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Surface Registration from Range Image Fusion

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Abstract—**The registration of full 3-D models is an important task in computer vision. Range finders only let to reconstruct a partial view of the object. The last years, many authors have proposed several techniques to register 3D surfaces from multiple views in which there are basically two aspects to consider. First, poor registration in which some sort of correspondences are established. Second, accurate registration in order to obtain a better solution. In this paper, a survey of the most common techniques is presented and includes experimental results of some of them.**

I. INTRODUCTION

3D registration from multiple views is an important topic in computer vision with many applications, such as reverse engineering, robot navigation, mould fabrication and visual inspection, among others. However, the most recent methods to get 3D models may only register a part of the object from a mechanical scanning. In order to get a complete model, it is necessary to fusion multiple views of the same object. Range image is a $2\,^1/_2$D image with some sort of information which leads to compute directly the 3D surface. A $2\,^1/_2$D image is given by laser scanning [1], by pattern projection [2] or by stereovision [3] [4] [5]. In order to fusion multiple images, known as image registration, Euclidean motion between views must be determined. One sort of methods is focused on finding an initial estimation of the motion, named *Poor registration* methods. The other sort of methods is focused on converging to a better solution from a previously known initial estimation of the motion, named *Accurate registration.*

This paper presents a survey on image registration. First, a new classification on 3D image registration is presented in section II. Then, section III and IV detail the methods based on Poor registration and Accurate registration, respectively. Furthermore, in section V, experimental results from some accurate registration methods are included. The article ends with conclusions.

II. A CLASSIFICATION OF REGISTRATION METHODS

Registration algorithms are based on finding the Euclidean motion between a pair of range images. The presented techniques differ whether initial information is required, so that only a poor registration can be obtain without an initial guess. Besides, if an estimated motion between views is available, a more accurate registration can be computed. The classification of the surveyed methods is shown in table I.

In poor registration, the main goal is to determine the rigid motion between two clouds of 3D points by determining point correspondences and then estimating the motion from these correspondences. There are basically two approaches: a) Extract some features of both surfaces in order to facilitate the correspondence search, or b) Use some invariants which do not require any feature extraction to solve the correspondence problem. All these methods are explained in the following section.

In accurate registration, the goal is to compute a better solution starting from the one given by poor registration. Basically, these methods can be classified into : a) *Iterative methods* and b) *Robust methods*. Both of them are presented in section IV.

Table I also classifies the methods in terms of: a) the registration strategy, i.e. Pair-wise or multi-view registration depending on the number of views that are aligned in every iteration; b) the use of an efficient search such as k-d trees in order to speed up the algorithm; c) the way of computing the minimization function in terms of a distance point-to-point or point-to-plane; and d) the way of computing the initial motion.

III. POOR REGISTRATION

Poor registration methods are based on obtaining an initial estimation of the Euclidean rigid transformation between pairs of 3D views so that every 3D view is related to the previous one leading consecutively to the complete registration of the surface. Most of these methods requires a previous computation of the correspondences between range images before determining the Euclidean motion. Besides, there are others that can find the rigid transformation directly. Hereafter, both of them are explained.

A. *Techniques based on feature extraction*

These methods are based on extracting some invariant features between every range image in order to find the correspondences between them. Most common features are points, curves, segments and surfaces. When some pair of correspondences are determined, it is possible to compute the rigid motion iterating until convergence.

In 1992, Zhang [6] codified curves with respect to the tangent direction of every point in the curve. Then, the author used this codification to find curve correspondences between range images. Furthermore, the author proposed a method to evaluate potential point correspondences. Finally, the motion was computed by the dual quaternion method. In 1997, Krsek [7] presented another method to match curves.

