriented 3D surfaces, also including the surface overlap as unknown parameter in the search process.

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2. BACKGROUND

2.1 Genetic Algorithms

Genetic Algorithms (GAs) represent a computer-based simulation of natural evolution where the principles of biological processes are used as heuristic search strategy. They achieved a great popularity through the work of Holland (1975) and are typically used for problems with a large and complex search space with an increased number of local optimums.

GAs are known to have a clear and simple structure and can be used for a variety of applications. The here proposed Genetic Algorithm was developed by Reed et al. (2005) for the optimisation of tunnel shapes and was adapted for terrestrial laser scan registration with only a few modifications; a proof of the great flexibility of GAs.

Charles Darwin characterised natural evolution mainly by one keyword: natural selection, also known as "survival of the fittest". This means that individuals with higher quality - called fitness - have a higher probability to survive and to reproduce themselves than others. The fitness function evaluates all individuals of a population and calculates their fitness. Each individual is represented as a chromosome and its subparts named genes. Hereby a single individual corresponds to a single mathematical solution, whereas a population is equal to a group of possible solutions.

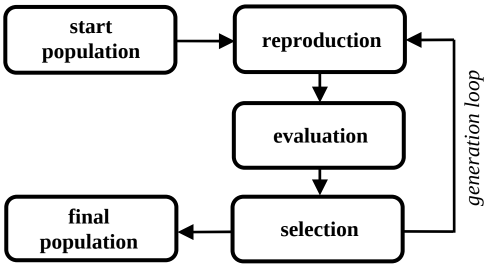


Figure 1. Structure of a Genetic Algorithm (GA)

Similar to natural evolution, also GAs have an iterative structure (figure 1), where the single steps are known as generations. Typically GAs are initialised by creating a start population. This can be done either by random or by using a given set of rough solutions. In the iterative process new individuals are reproduced by mutation (substitution of single gene parts) and cross-over (merging of two or more genes). Finally they are evaluated by the fitness function and only a certain amount of them is selected for the next generation. This is done until either a certain number of generations or a pre-defined termination condition is reached.

GAs are known to be "computationally expensive" and as in nature, also GAs usually can't provide neither perfect nor exact results, but good approximations. This means, that despite GAs are a good choice for complex or unknown problems where other approaches may fail, their application has to be well aimed to benefit from their advantages while minimizing their drawbacks.

2.2 Imperfect Features

Laser scanners are able to create a quite detailed representation of scenes in a fairly short amount of time. However, when working with real-life scenes it might be the case that we need to handle datasets where point density is partly very low or point clouds contain a significant noise level because of the roughness of the surface and/or the limited instrument precision. In other cases datasets can even be fragmentary or partly missing due to unpredictable situations.

Generally a number of scanning stations has to be used to gather a fairly complete representation of an object or a scene. Nevertheless it is useful to keep the number of scanning stations low to safe precious time. By doing so, occlusions - which generally can't be avoided - will arise in an increased quantity either due to the object itself or obstacles between the laser scanner and the object. At the same time also edges and borders which often have a round, bevelled or rough shape may emerge differently when scanning from different stations. Figure 2 shows typical problems in data acquirement which might continuously be encountered during on-site measurements.

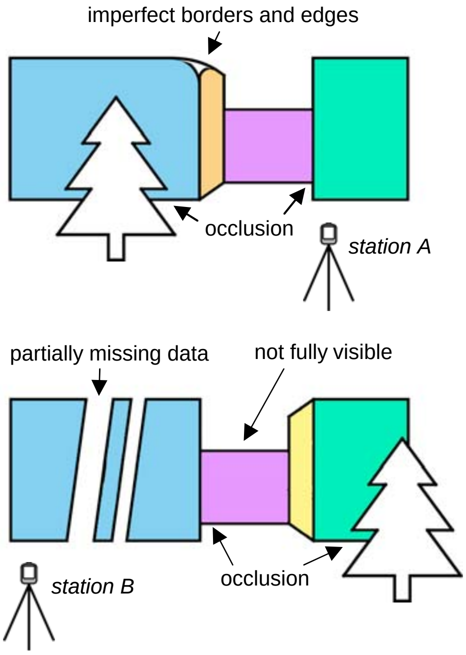


Figure 2. Typical problems in data acquisition

One way to perform the registration of such point clouds is to detect robust features (i.e. planes) inside the scans as they represent a more usable way of handling the original millions of points. But even when using robust features these datasets can still contain a certain amount of inaccuracy; such datasets are referred to as "imperfect" which means that we are able to work with them, but we have to be aware that they might be noisy or in the worst case even misrepresent the original scene.

