AUTOMATIC RANGE SCAN POINT CLOUD REGISTRATION USING HIERARCHICAL LEVELS AND FEATURE RECOGNITION FILTERS

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ABSTRACT: Range scan point cloud registration problem has been well studied from the extensive exploration of the range images' degrees of freedom to the most commonly used iterative closest point (ICP) approaches. However most iterative point-wise methods work well only when the range images are close enough to solution configuration, and there's no guarantee that ICP would work or not from a given arbitrary configuration. Furthermore, the pair-wise nature of registration demands that each corresponding range image sequential pair must be known beforehand for a complete all-around registration from a batch of unordered range scan to build a complete 3D structure. This paper proposes a novel approach that aligns a set of unordered range images without knowing the correspondence between pairs to the point where ICP is guaranteed to succeed in its finer level registration. The registration task is nicely divided into two phases: the coarse registration which approximates the range images to a probable solution space, and the fine registration that takes the pre-aligned set of point cloud and further refines them to an optimally registered configuration. By incorporating a multilevel hierarchical structure similar to the ones used in bounding volume collision detection methods, this paper aims to reduce unnecessary processes in registration pipeline.

Keywords: Registration, range image, point cloud, laser 3D scanning.

1. INTRODUCTION

In recent years the number of scanning devices available in the market has been multiplied, resulting in greater accuracy and cost competitiveness of 3D scanning. Because of this greater number of scanning devices, varied implementations of 3D reconstruction using these devices have been developed, from recreating sceneries for entertainment purposes and building virtual organs for medical purposes, to terrain reconstruction for robotic navigation. Besides the current applications, the nascent 3D printers technology greatly increases the possible number of future applications for 3D scanners. However, scanning and 3D reconstruction technology is limited to the range of view of the sensory devices. The foundation of the scanner limitations is the necessity of a set of scans that complete the total surface of the object from different points of view of the object. This set of images of the same object holds an unknown relation between them, a transformation matrix and the problem of finding the transformation matrix between corresponding range images is known as registration.

The problem of registration has been extensively explored with several different successful approaches. The most commonly used registration method is ICP which has a very high success rate for cases in which the range images are close enough to the correct orientation, but a very low rate for objects in orientations far from their original relation; this situation has lead to the divergence of registration approaches, the coarse and fine registrations. Coarse registration makes an initial guess that approximates the range images close enough to their original relation and the fine registration that takes the initial guess and further refines it, a commonly used method for fine registration is ICP. Another limitation of these approaches is the pairwise nature of them which restricts the possible inputs to pairs of previously known corresponding range images.

This work considers the possible limitations from some previously proposed approaches and addresses registration with a process that is able to coarsely register a set of unordered range images with no information of their orientation or translation to positions close enough to be refined with the final step of ICP. To do this, it uses surface descriptors and multiple hierarchical levels that are able to reduce the influence of external noises inherent to feature recognition algorithms as well as the large number of computations by using feature recognition filters that disregard improbable matching surfaces.

The remainder of this paper is organized as follows: Section 2 discusses some of the previous researches in the registration matter. Section 3 describes the hierarchical structure used to simplify the computations of the registration process. Section 4 explains the simplified computations used for the coarse registration at the pairwise phase and then the proposed metric implemented to complete the coarse registration at the batch phase. Section 5 explores the sets of experiments applied for the verification of the proposal. Finally, Section 6 contains the conclusions of this work and references for possible future works.

