AUTOMATIC TARGET IDENTIFICATION FOR LASER SCANNERS

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ABSTRACT:

Terrestrial laser scanners are becoming increasingly important for many fields of imaging applications, providing a great amount of 3D positional information in a fast and efficient way. This information is always expressed by means of coordinates in a somewhat random 3D space defined by the scanner orientation, which changes whenever the scanner is moved. Therefore, targets are usually employed either for registration (i.e. for the referencing of the data in a common 3D space) or for referencing of the data into a local coordinate system.

The use of targets for these purposes is a standardized process, which is invariably carried out by proprietary software. However, the algorithms used for the identification of targets (i.e. automated definition of the centre of the target) are not described by the software vendors. In this paper, methods for automating target identification which are based on fuzzy classification, gridding and averaging techniques are presented. Experiments are conducted using a Cyrax 2500 terrestrial laser scanner in laboratory conditions. The performance of the proposed methods is compared and assessed with reported methods from published literature. Furthermore, given the fact that due to reflectance topographic artefacts are observed on the surface of the reflective targets, experiments are also conducted for different scan angles and distances.

1. INTRODUCTION

Terrestrial laser scanning allows for detailed and precise documentation of objects of interest. In practice, collection and processing procedures are adapted to the type of application (e.g. use of different resolutions, acquisition of multiple, overlapping scans from different distances, points of view). However, regardless of the application (e.g. conducting metrological experiments, registering multiple scans, referencing the position of the data in a given coordinate system etc.), automatic target identification is a matter of great significance. Therefore, the need for a reliable and precise algorithm that identifies targets automatically is important. In this paper, the capabilities of a current commercial laser scanner system (Cyrax 2500) regarding target identification are explored and several new methods for automatic target identification are presented.

The second section of the paper gives a brief overview of the Cyrax 2500 system and presents two experiments conducted for evaluation of the repeatability of collected data from multiple scans. In the third section, the way that target centres are determined using the Cyclone software is described along with several methods for target identification proposed in published literature. The properties of the reflective targets are thoroughly examined and new algorithms for target identification are described. In the final section, experiments conducted to evaluate the stability, reliability and accuracy of the proposed methods are described and comparative results are presented.

2. SYSTEM OVERVIEW AND REPEATABILITY CHECK

The experiments presented in this paper were all conducted using a Cyrax 2500 laser scanner. The instrument has a field of view of 40^o by 40^o, and operates with a green laser beam of 532nm. The spot size is less than 6mm for distances up to 50m, distances are measured with an accuracy of ± 4mm and the angles are measured with an accuracy of ± 60micro-radians. The accuracy in the position of single points is, according to the manufacturer, approximately ± 6mm for distances that range between 1.5m – 50m. The scan rate is very high, namely 1000 pts/second. The system is operated using a laptop and the processing of the data can be carried out using the Cyclone software suite (www.cyrax.com).

Measurement repeatability is a very important property for a laser scanner system. In order to evaluate this property for the Cyrax 2500 system, two experiments were conducted. The former involved scanning four targets mounted on four pillars of the internal EDM calibration baseline of NTUA. The latter involved the scanning of five targets placed on a wall.

For both cases, nine scans were collected for each one of the targets. The collected data were exported into an ASCII format which contains the cartesian coordinates in the scanner's system along with the signal strength (reflectivity) for each point in the scan. The selection of the target image from each point cloud was performed through the proprietary Cyclone software.

Table 1: Results for repeatability check for the case of the baseline targets

	Standard deviation of mean position (m)			Standard deviation of position of radiometric centre (m)				Mean of absolute differences (m)		
target	X	Y	Z	Xrad	Yrad	Zrad	Rmean	(DX)	(DY)	(DZ)
1	2.30E-04	4.41E-05	3.35E-04	2.00E-04	1.56E-04	4.03E-04	1.34E+00	0.0007	0.0004	0.0010
2	8.33E-05	8.33E-05	2.73E-04	7.26E-05	1.41E-04	3.00E-04	1.30E+00	0.0006	0.0007	0.0007
3	8.33E-05	1.13E-04	1.05E-04	1.20E-04	2.60E-04	1.48E-04	1.89E+00	0.0007	0.0006	0.0015
4	2.19E-04	2.11E-04	2.00E-04	3.69E-04	3.10E-04	2.15E-04	4.27E+00	0.0004	0.0013	0.0024
mean	1.54E-04	1.13E-04	2.28E-04	1.90E-04	2.17E-04	2.67E-04	2.20E+00	0.0006	0.0007	0.0014