2.3 Subdivided Features

When working with real-life scenes generally a high number of features can be detected. It can however happen that due to unfavourable circumstances the number of valid feature-correspondences - i.e. when working with larger features such as planes - between the single scans can get rather poor for a correct registration. This might happen if only a small number of features is detectable and matchable in both scans, or features are influenced in some way either by occlusion and noise or simply by imperfect geometry. We propose to subdivide features into smaller subparts and work with those which are not influenced by occlusion and other effects anymore.

In the following the principles of subdivided features are exemplarily demonstrated by using planes; other subdivided features such as cylinders or lines are under development. Basically we are evolving the idea of raster cells (von Hansen, 2007) during coarse registration, and propose further to use the principal directions of the complete planes for their subdivision. We first detect the whole planes and calculate their principal directions. Next we establish a local coordinate system for each plane according to its principal directions and using its barycentre as origin. This coordinate system is then used to subdivide the planes into smaller subparts (figure 3).

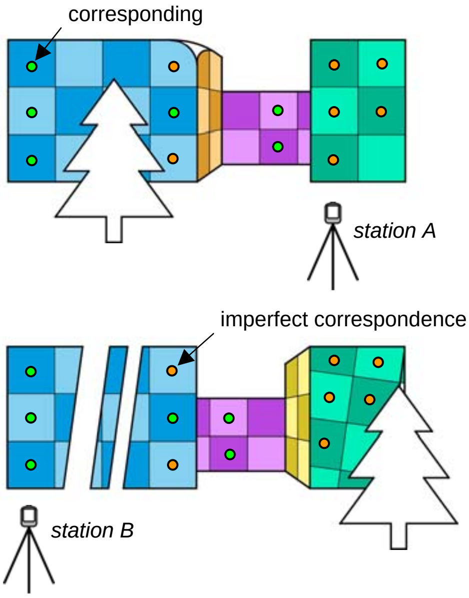


Figure 3. Subdividing and matching the acquired features

One of the main advantages of our approach is that those planes that are fully visible and detectable equally in two or more scans will have corresponding values and barycentres. In other cases, when a plane is not fully visible, partly occluded or contaminated with noise, and also in cases where the principal directions are ambiguous, the subdivision may result in a differing grid. In those cases the sub-planes can be handled the same way as imperfect features (“imperfect correspondence”).

3. REGISTRATION STRATEGY

The here proposed registration method combines and extends the positive aspects of different, already existing and well established methods, and works without artificial targets. It consists of three steps, namely scan analysis, pair-wise matching and multi-view matching.

In the first step all scans are analysed and region growing is used to detect characteristic features (planes) which are then subdivided into smaller sub-features.

Afterwards the pair-wise registration of the single scans is initiated, whereby three steps are subsequently executed. First feature matching with an extension for imperfect and subdivided features is used to find auspicious regions in search space, whereas in the second step a Genetic Algorithm is applied twice: first to reduce and refine the possible solutions using imperfect and subdivided features and in the second run - using the original, but reduced point clouds - to include as much geometric information as possible in the early registration process. The refinement of the solution is done with a classical iterative closest point (ICP) algorithm.

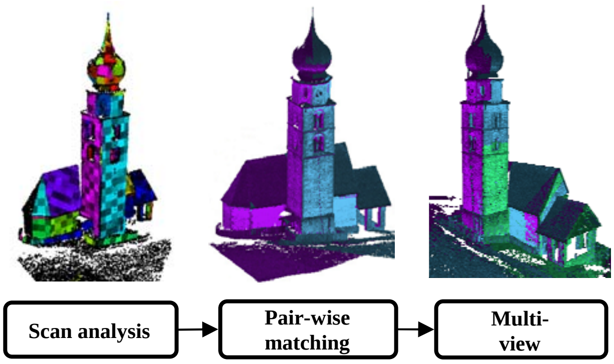


Figure 4. Automatic registration strategy

Finally the so-called multi-view matching is applied to combine the pair-wise matching results to a globally consistent solution. Figure 4 shows the three main steps of our algorithm which was successfully used to register the church of Seis, Italy, captured with a Trimble GX laser scanner.