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TABLE I

CLASSIFICATION OF REGISTRATION METHODS

			Registration strategy: Pair-wise registration	Registration strategy: Multi-view registration	Efficient search: k-d trees	Minimization distance: distance point-point	Minimization distance: distance point-surface	Motion Estimation: Least Squares	Motion Estimation: Least Median Squares	Motion Estimation: Eigenvectors	Motion Estimation: Quaternions
Poor Registration	Feature extraction	Zhang92	√		√	√					√
		Brunnström96	√			√		√			
		Chua96	√			√		√	√	√	√
		Kresk97	√					√	√	√	√
		Tarel98	√					√			
		Johnson99	√			√		√	√	√	√
		Wyngaerd02	√			√		√	√	√	√
	without feature extraction	Besl92	√			√					
		Chung98	√			√				√	
		Chen98	√			√		√			
		Park02	√					√	√	√	√
		Kim03	√							√	
Accurate Registration	Iterative methods	Besl92	√			√					√
		Chen92	√	√			√	√			
		Gagnon94	√			√					
		Bergevin96		√			√	√			
		Eggert98			√		√		√		
		Chung98	√			√				√	
		Kapoutsis99	√		√	√					√
		Greenspan01	√			√					√
		Jost02	√		√	√					√
		Kim03	√			√				√	
	Robust methods	Trucco99	√						√		
		Fitzgibbon01	√			√		√			
		Nishino02		√	√	√		√			√
		Zinβer03			√						√
		Chow03	√		√	√					

The author computed the inflection curves (where the first derivative is equal to zero) of the surface and then tried to match these ones between both range images.

In the same year, Chua [8] presented the point signature. This method characterizes a given point from the information of the points situated at a constant distance from a tangent plane at the given point. Finally, an array is built and used as a feature of the given point. The main goal of the author was range image recognition, however the same algorithm can be used to determine correspondences.

Brunnström [9], in 1996, used a genetic algorithm to find correspondences between range images. A genetic algorithm (GA) is a searching procedure that optimizes some objective function by maintaining a population of candidate solutions and employing operations inspired by genetics (called crossover and mutation) to generate a new population from the previous one. The most important part of a GA is the fitness function which gives an evaluation for each candidate determining how good a solution is. The author used some invariants as a fitness function. These invariants are the distance between two points in the same cloud, and the angles between the normal vectors of both points.

Two years later, Tarel [10] proposed a new method to estimate the motion between two range images. First of all, he proposed two implicit polynomial models from all the points of both range images. Then, Tarel used the information of the implicit polynomials to obtain a pose estimation. Pose estimation is based on the covariance of the parameters of the polynomial. This method does not need to find correspondences, so that the computation is very fast. Overall, both clouds of points should not vary considerably in order to obtain a good motion approximation.

In 1999, Johnson [11] introduced the *spin image* based on identifying corresponding points in different clouds of points. A spin image is a 2D image, in which one axis represents the distance between points and the plane tangent to the analyzed point, and the other axis represents the distance between the point and the orthogonal projection of all points to the tangent plane. This method was used by several authors [12][13][14] with few modifications among them.

In 2002, Vanden Wyngaerd [15] obtained a rough estimation of the motion by matching bitangent curves. The author found pairs of coplanar points in the same image and chained such points generating a pair of bitangent curves. In order to find these curves, the author generated a triangulated dual surface, where each point is characterized by the normalized coordinates of the tangent plane. In this dual space, two coplanar points coincide in a single point. So using this property, the author search all the bitangent curves. When all the bitangent curves are extracted, the author used the distance between a pair of these curves as an invariant. The author tried to match segments of the same length between two range images. With each segment, 4 point (endpoints) can be matched and the motion can be computed. Finally a verification based on the distance of the closest point is applied.

Overall, these groups of techniques let to obtain a good initial solution if most part of correspondences are good. However, the computational time needed to establish the correspondences is very expensive due to the exhaustive searching of correspondences in the clouds of points.

B. Techniques without feature extraction

This group of techniques is defined by the group of methods that determine an initial estimation of the motion without computing any feature of the surface.