Table 2: Results for repeatability check for the case of the targets on the wall

	Standard deviation of mean position (m)			Standard deviation of position of radiometric centre (m)				Mean of absolute differences (m)		
target	X	Y	Z	Xrad	Yrad	Zrad	Rmean	(DX)	(DY)	(DZ)
1	5.16E-05	1.43E-04	4.83E-05	4.83E-05	5.16E-05	8.76E-05	1.46E-01	0.0127	0.0124	0.0038
2	1.40E-08	8.76E-05	3.16E-05	0.00E+00	4.71E-05	5.27E-05	1.37E-01	0.0091	0.0007	0.0024
3	4.22E-05	1.49E-04	4.71E-05	3.16E-05	1.43E-04	1.05E-04	2.29E-01	0.0033	0.0099	0.0021
4	0.00E+00	9.49E-05	7.89E-05	4.83E-05	6.75E-05	1.06E-04	2.22E-01	0.0086	0.0070	0.0022
5	3.16E-05	1.14E-04	8.23E-05	4.22E-05	5.68E-05	9.94E-05	4.10E-01	0.0099	0.0068	0.0019
mean	2.51E-05	1.18E-04	5.77E-05	3.41E-05	7.32E-05	9.02E-05	2.29E-01	0.0087	0.0074	0.0025

In each scan, the mean X, Y and Z values were calculated for each of the targets. Also, in order to evaluate the repeatability of the reflectivity, the mean value and standard deviation were calculated. Another part of the process was the calculation of the radiometric centre of each target i.e. the weighted mean X, Y and Z values, using the reflectivity as a weight. Using the derived mean values, the standard deviation was calculated for each one of the targets. Furthermore, in order to see how the use of reflectivity values implemented in the calculations affects the results, the mean absolute difference of the mean and the weighted mean values were calculated in each case. These calculations, though fairly simple, provide an efficient way to evaluate the repeatability.

Table 1 shows the results from the target data collected at the baseline. In Table 2 the results for the case of the targets on the wall are given. The small standard deviation in both cases indicates that the repeatability of the scans is very high. Regarding the mean absolute differences, in the first case they appear to be rather small. This can be attributed to the fact that the acquired point clouds for each one of the targets were trimmed before any computations, so that the remaining points would describe only the target. However, this was not the case for the targets on the wall. The whole area that was scanned for each one of the targets was exported. This resulted in differences of a few millimetres, especially along the X and Y directions.

The above results indicate that the repeatability of the measurements is very high and that the reflectivity should definitely be used in order to identify the centre of the target.

3. ALGORITHM PRESENTATION

When Cyrax retroreflective targets are available, it is possible to define the position of their centres using the proprietary software. However, this is possible only during the data collection stage because of the way that this process is implemented. Specifically, the scanner acquires the data needed for defining the centre of the target after the user has selected a point near the actual centre of the target using the viewer of the software. The scanner then performs a dense scanning around the depicted position. A grid of 38x38 points is created and the centre of the target is defined using these data. The density of the scan data at this stage is found to be of approximately 1mm. However, the way that the centre of the target is defined remains unknown.

Although not very well documented, the topic of automatic target identification has been previously addressed in the literature (Gordon et al., 2001; Lichti et al., 2000)]. In Lichti et al. (2000) three different methods are described. The first defines the centre of the target as the position with the maximum radiance. The second defines the centre by the mean position of the radiometric centre of the 4 strongest returns. The third algorithm defines the centre of the target as the radiometric centre of all returns. These methods will be referred to henceforth as ‘maxrad’, ‘maxrad4’ and ‘radcent’, respectively. In the following experiments, these methods will be applied and used for comparison purposes with the new developed methods.