3.1 Scan analysis

The input datasets for registrations generally consist of an unsorted list of single points and commonly also of intensity or colour information. Our algorithm is applied directly on the point cloud and no additional structure such as a triangulated mesh is necessary. To ensure that the algorithm works almost independently of the object’s size, we adopt the idea stated in Gelfand et al. (2003). The point clouds are scaled uniformly so that the average distance of the points from the mass centre is 1; hereby the global scaling factor is set according to the first analysed scan. This helps to make sure that the registration thresholds are within a certain range. A kd-tree structure is used to efficiently gather the neighbours of each point on the surface, and a principal component analysis (PCA) is used to find the tangent plane and the normal vector in each point. Afterwards the resulting eigenvalues are used for the estimation of the change in geometric curvature called surface variation (Pauly et al., 2003). The surface variation is now used to identify seed points for the surface extraction (planes) through region growing as seen in Vieira and Shimada (2005). Finally the principal directions and the barycentre of each plane are used to create a local coordinate system and to divide the planes into smaller subparts.

3.2 Pair-wise matching

The pair-wise registration of two laser scans can be seen as search problem in six-dimensional space which is typically handled by using a coarse registration method first and an algorithm for fine registration afterwards. As we are working with imperfect features, this classical separation between coarse and fine registration is not recommended; actually in many cases the coarse registration cannot provide the results needed for the following fine registration. Therefore we suggest implementing a third step - in between coarse and fine registration - consisting of Genetic Algorithms (see figure 5).

Our pair-wise matching algorithm starts off with the coarse registration of the point clouds. As Brenner and Dold (2007) show, the number of possible combinations during feature matching can be very high when working with planar surfaces. Generally three pairs of corresponding features with linearly independent normal vectors are necessary to form a solution when working with planes. Sometimes it can be hard to find three planes satisfying these requirements. As mentioned in He et al. (2005) the barycentres of a pair of matching planes can be used for the registration so that only two feature pairs are necessary.

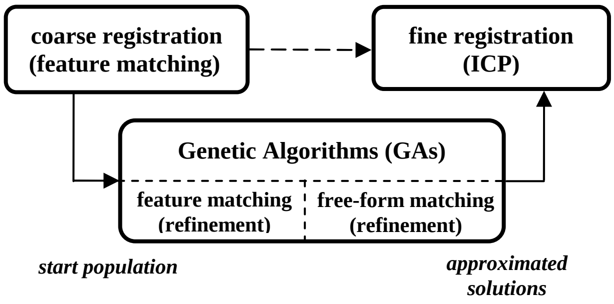


Figure 5. Pair-wise matching strategy using GAs

To keep running times low also when comparing and matching the subdivided features, we apply different checks in the following order: We first use the complete and not subdivided planes to calculate their bounding boxes and the angles between their normal vectors; these are then compared with the planes of the other scan. By doing so a great part of wrong matches can be eliminated before starting to process the subdivided features. In the next step the sub-planes of the remaining possible combinations are compared using the following four invariants (Brunnström and Stoddard, 1996): the barycentres' distances, the pair-wise relative orientations of two normals and an additional twist angle. Further the mean intensities and the surface variations of the sub-features are used to filter combinations with excessive differences. Next we use the idea of topology by Huang (2006) to compare the neighbourhoods of the sub-features. This filtering is especially effective near the borders of complete planes as it enables to roughly check the rotational component of the possible solution. By applying these filters consequently during feature matching, the number of possible solutions can be hold relatively low.

In the next step the possible solutions - resulting from the feature matching process - are supplied as start population to a GA which reduces and refines the results at the same time. Both steps - the feature matching and the GA - profit from each other: the GA is able to correct possible misalignments of the feature matching, whereas the feature matching identifies possible optimums which can then be explored in a more efficient and targeted way by the GA. Following this first GA, we propose to use a second GA doing free-form matching on a reduced form of the original point cloud. Although this step could already be seen as fine registration - i.e. when implementing the Surface Interpenetration Measure as proposed by Silva et al. (2005) - its main aim here is only to include as much geometry as possible in the early registration process to enable the later application of the ICP algorithm.

Typically our GAs run for 50 generations, but both algorithms will terminate earlier if no improvement of the results can be achieved within the last 5 generations. The quality of the solutions is determined by the robust fitness function of Silva et al. (2005); this minimizes the sum of the squared distances between the corresponding points while maximizing the number of inliners. We store a single individual (solution) X_i in the real-coded form of $X_i = (Q_i, T_{ix}, T_{iy}, T_{iz})$, whereby Q_i represents the quaternion of the rotation and T_{ix}, T_{iy}, T_{iz} are the components of the displacement vector.