2. RELATED WORK

3D point cloud registration is a problem that has been widely studied. However the nature of these works has been mostly dedicated to a pairwise registration excluding information that could be used to identify correspondences from several possible pairs. In [1] Fukai and Xu explore the six degrees of freedom of a pair of point clouds and evaluates them with ICP to find the best transformation between them, however the utilization of the ICP alignment error still finds absolute minimum with incorrect matches and even with a pairwise registration the search of all possible combinations is computationally expensive; as a solution to the great number of computations Makadia et al [2] propose a feature recognition solution that is able to find the most representative points in both range images named constellation images; the registration is done considering just these constellation points, even though the successful results of this approach, the introduction of a bumped surface caused by a low quality scanner will create the problem of identifying non-corresponding features for the constellation images; In [3] the exploration of the degrees of freedom is reintroduced but this time the computations are sped up with a random point sampling scheme and an octree to compute distances, the result is improved in the case of computational expenses however the random sampling introduces extra inaccuracy with the ICP error evaluation. [4] proposes the use of a random point sampling and surface descriptor named tensor that identifies the intersection with the other range image and obtains a metric that compares the possible pairs from a complete set of range images, however the fact that it creates the tensor grids from randomly selected points translates into the possibility that there may not exist correspondence between the points being registered. Finally [5] uses a feature description approach named local invariant feature; it describes the neighborhood for a point with a single scalar value then it compares the features and finds the corresponding points, the limitation with this approach is that the scalar descriptor may be identical in many different points for special cases like cubic shapes, where the different planes rotated will have a very similar local invariant feature in each face or even in repetitive shapes which could lead to an incorrect alignment.

3. HIERARCHICAL STRUCTURE

Fine level registration has a very efficient solution in ICP for the cases in which the initial guess is close to the actual transformation. This situation leads to the necessity of finding a proper coarse level registration. Considering the great amount of points included in each of the scans, the possible solutions search becomes highly expensive, even more considering the fact that a set of range images is to be compared in a round robin to find the most probable correspondences. To solve the point cloud complexity problem it is proposed to simplify the point clouds in an organized structure that allows the acquisition of point vicinity and a hierarchical structure without further computations; this structure is similar to the structures used in collision detection problems. The result of these structures used in collision detection is that they limit the number of elements at each level improving the complexity for the range images correspondence search and by simplifying the point clouds it reduces the induced noise influence during the feature recognition. The rest of this section will be focused in the explanation of the methodology used to create the hierarchical structure for the program.

3.1 Simplified Points (Level 1)

The first level of simplification this work proposes is an ordered, quasi-evenly distributed representation of the point clouds stored in a 30x30 array. This array is able to reduce the point clouds into a much smaller number of points that will be used for the coarse registration process instead of the thousands of points contained in the range images.

The process starts by obtaining an axis aligned bounding box (AABB) for each range image. The AABB dimensions are used to obtain the rough dimensions of the range images from the point of view of the scanner. The maximum and minimum values of the three axes are updated including all the point clouds to be registered. After that these dimensions are used to obtain the local surface size that will be used to compute the simplified points as in the following Equation (1):

$$Size(x, y, z) = \max(\max(x_p, y_p, z_p) - \min(x_p, y_p, z_p)) \quad (1)$$

The next step is to use the local surface dimensions that were obtained to create n local bins that contain the points within the bin boundaries, to do this a binary search tree that returns the points within a certain range is used; the ranges for each bin are obtained by dividing the range image:

$$HB(i, j) = (n(Size(x), n(Size(x) + Size(x)) \quad (2)$$

$$VB(i, j) = (n(Size(y), n(Size(y) + Size(y)) \quad (3)$$

Once all the bins have their corresponding points contained, the following step is to compute AABB for each bin; the obtained AABBs are then used to obtain the simplified points:

$$SP(x, y, z) = \left(\frac{AABB(x_1) + AABB(x_2)}{2}, \frac{AABB(y_1) + AABB(y_2)}{2}, AABB(z_1) \right) \quad (4)$$

The points obtained are stored in the array which maintains the information ordered. The ordered array optimizes the access to the points stored and finds the neighboring point indices with a simple formula instead of computing distances with all the points:

$$NP(i, j) = (i \pm 0 \parallel 1, j \pm 0 \parallel 1) \quad (5)$$

Then for the feature recognition filters, the normal vertex of each simplified point is computed first computing the surface normals of all the neighboring quads:

$$QN(i, j) = \frac{(\overline{P_{i+1,j} - P_{i,j}} \times \overline{P_{i+1,j+1} - P_{i+1,j}}) + (\overline{P_{i,j+1} - P_{i+1,j+1}} \times \overline{P_{i,j} - P_{i,j+1}})}{2} \quad (6)$$

Finally, the vertex normals are obtained using the surface normals of the neighboring quads:

$$N_p(i, j) = \frac{\sum_{s=0}^{q} QN_s}{q} \quad (7)$$

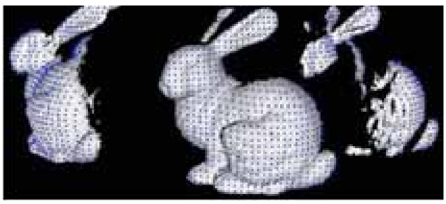

Figure 1: Example of Simplified Points.