All the aforementioned methods have significant flaws that are not mentioned in the literature. The methods ‘maxrad’ and ‘maxrad4’ often fail because the position with maximum signal strength does not always correspond to the actual centre of the target. This is clearly shown in Figure 1 which shows part of a target with three different markers indicating the position of the centre as calculated using each of the three aforementioned algorithms. The red points correspond to points of the target with a relatively large value of reflectance. They also show the topographic artefacts that are observed for the highly reflective areas of a target. In Figure 1a, a front view of the target and the calculated centres is given, whereas in Figure 1b, the same target is presented from a different angle for visualisation purposes.

In both figures, the ‘maxrad’, ‘maxrad4’ and ‘radcent’ positions of the centre are indicated in black, green and blue respectively. It is obvious that the ‘radcent’ algorithm has the best performance in this case. This was also confirmed by several experiments that were conducted and will be presented in the following section.

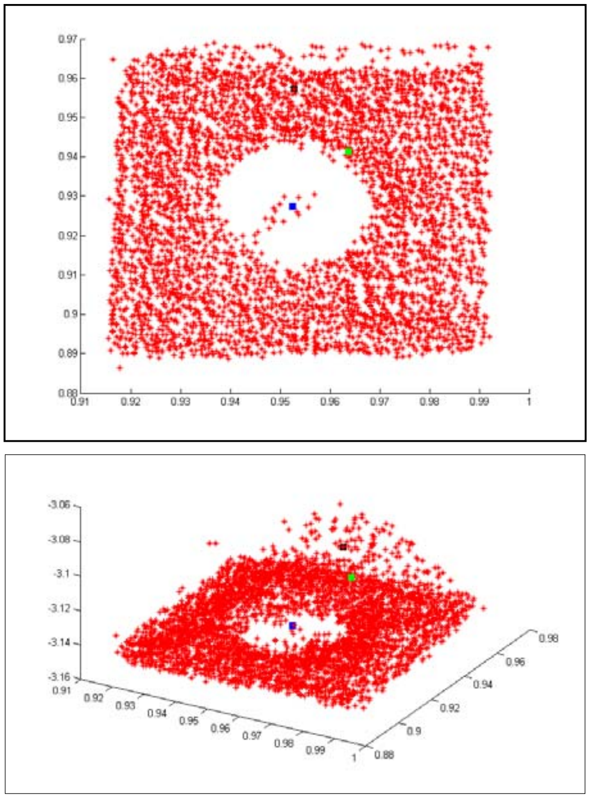

Figure 1: a) Front view of a target. b) The same target viewed from a different angle. In both cases, only the points of the target that correspond to highly reflective areas are presented for visualisation purposes. The maxrad, maxrad4 and radcent calculated positions of the centre are indicated in black, green and blue respectively.

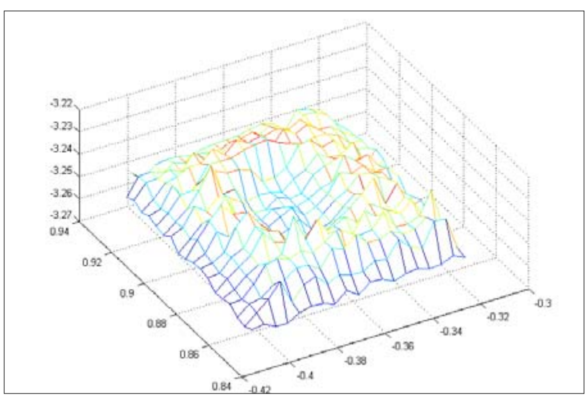

Figure 2: Surface model for a reflective target.

Thorough examination of several targets has revealed that the parts of the data that correspond to the highly reflective areas of the target are quite noisy. Several points seem to deviate from the surface of the target introducing topographic artefacts. On the other hand, this phenomenon does not occur in areas of lower reflectance. This is visible in Figure 2, where a model of the surface of the target is presented. Therefore, in order to determine the centre of the target as precisely as possible, it is critical to classify the points of the point cloud according to their reflectance. This is considered to be the key to precise automatic target identification, because classifying based on reflectance allows for thorough examination of the properties of the target. Knowing the properties of the target is a very good basis for developing more sophisticated methods of target identification.