In each generation new individuals are formed either by creating a mutant (with a 10% probability) or through a cross-over (90% probability). Additional mutation is applied on all new individuals with a 5% probability. These values were selected according to Silva et al. (2005) and according to our own test results. While mutants and mutation force the population to spread out and explore the search space, cross-over is mainly used to concentrate the population in auspicious regions and improve existing solutions. After evaluating all individuals with the fitness function we use a binary tournament, where repeatedly two individuals are randomly selected from the population and - according to their fitness - the better one is selected for the next generation.

In some cases - i.e. when working with symmetric point clouds - more than one correct solution is possible. To handle such cases we combine the first GA with a tabu search. The GA is restarted iteratively with the same start population, but those areas in search space close to the results of previous iterations are banned (tabu). This is repeated as long as solutions with a high quality - determined by the GA's fitness function - can be found or a user-defined maximum of solutions is reached; in our examples that search was limited to five solutions.

Our pair-wise matching algorithm ends with the refinement of the gathered solutions based on the well-known iterative closest point (ICP) algorithm proposed by Besl and McKay (1992), and by Chen and Medioni (1992). To improve robustness and stability of the algorithm we use the geometrically more stable version of Gelfand et al. (2003).

3.3 Multi-view matching

A lot of research has been done in multi-view matching, also known as multi-piece matching (Huang et. al, 2006). Similar to Pulli (1999), we take the pair-wise matching results and order them according to their quality. To improve the search for a globally correct solution we further apply the visibility-consistency approach of Neugebauer (1997); this approach is also used by Huber and Hebert (2003) to ensure that only globally consistent pair-wise matching results are used for the final reassembling. The best matching pair is fixed and iteratively another view is added to the fixed set. In every iteration step the already fixed views are realigned to ensure a globally consistent solution.

4. EXPERIMENTAL RESULTS

To prove the potential of our registration strategy (GAReg-ISF) we processed a number of real-life scenes. In this paper we mainly focus on the automatic registration of terrestrial laser scans in the fields of archaeology as they typically do not consist of classical geometric features such as planes. Other examples such as the pair-wise registration of Agia Sanmarina church in Greece can be found in Schenk and Hanke (2009).

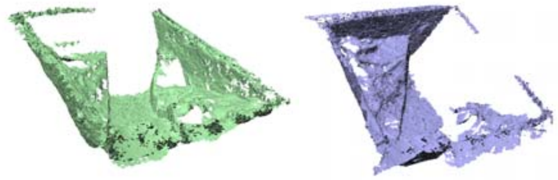
The scans were neither pre-processed nor ordered accordingly to their neighbourhood relationship. Feature detection, feature subdivision and the final ICP were carried out with a random subset of 100,000 points which increased the effect of "imperfectness"; 3,000 points were used in the second Genetic Algorithm for free-form matching. Since archaeological scans generally do not consist of "perfect" planes we increased the thresholds in plane detection. In both our test datasets we tried different sizes of subdivided planes. The tests however showed that the size of the subdivided features does not directly influence the results as long as at least some corresponding imperfect and subdivided features can be found; the quality of the final solution rather depends from the ICP used in the pair-wise and multi-view matching.

4.1 Archaeological excavation in Austria

To test the capabilities of our algorithm we applied it to a dataset documenting an archaeological excavation in Austria; the dataset includes four scans captured with a Trimble GX scanner (see figure 6).

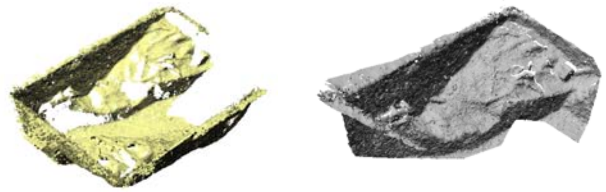
In 2007 and 2008 - in the frame of the Special Research Program HiMAT (an interdisciplinary research project dedicated to the history of mining in Tyrol and adjacent areas, sponsored by the Austrian Science Found) - archaeological investigations have been conducted in a prehistoric mining landscape in the lower Inn Valley, Austria. In this region intensive copper ore mining took place during the Middle European Late Bronze Age (1200 - 800 BC). From this period numerous traces of underground mining, mineral processing and ore smelting have been located by archaeological prospection (Hanke, 2007).