3.2 Bounding Spheres (Level 2)

Since the first level of simplifications results still in a great computation expense during the registration, a second level of simplification is proposed to further reduce it. However, the use of surface description is necessary to filter improbable matches and so far previous methods lack the proper utilization of hierarchical levels and their surface information. To solve this problem, the second level is also used to contain surface descriptors from the previous level. The second level is where all the surface information is kept which will later be used for the matching filters, making it the most frequently accessed level in the hierarchical structure. The structure representing this level is an ordered array of bounding spheres. The bounding spheres were chosen because the sphere intersection determination is the fastest of all the bounding volumes. Each bounding sphere contains a 3x3 level 1 simplified points allowing it to have an even description of the surrounding surface around the center point and an easy computation of the neighboring points which can be automatically found using the level 1 ordered array.

Using the 9 points for each corresponding surface patch, the bounding spheres are computed like this:

$$R_0(i,j) = \max length(AABB_x, AABB_y, AABB_z) \tag{8}$$

$$Center(i,j) = (\frac{AABB_x}{2}, \frac{AABB_y}{2}, \frac{AABB_z}{2}) \tag{9}$$

$$R_f(i,j) = \begin{cases} dist(p_s, Center) > R_f \rightarrow R_f = dist(p_s, Center) \\ else \rightarrow R_f = R_f \end{cases} \tag{10}$$

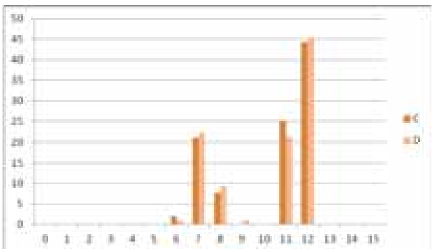

Figure 2: Example of a Local Feature Histogram.

Then using the technique of surface patch description proposed in [8], with all the possible pairs of points contained within each bounding sphere, the local feature histogram is created. For each element of the Level 2 structure a histogram is stored so that it can be compared to filter improbable surface matches.

Figure 3: Example of Bounding Spheres simplification.

3.3 Bounding Boxes (Level 3)

While executing registration at the second level, it can be observed that several computations still happen even where the collision between range images is not happening. Considering how collision detection algorithms solve this problem with higher hierarchical levels that simplify the mesh to avoid unnecessary collision computations, the third level encompasses level 2 bodies to reduce computations. The third contains a 2x2 bounding spheres set within an ordered array of AABBs. The choice of bounding volume in this case is because not all the resulting simplified points meshes are approximately even in their x and y dimensions and that causes that the resulting bounding spheres become too large in order to contain the points from level 2 which would not be an accurate representation of the range image. It was found in our experiments that a correct surface match was volatile due to the level of detail lost at this simplification scheme; because of this, the third level is used solely with the purpose of collision detection.

After this level, further simplification of the point cloud becomes so rough that it does not represent the range image and as a result it only increases the number of operations needed to find if the range images are overlapping.

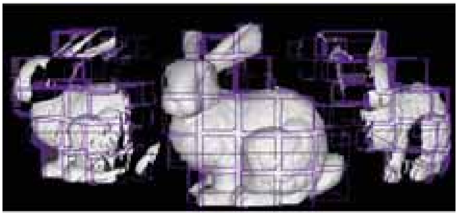

Figure 4: Example of AABBs simplification.