Given the fact that reflectance varies according to the distance between the scanner and the target and according to the angle by which the target is viewed, it is very difficult to model the reflectance. Therefore, classification of the data using thresholds cannot be a solution. Other forms of classification, which require the user to give training data, are also considered inappropriate, as this would lead to a semi-automatic solution. A method that would classify the data into the desired categories without any input from the user is required. One such method is the fuzzy clustering technique.

Clustering of numerical data forms the basis of many classification and system modelling algorithms. The purpose of clustering is to identify natural groupings of data from a large dataset so as to produce a concise representation of a system's behaviour. Therefore, this kind of processing is ideal for the case of targets. In order to create the fuzzy clusters, the Fuzzy Logic Toolbox of Matlab was used.

Fuzzy c-means (FCM) is a data clustering technique wherein each data point belongs to a cluster that is, to some degree, specified by a membership grade. This technique was originally introduced by Bezdek (1981) as an improvement on earlier clustering methods. It provides a method that shows how to group data points that populate some multidimensional space into a specific number of different clusters. The Fuzzy Logic Toolbox command line function 'fcm' starts with an initial guess for the cluster centres, which are intended to mark the mean location of each cluster. The initial guess for these cluster centres is most likely incorrect. Additionally, fcm assigns every data point a membership grade for each cluster. By iteratively updating the cluster centres and the membership grades for each data point, fcm iteratively moves the cluster centres to the "right" location within a data set. This iteration is based on minimizing an objective function that represents the distance from any given data point to a cluster centre weighted by that point's membership grade. The output of the 'fcm' command line function is a list of cluster centres and several membership grades for each data point. Before describing the new algorithms that were developed, it is useful to give an example of the way that fuzzy clustering can substantially aid in data interpretation for the case of the targets.

The 'fcm' function is used to group the points of a target into three classes based on their reflectance. One class comprises the points of high reflectance, the second class consists of the points of low reflectance and the last class consists of the points of moderate reflectance. In Figure 3, a single target is shown from two different scan angles. The points that belong to the first class are depicted in red, the points of the second class are depicted in blue, and the remaining points are shown in green. The first image of Figure 3 presents the target scanned with the z-axis of the scanner system forming an angle of 90^o degrees with the surface on which the target belongs. In the second image this angle is 45^o degrees.

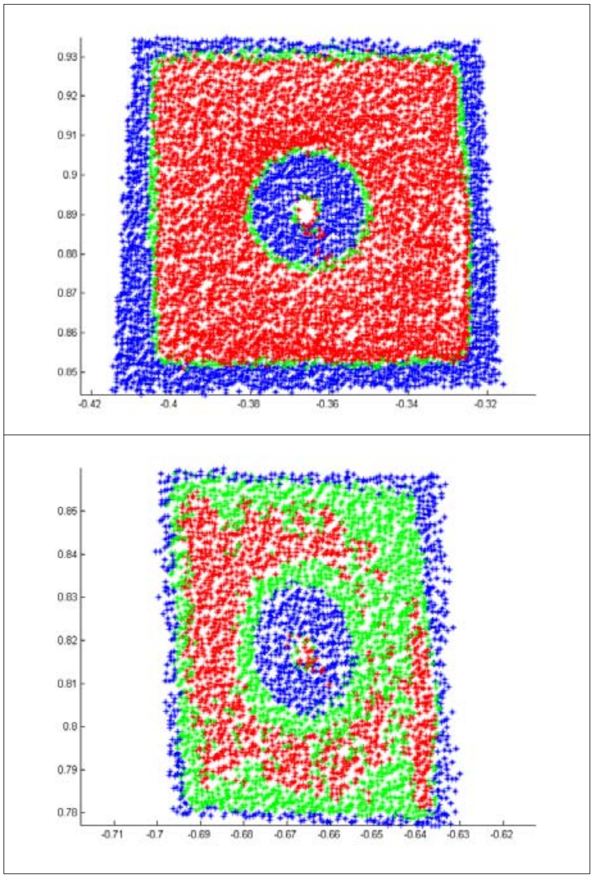

Figure 3: A single target scanned from different positions. The angle that is formed by the z-axis of the scanner and the surface on which the target belongs is 90^{o} for the first and 45^{o} for the second image respectively.