The approach was to provide a kind of "permanent care" surveying team in place at the excavation for about 5 weeks to guarantee a 3D documentation of the process at any time. In summer 2007 a first field was excavated and in 2008 the neighbouring four places followed. The size of a single excavation field varied from about 4 to 5 m by 3 to 4 m with a depth of 0.5 to almost 2 m. The data acquisition was realized by a Trimble GX laser scanner with at least 4 stations for a single field. The average density of the point cloud was about 5 mm at a distance of 4 m. Up to 3 different archaeological layers per field have been recorded.



Scan 1
1,370,711 points

Scan 2
1,227,283 points



Scan 3
1,360,906 points

Scan 4
579,645 points

Figure 6. Four single scans of the excavation (meshed)

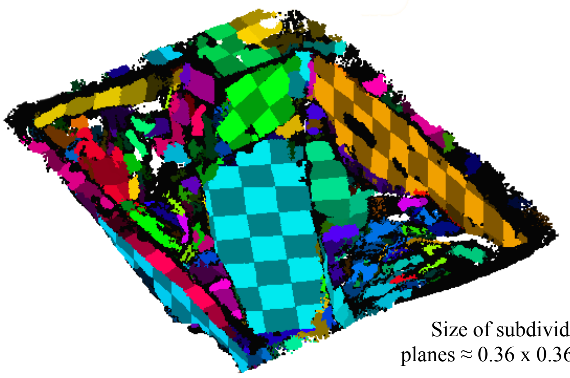


Figure 7. Subdivided features of one single scan

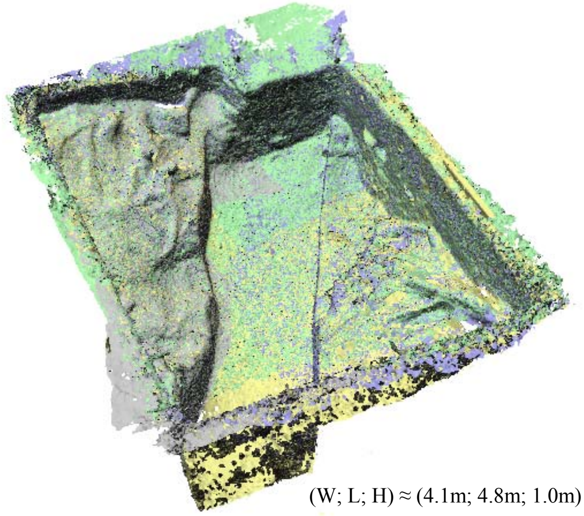


Figure 8. Multi-view matching result (meshed)

As seen in figure 7 the single scans were analysed, and the detection and subdivision of features were used to describe characteristic areas in each scan. Afterwards pair-wise and multi-view matching was applied to reassemble all scans as shown in figure 8.

We compared the results of the target referencing method - using artificial target spheres - with our registration method (GAReg-ISF) which utilises the geometric information of the point clouds itself. The first method directly uses the known centres of the artificial target spheres for a registration, whereas in the second approach the best transformation parameters were calculated by the GAReg-ISF algorithm - relaying on the point clouds itself - and were only afterwards applied to the same spheres as in the first approach.

Table 1 shows the centres' coordinates of the used spheres after the registration as well as their mean values and the standard deviation of each method. Further the spatial discrepancy between the mean sphere centres of both methods was provided to give quantitative information about their actual difference. It is important to mention in this context that the results are correlated; the scanned (unregistered) spheres contain already a certain amount of error due to the measurement itself and/or the limited instrument precision (see deviation in column "target referenced"). Although the registration parameters of GAReg-ISF are not influenced directly - as the algorithm works on the object's point clouds and not on the spheres - the mentioned error is introduced when applying its results to the unregistered sphere coordinates for comparison.