4. COARSE REGISTRATION

One of the main purposes of this approach is to find an accurate initial guess that is close enough to the actual transformation of a set of range images so that the ICP algorithm can further refine the transformation using the point to point distance optimization. The related works that have been mentioned so far in this work cover a wide area of ideas from brute force approaches where the degrees of freedom are exhaustively explored to the feature detection algorithms that refine the meshes to a small number of points that are later optimized with ICP variations.

Our proposal to solve this problem is divided in two stages: first the pairwise registration in which all the possible pairs of range images are explored to find possible matching surfaces, and second the batch registration that decides the order in which range images should be registered. In order to find the batch registration it is necessary to obtain an evaluation metric from the pairwise registration process so that it can be identified which is the best combination. The proposal in this case is to take advantage of the hierarchical structure to speed up the computation and use the feature descriptors to reduce even further the exploration.

4.1 Pairwise Registration

The main idea of this work for the coarse registration integrates aspects of the related works that have been explored in Section 2. The exhaustive exploration of the combination of points is used to find the orientation and translation of the range image that is being registered. This approach takes elements proposed in [1] and [3] where they explore exhaustively the transformation space; but our solution proposes to limit the range of transformations using a simplification structure. Considering [6], a hierarchical structure was implemented; however, instead of neglecting all the information included in the point clouds, a multi-level hierarchy is used where the level of detail keeps incrementing as it advances in the hierarchical tree. The hierarchy levels serve to improve the process as well by speeding up the verification. Another contribution in this work is the use of feature filters, the proposed algorithm takes the feature description to filter out transformations that are not probable by using just similar surfaces to register pairs of points. This modification maintains all the information available to execute the metrics of the registration quality instead of limiting the number of points available for the registration where some of the remaining points may not be part of the overlapping area between the range images.

Figure 5: Pairwise Coarse Registration Example 1.

The first step is to explore all the possible level 2 pairs formed from the two range images. The process starts by choosing the central point from a bounding sphere from the source range image and the destination range image; in this case the central points are already known thanks to the ordered arrays. Then the histograms corresponding to each bounding sphere are compared as a filter, in the case that the pair meets the criteria, it continues to the next step, otherwise the pair is discarded. For the next step, the normal from that central source point in the range image to be registered is then rotated to obtain the same orientation of the central point in the destination range image and translated to make the points coincidental. After that, the orientation needs to go through a correspondence filter; if it fails, the pair is discarded; otherwise a chain of overlapping volumes is searched with the help of the hierarchical structure. All the possible pairs of points from level 2 are searched and the ones that have a value above the threshold are saved for the final metric evaluation. If no pair is found after all the tests then the algorithm determines that there is no correspondence between the range images pair.

The algorithm proposes the use of two filters, a filter for the surface similarity and a filter for the correct orientation. The use of these filters intents to reduce all the possible mismatches as well as the total number of deep explorations in search of a chain of coincidences that would result time consuming and unproductive.

The surface similarity filter uses the feature recognition techniques used in [6]. The surface histogram stores the information of the curvature inside the level 2 bounding volume and it is used to compare the pairs. A matching patch of surface from the source range image should be similar to the matching patch of surface from the destination range image. Using the histograms distribution, they are compared bin to bin and a percentage of similarity is computed, if the percentage is greater than the threshold percent then the points are treated as possible matches and kept for further exploration.

The next filter checks that the simplified points contained in the level 2 bounding spheres have a matching surface orientation between the explored pair. It starts by finding the closest point to each of the level 1 points between the source and destination range images; each of them should have a distance less than the half the length of the level 1 bins (MD/2) if not the pair is rejected. Then for each point, the closest point normal vector difference should be less than 10 degrees, if more than 3 of the points fail it is rejected.

And finally, the incremental orientation; the central point in both range images are incremented, if the incremented points are not the closest to each other, then the source is rotated around the normal vector until the incremental closest points are coinciding.

The next step is to find the number of level 2 bodies intersecting each other from both range images, this process is named chain search. In this step all the surviving pairs are explored. For each explored pair the central points of the bounding spheres are aligned first.