For targets scanned with the scanner facing directly the surface on which the targets belong, a rather strong pattern appears. All points are classified in the correct classes. When the scanning angle increases, the classes of higher and medium reflectance appear to get confused. Furthermore, the points that belong to these classes are distributed unevenly. This indicates that the results of the ‘radcent’ algorithm will be poorer, due to the fact that the weighting will be forcing the centre of the target towards the centroid of the class that consists of the points with the highest reflectance.

Another interesting aspect is that the class that consists of the points with low reflectivity presents the same behaviour in all cases. Taking all of these into account, two algorithms were developed.

The first algorithm is named ‘fuzzypos’. The initial step for this algorithm is to classify the points of the target according to their reflectivity. Using the ‘fcm’ function, it is required that all points are classified into three classes. After classification is completed, the classes are recognized by calculating the mean value of the points that are assigned to each one of them. Finally, the coordinates of the centre of the target are derived by simply calculating the mean position using the two clusters with the largest mean reflectivity values. This process yields substantially better results than the ‘radcent’ algorithm, as no weighting occurs. In this case, weighting is redundant because the two classes that are used cover the whole reflective area of the target.

The second algorithm, named ‘fuzzyposfine’, uses initially the ‘fuzzypos’ algorithm to calculate the centre of the target. Afterwards, a plane is fitted on the surface of the target and using the parameters of the plane, the ω and φ rotations of the surface are calculated. The origin of the system is transferred to the calculated centre of the target, and the rotations are applied in order to transform the points of the target to the XY-plane of the new system. Then, a square area of 5cm x 5cm centered at the origin of the new system is selected and only the data contained in that very area are used hereafter. The classification process is repeated, and the points that belong to the class with the lowest mean reflectance value are used for estimating the centre of the target. This class has been found to correspond to the circular area of low reflectance, which surrounds the centre of the target. By calculating the centre of this cluster and transforming back to the original system, the coordinates of the centre of the target are derived. These algorithms may seem rather complex but the quality of the results is significantly better than any other seen in the literature. This is confirmed by the experiments presented in the following section.

Two more groups of algorithms were developed using grid and tin surface models. The first group is based on gridding. Using the Matlab function griddata, a grid is created for the target using the coordinates of the points of the point cloud. In order to achieve better results, the data are statistically processed for the noise to be removed. Specifically, a plane is fitted on the surface of the target and the standard deviation of the distance between the points and the surface is calculated, but only the points that are within ± 1.96 σ (95% level of confidence) from the calculated surface are kept. The spacing of the grid is set to 5mm and the surface model of the target is created. Using the grid, a model for the reflectance is also calculated. Using the two grids, two algorithms were created. The first one is named ‘gridrad’ and calculates the centre of the target in the same way the ‘radcent’ algorithm does, by using the information of the two grids. The second algorithm is named ‘fuzzygridrad’ and applies the ‘fuzzypos’ algorithm for the data of the grid. The second group of these algorithms is based on delaunay triangulation. The two new algorithms are named ‘delrad’ and ‘fuzzydelrad’ and the only difference to the previous ones is the model used.

4. EXPERIMENTS AND RESULTS

Several experiments were conducted to evaluate the performance of the new algorithms and compare it with the performance of the algorithms mentioned in literature. In particular, two series of experiments were designed and conducted. The first series, involved scanning several targets that were mounted on the pillars of the EDM internal calibration baseline at NTUA. Multiple scans of the targets were obtained from two positions. The second series involved the scanning of five targets that were mounted on a wall. The scanning in this case was carried out from various distances and angles. The data collected for both cases were subdued to processing in order to evaluate both the internal and external accuracy of the results produced by the aforementioned algorithms.