In 1992, Besl [16] introduced the Iterative Closest Point algorithm. The Closest Point is the nearest point in the second cloud of points with respect to a given point in the first cloud of points. The author used this definition with the aim of finding corresponding points. However, it is only available if the motion between the clouded points is very small. In order to obtain an initial approximation, different standard initial configurations were proved. Then, the configuration that minimizes the sum of distances between point correspondences was chosen. When a significative amount of closest points is computed, the Euclidean motion is computed by using quaternions and eigenvector analysis. This method is very slow due to the fact that it is necessary to compute all the distances between points. The author proposed as a further work the use of k-d trees in order to fast the method. A drawback of

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Besl's method is that only can work in total-overlapped range images, so that modifications are required to register partially-overlapped range images.

In 1998, Chen [17] determined the motion from 3 pairs of points by RANSAC-based DARCES method. The author chose three points (primary, secondary and auxiliary point) in the first cloud and characterizes these triplet by the distances among such three points. Then, he supposed that each point in the second cloud can be considered as the primary point correspondence. Secondly, the secondary point is searched from the points in the second cloud situated at similar distances between primary and secondary points in the first cloud. If no points are found, the algorithm restarts considering another primary point. Otherwise, a third point in the second cloud that satisfies the distances defined in the triplet in the first cloud is searched, which if it is satisfied leads to determine the rigid transformation. For every rigid transformation obtained, it is possible to compute the number of points in the overlapped region. Finally, the author chose the transformation with a greatest number of overlapping points as the correct solution. The author demonstrated that the method can be used in registering partially-overlapped range images. The same author proposed a more robust estimation method by considering the addition of more points, called control points, that are only used when the rigid transformation is computed in order to prove whether the rigid transformation is correct.

In 1998, Chung [18] proposed a new registration algorithm using the direction vectors of the clouded points. The method consisted of calculating a covariance matrix for each range image. Then, it is possible to compute the main axis by singular value decomposition. The rotation is determined by the product of the eigenvector matrices, and the translation by the difference between centers of mass of both clouded points expressed with respect to the same axis. A similar idea was used by Kim [19][20], in which the difference between them are concerned in the accurate registration step, explained in section IV.

In 2002, Soon-Yong Park [21] presented another kind of poor registration method. The author obtained partial reconstruction in a rotation stage and then, he registered different views by matching tangent planes. The author placed an object on a turning table, and used the surface of the table as the Base Tangent Plane (BTP), which is invariant with respect to the object position. Then, the object is reconstructed from another position, and a second plane is found. The author found all the tangent planes using Extended Gaussian Image of the model, and eliminated the planes that did not satisfy some constraints: a) *Base plane constraint*; b) *Stability constraint* and c) *Height constraint*. Finally, the Euclidean motion for each pair of tangent planes is computed and the transformation that minimizes the distance between the vertexes of both surfaces is chosen.

IV. ACCURATE REGISTRATION

The term accurate registration is used when an initial estimation of the motion is previously known and the main goal is to converge to a more accurate solution. In order to solve this problem, a function is minimized. Some authors use the distance between point correspondences, while others use the distance from a given point to a plane tangent to the closest point. Although, there are many methods, they can be classified into two groups: a) Iterative methods and b) Robust methods. The first group is only focused in function minimization, whereas the second pretends to remove false correspondences given by bad alignment. Most part of the methods in the second group are modifications of the first ones.

A. Iterative methods

The most important iterative method was presented by Besl [16]. The author proposed an Iterative Closest Point (ICP), which pretends to obtain an accurate solution by minimizing the distance between point correspondences, known as closest point. When an initial estimation is known (see Section 2), all the points are transformed to the same coordinated axis applying the Euclidean motion previously estimated. Then, Closest Points are searched again and again, iteratively until convergence.

A lot of authors have proposed some modifications of this method in order to improve: accuracy, precision, computational cost and robustness. The robust improvements are presented in the section IV-B, whereas the rest are hereafter discussed.

In 1998, Chung [18] presented a version of the ICP algorithm, in which the closest points are computed using reverse-calibration technique. 3D points are projected to the camera and the correspondences are searched in the image plane by using only two dimensions. This modification increments the velocity of the algorithm because no iterations are required to obtain correspondences. Furthermore, the initial estimation algorithm (commented in section 3) provides a good starting point, which accelerates convergence. A similar method was presented by Kim [19][20]. The author used the projective matrix representing the projection of the 3D space to the 2D image to compute the camera position. Then, Kim used this information to determine the overlapping region and the motion.