The chain search is where the suggested solution takes advantage from the techniques used in collision detection and the constructed hierarchy structure. The chain starts with the current registered level 2 pair and checks for collision between them. The process is repeated to all the level 2 spheres that share the level 3 parent node with the origin. It then follows with the neighboring level 3 volume from the source range image, it finds if it is intersecting with some other level 3 volume from the destination range image. Then it searches the intersections on the level 2 spheres and for the found collisions it adds the pairs to the chain. This process grows at the level 3 volumes and explores deeper only in case of probable chains links inside the explored branch.

After obtaining the chains of coincidences the pairs go into the last filter. The chains of coincidences whose number of elements are greater than the threshold are stored as possible final registrations and evaluated to determine the best possible option.

All the pairs of points that have a chain larger than the threshold are then explored in detail to have its closeness measured. The tool used for this metric is a Quadtree that contains the destination range image. This Quadtree obtains the minimum distances from all the level 1 points in the source mesh to the destination mesh level 1 points in asymptotical time of O(logN). There are two possible ways of evaluating the registration, using the average error or using the number of coincidences.

The Quadtree is constructed from the root to the leaf nodes; it starts by obtaining the AABB from all the points in the level 1 array. The AABB is then split by the half along its two greater axes.

All the points are divided in the 4 resulting sections of the parent node. This process is repeated iteratively until all the leaf nodes have less than 8 points. The Quadtree receives the 3D points from the source point cloud and it computes the closest leaf node to each point from the destination point cloud then returning the minimum distances between points.

The registration starts with the point p in the level 1 hierarchy from the source. It computes the minimum distance from the point to the destination with the Quadtree. Then error accumulation is added with the minimum distance and after repeating the process for all the points available in the source range image the error is computed like this:

$$Error = \frac{\sum_{s}^{n} \min Dist(p_s)}{n} \tag{11}$$

The error is compared with all the probable registration chains and the registration with the lowest error is chosen as the correct coarse registration.

Figure 6: Pairwise Coarse Registration Example 2.

Besides this metric, our approach includes a different metric. The other method uses the Quadtree also to compute the minimum distance from each point of the source image to the destination image, but in this case instead of using the distance to compute the error, the value is compared and if it is less than the threshold, an occurrences counter will be incremented. The total number of occurrences is then used as the metric.

4.2 Batch Registration

The solution assumes that the range images received contain no information concerning their order or which range image is supposed to be registered with the others. To solve this problem, first it registers all the possible pairs of range images formed with the first range image; the metrics returned from the pairwise registrations are used as reference. Depending on the metric, the minimum error or the maximum number of occurrences, determines which is the corresponding range image.

The process is repeated with the next range image and the remaining available. The Quadtree is created with all the range images that have already been registered to increment the probability of finding the correspondence. These steps are repeated with all the remaining range images available or until the remaining point clouds have been found not coincident with the all the range images.

The result of this approach however is dependent of the point clouds exploration order which could lead to choose an incorrect first alignment that would close the cycle prematurely, because some remaining point cloud had no possible registration with the remaining range images. To avoid this problem, the solution was modified to a comparison between all the possible pairs of point clouds.

The program compares the point clouds in a round robin to find the registration between them, from this possible registration the error is stored as a metric for that match. After all the matches are computed, the point clouds are sorted increasingly according to their number of possible matches. The possible matches are those pairs of point clouds that have at least 25 percent of level 2 collisions. Starting by the point cloud with the least number of possible matches, the algorithm chooses the match that has the smaller level 1 error after the registration and then continues to the next point cloud in the sorted array. With this the algorithm finds a route that goes through all the point clouds with no inner cycles and that has the least error possible. However, the results of this approach were not satisfactory; this could be explained by the fact that the minimum distance average depends of all the points and even the points outside the overlapping region account for the error, leaving a big space for local minima. To improve the influence of the non-corresponding area, the error metric was substituted by the number of corresponding points between the pair. This approach depends only of the points that are included in the found overlapping area and works as a better judge for the correspondences.

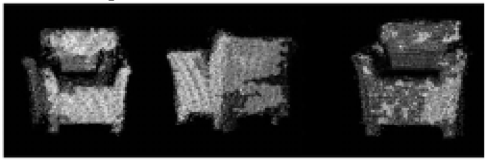

Figure 7: Batch Coarse Registration Example 1.