For the first series of experiments, four targets mounted on the pillars of the EDM calibration baseline were scanned. The targets were placed at various distances that ranged from 3m to 25m. The scans of the same targets were collected from two different positions, A and B. At position A, four scans of 1mm spacing were acquired along with a fine scan for each one of the targets. At position B, nine scans of 1mm spacing and a fine scan for each one of the targets were collected.

For the A position, the centres of the targets were calculated using the fine scans, a single and four merged scans. For the B position, the centres of the targets were also calculated for nine merged scans. In both cases, using the coordinates of the targets as derived from the fine scans as reference, and the coordinates of the targets that were calculated for the other datasets of the same position, the transformations were calculated. Also, the mean absolute error was derived in order to evaluate the internal accuracy of the algorithms. The results are summarized in Table 3. Clearly, the performance of the 'fuzzyposfine' algorithm is superior.

This is also confirmed by the results presented in Table 4. These results were derived using data from the second series of experiments. Five targets that were mounted on a wall were scanned 10 times each from a distance of approximately 5m with the scanner facing directly the targets. For each one of the targets a broad area containing the target was scanned. In order to create the reference dataset, a single scan for each one of the targets was used. For the reference dataset, the data were trimmed so as to contain only the target. The other data were exported as collected (along with the area that was surrounding the target). Three datasets were created using a single, four merged and nine merged scans for each one of the targets. The 'fuzzypos' and 'fuzzyposfine' algorithms once again perform better, indicating that these algorithms have a very high internal accuracy. The results of the 'fuzzygridrad' and 'fuzzydelrad' algorithms are also quite satisfactory in both cases.

The second part of the results refers to the evaluation of the external accuracy of the algorithms. In the results to be presented, both single and multiple scans collected from different positions of the scanner are used.

For the case of the targets of the EDM baseline, the process of calculating the mean absolute error was carried out using the fine scan, a single scan and four merged scans from positions A and B. Additionally, using the fine scans, the centres of the targets were determined using the Cyclone software and the registration process was carried out for the data that were selected from the two positions of the scanner. The mean absolute error of the transformation as derived by the Cyclone software was 1mm. This value is used later on for the evaluation of the algorithms.

In Table 5, the results for the evaluation of the external accuracy of the algorithms are presented. In this case, using the fine scans, only the 'fuzzyposfine' algorithm gives a Mean Absolute Error equal to that of the Cyclone software. Additionally, using the other datasets, the results yielded by this algorithm are better than 1mm (i.e. 0.7mm for single scan datasets and 0.8mm for datasets of four merged scans).

Table 3: Internal accuracy evaluation experiment (1)

DATA	Mean Absolute Error (mm)					Mean Error (mm)
	Position A		Position B			
	1sc	4sc	1sc	4sc	9sc	
radcent	1.2	1.2	0.8	0.6	0.6	0.9
maxrad	16.8	17.4	13.2	9.2	9.4	13.2
maxrad4	14.0	14.5	13.7	13.1	14.7	14.0
fuzzypos	0.7	0.7	0.6	0.4	0.4	0.6
fuzzyposfine	0.6	0.6	0.5	0.2	0.1	0.4
gridrad	1.0	1.4	0.4	0.9	1.0	0.9
delrad	0.4	1.0	1.1	1.0	1.6	1.0
fuzzygridrad	0.8	0.6	0.7	0.5	0.7	0.7
fuzzydelrad	0.9	1.2	1.1	1.7	1.8	1.3

Table 4: Internal accuracy evaluation experiment (2)

		Mean Absolute Error (mm)			Mean Error (mm)
		reference data			
		1scan	4scans	9scans	
METHOD	radcent	4.3	4.3	4.3	4.3
		17.6	11.9	8.2	12.6
	DATA	10.4	8.4	8.9	9.2
		0.2	0.2	0.2	0.2
	fuzzyposfine	0.2	0.1	0.1	0.1
	gridrad	4.7	4.7	4.7	4.7
	delrad	3.8	3.2	4.1	3.7
	fuzzygridrad	1.6	1.6	1.5	1.6
	fuzzydelrad	1.4	1.3	1.3	1.3

Table 5: External accuracy evaluation experiment (1)