In 1999, Kapoutsis [22] used an ICP modification to register range images. He organized the 3D points in a three-dimensional box and constructed a Voronoi diagram of the model points in order to decrease the computational cost of finding the closest point, the most common drawback in the ICP algorithm. Another modification of ICP with the aim of decreasing the computational time was proposed by Jost [23], in which multi-resolution information is used obtaining a speed factor of 27 times faster compared to traditional ICP algorithms. Other authors used k-d trees structures to compute faster the closest point [22][24][25][26].

In 2001, Greenspan [27] used the same principle of Besl, introducing constraints in order to increment the velocity of the search. The proposed constraints were the so-called Spherical and Triangle constraints, which were used to remove false matching. The author demonstrated that this method is more efficient than k-d trees methodology.

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In 1991, Chen [28] proposed a method similar to the method of Besl, based on minimizing the distance between points and planes. So, given a point in the first image, the author looked for the intersection between the normal vector at this point and the second surface. In the intersection point, a tangent plane is computed, and the distance between this plane and the given point is the minimization function.

In 1994, Gagnon [29] presented a similar method to Chen's, but using a different algorithm to find the distance between points and planes with the aim of speeding up the process. First of all, the author projected the surface of the second range image on a plane partitioned in a set of squares like a chessboard. The normal vector at a given point in the first range image is projected on such a partitioned plane obtaining at the edge of every square two interesting points. The square where the sign in the z-coordinate of both intersecting points changes is selected and the point which interests the square computed and considered as the correspondence point. Then, the plane tangent to such correspondence point is computed and the distance to the given point in the first range image evaluated. Then, the author iterates to obtain the motion parameters that minimizes the point-to-plane distances.

In 1995 and 1996 Bergevin [30][31] presented a modification of the Chen's method. The author implemented a multiview registration method and minimized the distance between a point and an interpolated surface from all the other views.

In 1998, Eggert [24] presented a multiregistration method by using force-based optimization. The author registered simultaneously all the range images to obtain the best global solution. The author searched for the corresponding points similar to Besl and Chen, but adding more information. This information consisted of the difference between the normal vector of two point correspondences weighted by a scale factor. The author used this distance to find correspondences by using a k-d tree search.

B. Robust methods

In general, robust methods pretend to remove false correspondences to improve the accuracy in the registration. There are basically the following groups of robust methods: a) Outlier thresholding; b) Median estimation; and c) M-estimation.

Outlier thresholding is based on estimating the standard deviation and removing the points which have errors larger than $|k\sigma|$. The second group use the median of the error as a threshold. M-estimation is based on defining the probability of a pair of correspondences of being correct.

In 2003, Zinβer [25] proposed a robust method based on outlier thresholding known as the Picky ICP algorithm. The main difference from ICP is the selection of the control points and the use of k-d trees with the aim of reducing computational time. The selection of the control points consisted of using few points in the beginning. When the algorithm is near convergence, the number of points is increased. Furthermore, only the rigid transformation is applied in each iteration if the registration errors decrease.

In 1999, Trucco [32] implemented the RICP method, that is a robust ICP algorithm based on the use of Least Median of Squares. The method is based on registering k sets of m points in every range image of n points, with the aim of obtaining a combination without outliers. Monte Carlo technique is used in order to estimate the k number of necessary combinations. The rotation in each combination is computed by least-squares. When all combinations are computed, the solution that minimizes the median of the residuals is chosen. Finally, the correspondences with a residual greatest than 2.5σ are removed and rotation is computed from the rest of points [33]. Translation can be computed by the subtraction of the center of mass of both corresponding points express in the same coordinated frame.

In 2001, Fitzgibbon [34] proposed to solve the registration problem using the Levenberg-Marquardt algorithm instead of the traditional ICP algorithm. LM algorithm had been already used for image registration [35], but without considering the presence of outliers. The main advantage of this method is the facility to include robustness without incrementing the computing time. The robustness is added by modifying the error function including a robust kernel, like Lorentzian or Huber kernels.