Figure 8: Batch Coarse Registration Example 2.

5. RESULTS

The experiments implemented to test the registration of sets of range images were developed first to denote the optimal values needed to obtain a better performance of the hierarchical structure, second to understand the characteristics needed to obtain a successful registration and third to find if given the correct range images set the algorithm could perform a correct registration regardless the initial position of the images.

5.1 Parameter Settings

The first set of experiments utilized a batch of range images of both scanned and virtual point clouds to define the simplified points' array size. Since we know that the level 2 structures consists of 3 x 3 level 1 points clusters, then the squared array of level 1 must be a multiple of 3 to obtain an exact division in the previous hierarchical level.

Table 1: Level 1 Array Size Registration.

	Hierarchy (s)	**Coarse (s)**	**Fine (0.85, 200) (s)**	**Fine (0.50,0.50) (s)**
Chair (18x18)	2.285	2.264(*)	6.855(*)	1.328(*)
Bunny (18x18)	14.850	0.982(*)	70.048(*)	50.359(*)
Chair (24x24)	2.315	6.926(*)	8.219(*)	1.556(*)
Bunny (24x24)	15.303	1.968(*)	71.734(*)	15.361(*)
Chair (30x30)	2.100	26.500	6.953	1.273
Bunny (30x30)	15.225	8.491	246.414	39.116
(*) = unsuccessful registration				

The level 1 array sizes were set and the time of the pre-computations, the time of the coarse alignment and the time of the fine alignment were obtained for the analysis. From the results we can observe that for lower values of the level 1 arrays, the pre-computation time is very close. For the registration we can observe how the time increments exponentially as the array size grows for both types of registration, however the lower sizes return no convergence for the batch registration; the cause of this is that the lower sizes fail to represent the level of detail needed for feature recognition, therefore we can determine that the optimal level 1 size N=30. It is also important to remark that the fine registration returns a very similar result after the coarse registration with the configuration of 200 iterations and 85 percent of sampling and the configuration of 50 iterations and 50 percent of sampling. The explanation of this is that the coarse alignment is close enough to the optimal solution of the ICP algorithm that the sampling and the iterations can be reduced and it will still return a close fine registration.

The histogram comparison works as a filter to speed up the registration by eliminating the pairs that are not probable corresponding surface patches because of their different surface properties. This means that a great number of improbable registrations will be rejected and the time consumed analyzing these incorrect solutions will be saved.

The second experiment took a pair of virtual range images and the percentage of acceptance was incremented starting at 50 percent until 95 percent; this time was also saved for the analysis and the outcome of the registration.

It can be observed that the registration time is reduced dramatically as the parameter is increased; however at the when we reach the 90 percent of similarity no correct registration is found. That is because the representations of the surface patches are very similar to the original but not identical due to the information lost during the simplification process. According to these results we can conclude that an 80 percent of similarity is enough to filter the improbable registrations and to keep a safe margin of detection of surface coincidences.

Table 2: Similarity Percentage Times.

Percentage	Mesh1 (s)	Mesh2 (s)	Mesh3 (s)	Mesh4 (s)	Mesh5 (s)
0.5	7.625	22.818	16.798	64.602	7.426
0.55	7.305	19.657	16.784	59.149	7.459
0.6	7.215	19.114	16.834	37.205	7.425
0.65	6.894	18.875	16.525	26.584	7.387
0.7	6.562	17.122	13.571	24.355	7.321
0.75	5.682	13.649	11.987	22.795	7.258
0.8	4.868	11.898	10.694	20.378	7.258
0.85	4.126	10.489	9.167	13.488	6.951
0.9	3.628	8.399	8.027	11.315	5.268
0.95	2.865	7.479	8.519	11.537	6.121

The minimum point to point distances are important for the creation of the chains of coincidences and for the metric. The next experiment explored the effects of the minimum distance. Considering that level 1 points are a grid that is spaced at a maximum distance of MD, the experiments take MD as the threshold value and then a percentage of it is used incrementally to observe the outcome of the registration.