Centre of sphere 1						
Scan	**target referenced**			**GAReg-ISF**		
	X [mm]	**Y [mm]**	**Z [mm]**	**X [mm]**	**Y [mm]**	**Z [mm]**
1	7489.7	-4271.5	3744.9	7489.7	-4271.5	3744.9
2	7490.4	-4272.2	3745.0	7489.0	-4272.6	3746.9
4	7490.4	-4271.7	3745.8	7488.8	-4273.0	3745.5
mean	**7490.2**	**-4271.8**	**3745.2**	**7489.2**	**-4272.4**	**3745.8**
std. dev.	**0.4**	**0.4**	**0.5**	**0.5**	**0.8**	**1.0**
sphere 1: spatial discrepancy of the solutions: 1.3 mm						
Centre of sphere 2						
1	7902.3	-1688.0	3877.8	7902.3	-1688.0	3877.8
2	7901.4	-1687.9	3878.8	7900.5	-1688.4	3881.7
3	7904.4	-1686.4	3879.6	7905.4	-1684.0	3882.7
4	7902.0	-1688.2	3878.4	7900.2	-1689.6	3880.4
mean	**7902.5**	**-1687.7**	**3878.6**	**7902.1**	**-1687.5**	**3880.6**
std. dev.	**1.3**	**0.8**	**0.8**	**2.4**	**2.4**	**2.1**
sphere 2: spatial discrepancy of the solutions: 2.1 mm						
Centre of sphere 3						
1	6264.9	-7304.0	2930.7	6264.9	-7304.0	2930.7
2	6266.0	-7304.2	2929.7	6263.8	-7303.9	2930.5
4	6265.1	-7303.1	2929.4	6264.5	-7303.9	2925.5
mean	**6265.3**	**-7303.8**	**2929.9**	**6264.4**	**-7303.9**	**2928.9**
std. dev.	**0.6**	**0.6**	**0.7**	**0.6**	**0.1**	**2.9**
sphere 3: spatial discrepancy of the solutions: 1.4 mm						
Centre of sphere 4						
1	-1087.4	-8361.4	-888.3	-1087.4	-8361.4	-888.3
2	-1087.4	-8361.0	-887.1	-1090.0	-8357.5	-886.7
3	-1089.1	-8360.0	-888.6	-1087.7	-8357.6	-886.1
mean	**-1088.0**	**-8360.8**	**-888.0**	**-1088.4**	**-8358.8**	**-887.0**
std. dev.	**0.9**	**0.7**	**0.8**	**1.4**	**2.2**	**1.1**
sphere 4: spatial discrepancy of the solutions: 2.2 mm						
Centre of sphere 5						
3	4271.1	1969.7	1874.1	4273.2	1972.1	1875.2
4	4272.4	1971.6	1874.5	4272.8	1971.6	1875.1
mean	**4271.8**	**1970.7**	**1874.3**	**4273.0**	**1971.8**	**1875.2**
std. dev.	**1.0**	**1.3**	**0.3**	**0.2**	**0.4**	**0.1**
sphere 5: spatial discrepancy of the solutions: 1.9 mm						

Table 1. Comparison of target referencing and GAReg-ISF

The resulting values of table 1 show that the spatial discrepancy between both solutions reaches a maximum of 2.2 mm. GAReg-ISF generally produces slightly higher standard deviations but sometimes also lower values (see target sphere 5) compared to the target reference method. One possible explanation for the higher standard deviations is the fact that only the limited amount of 100,000 points was used during the whole registration process (including the ICP algorithm) with GAReg-ISF. This corresponds approximately to 1/5 - 1/13 of the original number of points. Despite - or perhaps because of - that the results can be considered remarkable and encourage further researches.

4.2 Part of the cave in Mauken, Austria

Another dataset (see figure 9) we tested GAReg-ISF on is the dataset of a 30 meters deep prehistoric mining cave in Mauken, Austria, originating from the same project as the one above. The aim was on the one hand to document the geometric form of the cave, its development and the outstanding mining traces on its surface. On the other hand the archaeologists again needed a continuous multi-layer documentation about their excavation process of the underground mining procedure.

As for the limited vertical field of view of our Trimble scanner and the constrictive space available in the cave we faced the challenge to have at least 3 to 4 target spheres within each scan to guarantee the registration between them. This cost us a lot of additional time working in a dark, demanding and hostile environment.

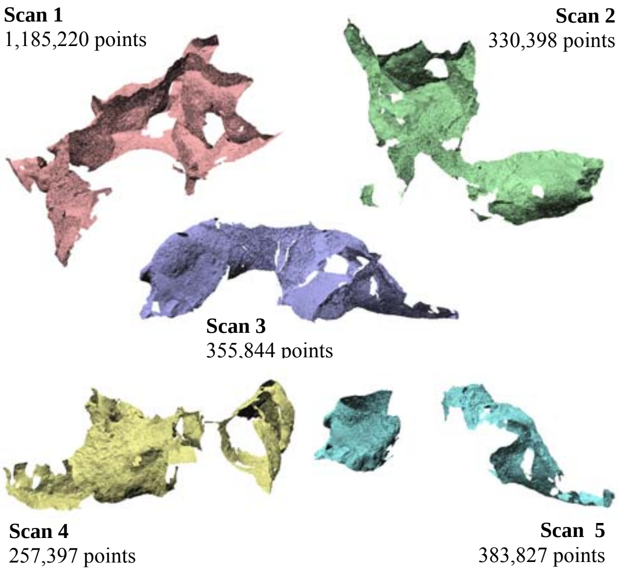


Figure 9. Five single scans of the cave (meshed)