	DATA	Mean Absolute Error (mm)			Mean Error (mm)
		A fine B fine	A 1scan B 1scan	A 4scans B 4scans	
METHOD	radcent	1.4	2.4	2.4	2.1
	maxrad	9.3	5.4	10.0	8.3
	maxrad4	5.1	3.3	10.5	6.3
	fuzzypos	1.4	1.2	1.2	1.3
	fuzzyposfine	1.0	0.7	0.8	0.9
	gridrad	1.4	1.6	1.8	1.6
	delrad	1.3	1.5	1.5	1.4
	fuzzygridrad	1.5	1.1	1.2	1.3
	fuzzydelrad	1.4	1.3	1.2	1.3

Table 6: External accuracy evaluation experiment (2)

	DATA	Mean Absolute Error (mm)						Mean Error (mm)
		3m			10m			
		90^o	45^o	15^o	90^o	45^o	15^o	
METHOD	radcent	4.2	4.9	6.4	4.4	5.1	5.8	5.1
	maxrad	15.0	14.4	21.0	25.4	23.1	19.6	19.8
	maxrad4	14.0	10.7	15.5	7.3	11.2	18.5	12.9
	fuzzypos	0.6	0.9	1.2	0.9	0.7	1.2	0.9
	fuzzyposfine	0.4	0.6	0.7	0.4	0.4	0.4	0.5
	gridrad	4.8	5.2	7.5	4.4	5.2	6.4	5.6
	delrad	3.3	4.1	5.3	3.5	4.1	4.7	4.2
	fuzzygridrad	1.9	1.9	2.9	1.6	1.8	2.6	2.1
	fuzzydelrad	2.0	1.8	2.7	1.4	1.4	2.3	1.9

The second series of experiments involved the scanning of five targets that were mounted on a wall, from different angles and distances. The reference dataset is created using four merged scans for each one of the targets, collected from a 5m distance with the scanner facing the wall. The other datasets were acquired by scanning the same targets from distances of 3 and 10 meters and with the z-axis of the scanner's system forming a 90^o, a 45^o and a 15^o angle. This way, 6 datasets were created and the results derived following the same procedure as previously are summarized in Table 6.

The results of the 'maxrad' and 'maxrad4' are very unstable, ranging from 7mm to more than 25mm. As for the results of the 'radcent' method, the mean absolute error is within the accuracy specifications of ± 6 mm of the Cyrax system. The results of the 'fuzzypos' and 'fuzzyposfine' methods are once again the best, especially those of the 'fuzzyposfine' method (i.e. 0.4mm for every case at the 10m distance). For the case of the 3m distance, it seems that as the angle becomes smaller, the Mean Absolute Error tends to be greater. The performance of the 'fuzzyposfine' method appears to be even better for the 10m distance, in comparison to the case of the 3m distance. As for the other methods, the results of the 'gridrad' and 'delrad' algorithms are similar to those of the 'radcent' algorithm. For the 'fuzzygridrad' and 'fuzzydelrad' algorithms, the results are also quite satisfactory, with a Mean Absolute Error of about 2mm, which is also better than the accuracy specifications of the system.

5. CONCLUSIONS

In this paper, the repeatability of measurements obtained by the Cyrax 2500 laser scanner, a widely used system, has been examined. It was shown that the repeatability is high for all datasets collected in laboratory conditions. Furthermore, the properties of the Cyrax reflective targets were thoroughly examined and presented.

A number of new algorithms for target identification have been proposed. With datasets collected in different experiments, both the internal and external accuracy of all of the algorithms was examined. It was shown that using Fuzzy clustering techniques gives insight to the processing of the data of the targets, and therefore it is highly recommended as a tool for further research. The results of the proposed methods, especially those of the 'fuzzypos' and 'fuzzyposfine' methods, are proved to be very accurate and reliable. These methods can be used when there is a high demand in accuracy, for instance for metrological experiments, deformation monitoring, registering multiple scans etc. They may be more demanding in calculations compared to other methods, but the results are substantially better.

For future work, more experiments need to be conducted in order to evaluate the performance of the algorithms for various resolutions, greater distances and non-laboratory conditions.

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