The results of the experiments reflect that a 0.50md is the optimal threshold value. The explanation for this is that a point from the first point cloud that is correctly registered at the second point cloud could be at maximum in the exact center between two points in the grid. Greater values than this would account for incorrect coincidences and the lower values would fail to account a number of correct coincidences.

Table 3: Similarity Percentage Results.

Percentage	Mesh1 (s)	Mesh2 (s)	Mesh3 (s)
0.5	OK	OK	OK
0.6	OK	(*)	OK
0.7	OK	(*)	(*)
0.8	(*)	(*)	(*)
0.9	(*)	(*)	(*)
1.0	(*)	(*)	(*)
1.1	(*)	(*)	(*)
(*) = unsuccessful registration			

5.2 Algorithm Validation

Once the optimal parameter settings were defined, a series of experiments were developed to prove the effectiveness of the solution. The experiments test the overlapping area between the range images, the initial configuration of the range images and compare the proposed algorithm with the ICP alignment.

Figure 9: Overlapping Percentage Alignment.

To determine if a registration was correct, a four step metric was proposed. The test consist of the ICP error before the fine registration and after the fine registration checking if the error has indeed been optimized by the ICP algorithm after the coarse registration. The next step measures the time it took to obtain the complete registration including the hierarchical structure creation. And the final step consists of the intervention of a person; that is because for the computer the registration could be considered as a success if it has found any similar surfaces large enough to pass the threshold, even when it is an incorrect registration. It can only be determined if it is indeed correct or not by manual inspection. The last metric is a Boolean indicator that describes if a user observes a correct registration.

Table 4: Overlapping Percentage Alignment.

C. Points	%	Alignment
531	91	OK
449	77	OK
412	71	OK
334	57	OK
299	51	OK
223	38	(*)
(*) = unsuccessful registration		

Table 5: 4-Step Metric.

Mesh	Coarse Error	Fine Error	Visual	Time (s)
1	0.00134	0.00027	OK	38.165
2	0.01503	0.00121	OK	26.702
3	0.00414	0.00027	OK	39.254
4	0.02211	0.01199	OK	3.931
5	0.08741	0.04074	OK	4.202

This test was conducted to five pairs of corresponding point clouds. The point clouds were chosen as two pairs of scanned data point clouds that included a moderate level of noise that did not deform the overall shape of the objects (chair and car), then a pair of virtual data point clouds with large uniform surfaces (car), and finally two pairs of high quality real data point clouds with very unique surfaces (armadillo and dragon).

The results of this experiment show that the minimum percentage of overlapping area is near the 50 percent. This value could be reduced if all the threshold values were modified, however that would eliminate all of the filters advantages to reduce the computations proposed in this work.

The next set of experiments were use to determine the reliability of the algorithm depending on the initial orientation of the range images was tested. The two independent experiments check first the impact of the original position in the outcome of the algorithm and the second experiment checks the impact of the original orientation in the outcome of the algorithm.

The experiments were conducted on a pair of virtual range images. The translation test consists of moving one of the range images along the three axes, and registering the outcome and the registration time. The measuring unit for the distance in this case is MD.

The results of the experiment showed that the distance between point clouds did not affect the outcome of the algorithm, which is an expected result because the registration problem tries to optimize the distance between points in every proposed solution.

The orientation test consisted of rotating one of the range images around the three axes before registering the point clouds. The experiment showed that the registration algorithm works in almost every original condition with the exceptions of the 90 and -90 degrees around the z axis, this is because it does the rotation angle computations as a 2D planes and when a vector is aligned with the axis it would need a division by 0 which is an error. To solve the problem the orientation of that range image can be slightly modified to avoid the division by 0.

6. CONCLUSIONS

The main objective of this work is to develop an algorithm that is capable of registering unordered range images with error induced from low definition scanning devices. To solve this problem, this work proposed an innovative method for the automatic range image registration that combines different types of registration: the optimization of a metric, the feature recognition and an exhaustive search of the transformation range with a multilevel hierarchical structure that reduces the complexity of the match evaluation but maintains details accessible to differentiate possible matches.