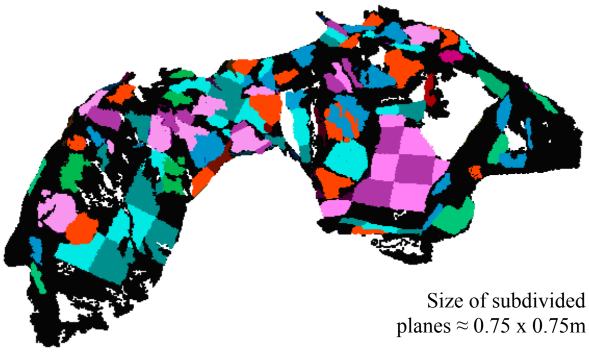


Figure 10. Subdivided features of scan 3

Contrary to the above presented excavation, the cave does only provide limited possibilities for the application of feature subdivision but the more for the use of imperfect features (see figure 10). Although the rough surface of the cave would suggest decreasing the size of subdivision we - on the contrary - increased the size to test the capabilities of the algorithm.

For sure the here presented algorithm is mainly suited for architectonical environments and objects consisting of classical features such as planes. Nevertheless also the comparison of the cave's results suggests that the algorithm has great capabilities - especially when implementing more and different kinds of features such as cylinders or even quadrics.

Scan	**target referenced**			**GAReg-ISF**		
	X [mm]	**Y [mm]**	**Z [mm]**	**X [mm]**	**Y [mm]**	**Z [mm]**
Centre coordinates of sphere 1						
1	-3784.5	-1180.6	504.7	-3784.5	-1180.6	504.7
3	-3782.8	-1180.9	505.4	-3784.0	-1181.3	505.5
4	-3783.2	-1181.6	505.2	-3783.8	-1182.1	505.0
5	-3782.4	-1181.9	505.5	-3784.4	-1182.2	505.9
mean	**-3783.2**	**-1181.2**	**505.2**	**-3784.2**	**-1181.6**	**505.3**
std. dev.	**0.9**	**0.6**	**0.4**	**0.3**	**0.8**	**0.5**
sphere 1:	**spatial discrepancy of the solutions: 1.0 mm**					
Centre coordinates of sphere 2						
1	-3051.3	1630.2	1097.7	-3051.3	1630.2	1097.7
2	-3051.1	1632.1	1097.6	-3049.9	1633.0	1096.9
3	-3050.4	1627.6	1097.6	-3051.5	1626.9	1099.4
4	-3050.1	1628.2	1097.8	-3051.3	1627.5	1098.7
mean	**-3050.7**	**1629.5**	**1097.7**	**-3051.0**	**1629.4**	**1098.2**
std. dev.	**0.6**	**2.1**	**0.1**	**0.8**	**2.8**	**1.1**
sphere 2:	**spatial discrepancy of the solutions: 0.6 mm**					
Centre coordinates of sphere 3						
1	2178.6	-1543.4	1067.8	2178.6	-1543.4	1067.8
2	2175.3	-1542.9	1067.9	2175.8	-1543.1	1069.3
5	2173.6	-1544.2	1068.1	2171.3	-1546.8	1070.3
mean	**2175.8**	**-1543.5**	**1067.9**	**2175.2**	**-1544.4**	**1069.2**
std. dev.	**2.6**	**0.7**	**0.1**	**3.7**	**2.0**	**1.2**
sphere 3:	**spatial discrepancy of the solutions: 1.6 mm**					
Centre coordinates of sphere 4						
1	-1636.0	-2662.0	1226.3	-1636.0	-2662.0	1226.3
2	-1635.2	-2663.3	1226.0	-1634.9	-2662.6	1227.5
3	-1636.4	-2659.6	1225.8	-1638.6	-2660.7	1227.2
4	-1636.3	-2659.5	1225.9	-1637.2	-2660.0	1226.2
5	-1635.1	-2660.0	1225.6	-1637.9	-2661.0	1227.0
mean	**-1635.8**	**-2660.9**	**1225.9**	**-1636.9**	**-2661.3**	**1226.8**
std. dev.	**0.6**	**1.7**	**0.3**	**1.5**	**1.1**	**0.6**
sphere 4:	**spatial discrepancy of the solutions: 1.5 mm**					