In 2002, Nishino [26] proposed a M-estimator technique to obtain a robust method. The author used Lorentz function to estimate the weight of different correspondences. The proposed method can solve multi-view registration problems and k-d trees are used to reduce the searching time.

Recently, Chow [36] proposed the used of a genetic algorithm to register range images. The author used the registration error function as a fitness function, which is based on the median of the errors. The used of the median lets to register surfaces with more than 50% overlapping. Furthermore, an adaptive mutation was proposed to readjust parameters of Euclidean motion in each iteration. Each chromosome is randomly in an adaptive range. So that, the range is reducing when the solution is converging

V. EXPERIMENTAL RESULTS

Some of the methods here explained have been implemented and tested considering synthetic data.

An accurate registration of two cloud of synthetic points is shown using the traditional algorithm of ICP [16] is shown in figure 1. In this experiment, 1800 points have been used and a given motion has been considered to obtain both clouds of points. Furthermore, we have added gaussian noise in the 3D coordinates. Figure 2 shows the results of the same experiment with a 3% of outliers. The registration errors are quite important due to the fact that the method does not cope with outliers. In order to reduce such errors, a robust ICP algorithm with outlier thresholding [25] was implemented (see the results in figure 3).

Furthermore, some accurate registration methods were compared using different error measures (see table II). The measures computed are: the length of the error of the translation vector (Δt), two errors of the rotating angles (α,φ), the mean

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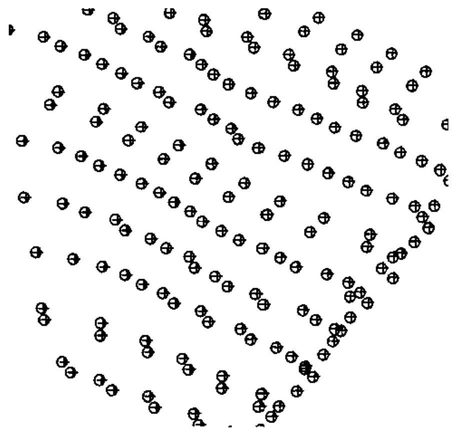

Fig. 1. Accurate Registration with ICP algorithm with 1800 synthetic points, with gaussian noise($\mu = 0$, $\sigma = 0.5$) in 3D coordinates and without outliers

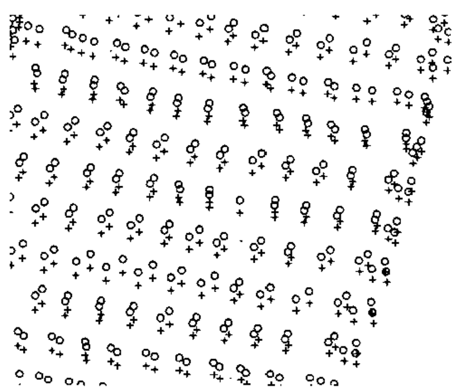

Fig. 2. Accurate Registration with ICP algorithm with 1800 synthetic points, with gaussian noise($\mu = 0$, $\sigma = 0.5$) in 3D coordinates and with 3% outliers

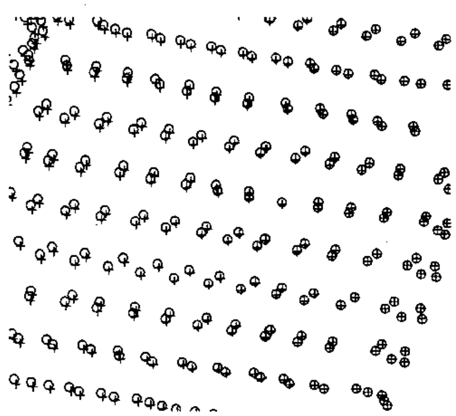

Fig. 3. Accurate Registration with robust ICP algorithm with 1800 synthetic points, with gaussian noise ($\mu = 0$, $\sigma = 0.5$) in 3D coordinates and with 3% outliers

(μ) and deviation (σ) of 3D error and finally the computational time. For this experiment, 500 synthetic points were used. In general, all the methods converge to a good solution, however, the presence of noise and outliers decrease the quality of the obtained results. In general, the ICP method presents the best results, although the robust approach eliminates some correct correspondences so the results are obtained considering fewer points than the other methods, a fact that affects directly the accuracy of the results.