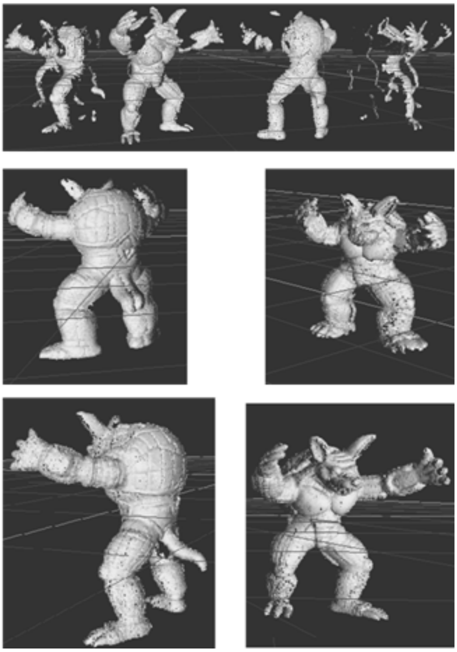

Figure 10: Coarse and Fine Registration Example.

After the experimentation conducted on the algorithm, it can be observed that the proposed hierarchical level approach optimizes the asymptotical time of the registration problem. The utilization of the feature recognition filters also reduces the search space by eliminating all of the improbable solutions.

Compared to other methods with hierarchical levels or feature recognition, instead of consisting only of two levels that are the complete point clouds or a few points, the utilization of the multiple levels is an improvement in the sense that it can keep valuable information for the registration easily accessible and be used as well as a simplification of discarding unviable solutions.

Finally, the definition of the simplified mesh consists of a known maximum number and this fact compared to the approaches referenced in this work will reduce all the range images independently of the number of points in the range image. This approach applied to low definition scanning devices, like some of the sets used in this project, results in a simplification that is detailed enough to find the surface properties but coarse enough that neglects the error induced by the scanner noise.

The proposed solution is limited to cases in which the objects shape is unique enough to be differentiated from each different point of view. That is because the algorithm is designed to choose the greatest surface with the same descriptor which in some cases like spherical shapes in general, large planes, or other uniform surfaces would find absolute minima in the same shapes that would not reconstruct the object but align incorrect surfaces.

Because of the point simplification process the algorithm is supposed to work in cases where the contour is enough to find correspondences. If the details mark the difference to find correct correspondences, then this approach would not be able to find it correctly, however the assumption of a low definition scan means that the level of detail is not good enough for those cases.

The results of the experiments conducted to the different types of range images showed that as many other previous approaches this solution still finds correspondences for large surfaces of similar curvature even when they are not correct correspondences. This problem can be reduced by the type of scans that are delivered to the program. With a greater area of overlap between the range images, the greatest patch that can be found would be the corresponding overlapping areas of each point cloud. However, the unordered batch alignment for very uniform surfaces like chairs, cars, etc., translates into a greater problem, since possible matches could be found in almost every pair. In these cases the possible solution is to solve the registration in the delivered ordered cycle.

7. FUTURE WORK

The results obtained from this work leave the door open for improvement by using some of the related works as reference. The use of the same structure configuration to parallelize the multi-view range images registration and speed up the process used in [2] as well as the update of the complete structured registered could be adapted to the proposed solution. Another area of opportunity is present in the evaluation metric of the registration; the algorithm uses the ICP or ICRP metrics, however these methods are known to be faulty in the sense that there may exist absolute minimum values that are not the correct solution. The research of an extra constraint to neglect the non-coincident absolute minimum value is a matter of great importance for this and any other work related to the registration.

Lastly, ICP uses a randomized sampling process to select the points that will be optimized for the fine registration, however choosing a small sample the algorithm may receive points outside the overlapping areas of the point clouds, and therefore it becomes necessary to use a greater sample. The use of a large sample makes a very expensive process, but considering that our coarse registration is close enough and that the hierarchical structure is already detecting the intersections between the point clouds, then it could be possible to pass that information so that the sampling is only to be done in the intersecting areas.

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