Table 2. Comparison of target referencing and GAReg-ISF

Table 2 reveals that the discrepancy between the target reference method and GAReg-ISF reaches a maximum of 1.6 mm in this example. The close results show that the concept of combining Genetic Algorithms with imperfect and subdivided features for the coarse registration of laser scans is well working; further improvements may be achieved by enhancing the multi-view matching and using the complete point cloud for the refinement. Figure 11 shows an external view of the cave after the multi-view matching as well as a horizontal and a vertical section.

CONCLUSION

A method for the automatic registration of point clouds without artificial targets was proposed in this paper. Our approach can be seen as improvement to the state of the art as it combines the positive aspects of different already well studied methods such as feature matching and the application of Genetic Algorithms (GAs). By combining their positive aspects and using them in a targeted and efficient way we were well able to perform the automatic registration of partially occluded point clouds characterized by a significant noise level and imperfect geometry.

Among our key concepts is the idea to strictly accept a certain amount of inaccuracies ("imperfectness") in our datasets and features, and to generate a registration framework capable to handle them. The subdivision of features into smaller sub-features allows overcoming occlusion and, together with the implementation of GAs as clearly targeted steps in between classical coarse and fine registration, increases both robustness and computational performance also when registering objects of bigger size.

Our examples show that the approach of subdivided features is not only applicable to scenes consisting of classical geometric primitives such as planes (as in most architectural applications); due to the extension to imperfect features also scenes consisting of approximated features are handable. We are currently working on implementing more features such as spheres, cylinders and lines.

Even though the presented method is still under development, it again showed a great potential in all our tested datasets.

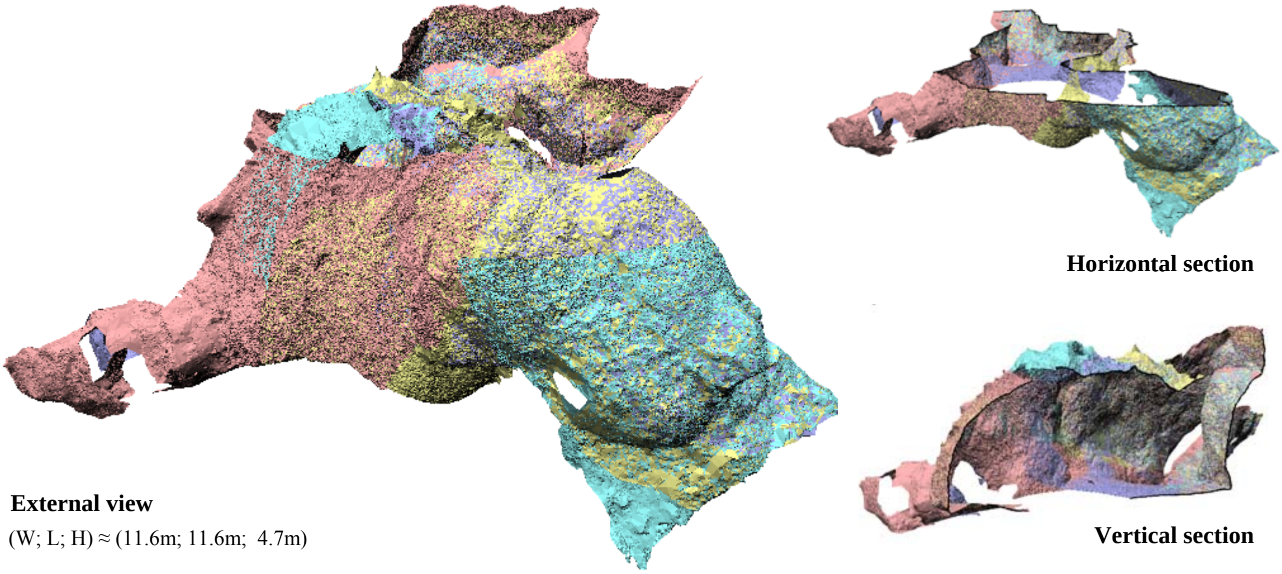


Figure 11. External view of the registered scans (meshed) and a horizontal and vertical section

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