VI. CONCLUSIONS

This article surveys the most common registration methods. These kind of methods are used to reconstruct complete models of objects. The main classification is based on the accuracy given. Poor registration techniques are used when an initial estimation of the Euclidean motion is unknown. However, results obtained with these techniques present a rough accuracy. The procedure of these techniques is based on finding correspondences between clouds of points and then computing the Euclidean motion. Different kind of correspondences can be used, as points, curves, surfaces and directional vectors. Besides, accurate registration methods are based on converging to a solution from an initial estimation of the rigid motion. Depending on the method used, a good initial guess is required because some methods have problems of convergence due to the presence of multiple local minims.

ACKNOWLEDGMENT

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TABLE II

EXPERIMENTAL RESULTS OF IMPLEMENTED METHODS

		ICP						Chen					
Gaussian noise	Outliers (%)	Δt	Δα	Δφ	μ(3D)	σ(3D)	time	Δt	Δα	Δφ	μ(3D)	σ(3D)	time
0	0	0,00	0,00	0,00	0,00	0,00	1,85	2,76	0,46	0,21	0,07	0,03	348,43
0,5	0	1,87	0,10	0,15	0,68	0,29	5,94	12,75	3,49	0,87	1,12	0,43	345,50
0	2	0,21	0,00	0,00	0,07	0,22	7,61	13,98	2,35	0,56	1,38	1,46	506,16
0,25	2	1,45	-0,10	0,06	0,52	0,25	7,59	10,82	0,16	0,20	0,89	1,46	514,53
0,5	2	3,68	-0,19	0,17	0,70	0,32	6,75	12,98	1,98	0,51	1,38	1,46	485,30
0,25	5	2,00	-0,01	0,00	0,60	0,36	8,80	46,35	-0,10	0,12	1,51	3,91	501,52
0,5	5	3,58	0,00	0,00	0,77	0,39	8,08	47,20	-0,06	0,11	1,90	3,80	425,13
0	10	4,61	-0,01	0,02	0,61	0,33	18,59	218,24	-0,94	1,57	5,80	7,31	327,95
0,25	10	7,42	-0,03	0,03	0,84	0,42	8,65	221,14	-0,94	1,57	5,95	7,25	370,34

		Jost						Zinber					
Gaussian noise	Outliers (%)	Δt	Δα	Δφ	μ(3D)	σ(3D)	time	Δt	Δα	Δφ	μ(3D)	σ(3D)	time
0	0	0,00	0,00	0,00	0,00	0,00	0,36	0,00	0,00	0,00	0,00	0,00	5,51
0,5	0	7,18	0,94	0,50	1,36	0,58	1,49	2,78	0,15	0,25	0,66	0,25	12,63
0	2	0,62	-0,18	0,12	0,12	0,31	0,87	3,12	0,15	0,18	0,66	0,25	10,42
0,25	2	3,05	-0,07	0,30	0,92	0,41	1,21	2,30	-0,05	0,11	0,48	0,18	12,10
0,5	2	7,44	0,58	0,76	1,35	0,59	1,45	3,89	0,10	0,29	0,67	0,25	11,09
0,25	5	5,20	-0,01	0,01	0,97	0,47	1,69	3,44	0,01	0,01	0,52	0,20	14,97
0,5	5	11,61	0,00	0,02	1,36	0,66	1,55	11,61	0,00	0,02	1,36	0,66	1,55
0	10	11,29	-0,02	0,03	0,93	0,44	1,38	3,43	-0,03	0,01	0,46	0,21	23,59
0,25	10	7,05	-0,01	0,02	1,10	0,47	1,52	4,32	-0,02	0,02	0,63	0,24	13,16

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