A REVIEW OF RECENT RANGE IMAGE RECONSTRUCTION ALGORITHMS

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ABSTRACT:

Preparing virtual models by data acquired from indoor and outdoor objects, comprehensively, have been ingratiated with specialists of geomatic science. Since previous years, specialists of computer science have implemented some researches in relation with indoor data. Hence, in this paper a comprehensive review has been created to reconstruct range data which are based on indoor objects. This review is consists of 30 techniques executed in the last years. It can be ingratiated with many researchers of geomatic science. We have used a pyramidal method to review reconstruction techniques. The achieved conclusions of this review give researchers and developers, who are concerned with this subject, an appropriate outlook and they can relate their activities around it for creating novel algorithms and approaches

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1. INTRODUCTION

In recent years, geomatic is exited from classical concepts of map extraction from real world and progressed in the way of providing model from real objects and existent phenomena. Preparing virtual models by data acquired from indoor and outdoor objects, comprehensively, have been ingratiated with specialists of geomatic science .In this way, extracting models automatically is one of the most important and the most fundamental problem in creating models. Thus, fundamental concepts of computer vision science such as object recognition, feature extraction, segmentation and ultimately reconstruction have been entered to the field of geomatic science particularly photogrammetry and remote sensing.

Since previous years, specialists of computer science have implemented some researches in relation with indoor data. Hence, in this paper a comprehensive review has been created to reconstruct range data which are based on indoor objects. This review is consists of techniques executed in the last years which can be ingratiated with many researchers of geomatic science.

We have used a pyramidal method to review reconstruction techniques. To consider multiplicity of applied techniques, Pyramidal Comparison Method (PCM) creates a perfect surround for researchers. Comparing levels in this pyramid have been designed as moving from upper levels to lower ones, comparing more details of algorithms (see Figure 1). The number of 30 algorithms since 1981 to 2007 in relation with reconstruction methods has been reviewed with PCM. The steps of a reconstruction procedure can be consists of segmentation, registration, recognition, and noise and outliers. Different algorithms have performed whole or some of these steps. In this paper we have reviewed just the approaches whose researchers have achieved a reconstruction model. The stages involved in carrying out PCM can be summarized as follows:

1) At the top of comparison pyramid, algorithms have been separated into two sets which are based on conventional-computing and soft-computing, respectively.
2) The fields which are located into the second level of comparing pyramid are composed of input, noise reduction and outliers, segmentation, registration, recognition, efficiency and output.
3) In the third level of pyramid, the stages as segmentation, registration, recognition and output, which are into the second level, have been divided into subsets. Each of the algorithms according to complexity and extension of these steps have been reviewed separately via taxonomies which are used in the scientific references.
4) The fields into the fourth level represent applied stages in each of the reconstruction algorithms that are mentioned in section 3.

The following section describes various classifications for the reconstruction of range images. The third section elaborates on the details of each algorithm and describes their advantages and disadvantages. Conclusions are presented in section four.

2. A CLASSIFICATION FOR RECONSTRUCTION ALGHORITHMS

A reconstruction procedure is commonly composed of input, registration, segmentation, recognition, noise and outliers, and output. Due to the variety of reconstruction methods, authors who propose reconstruction algorithms according to input and output data employ different algorithms. Thereby, algorithms have various formations in carrying out aforementioned stages; however, depending on the nature of each algorithm, some of the stages are removed. Finally, we try to elaborate each algorithm in our pyramidal comparison but for detailed

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reconnaissance of algorithms readers can refer to original resources.

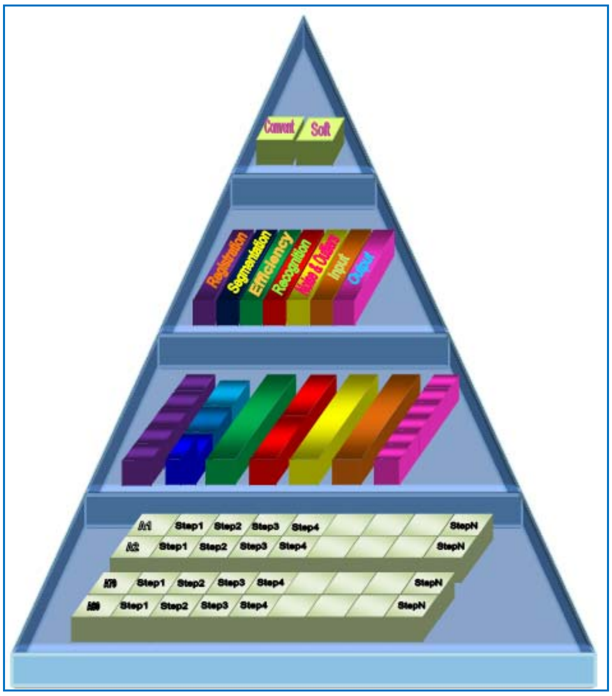

Figure 1. Comparison pyramidal method (PCM)

2.1 Registration

Registration is the process of aligning a target image to a source image. More generally, it determines the transform that maps points in the target image to points in the source image. The goal of registration is to find the Euclidean motion between a set of range images of a given object taken from different positions in order to represent them all with respect to a reference frame. The proposed techniques differ as to whether initial information is required, so that a rough registration can only be estimated without an initial guess. If an estimated motion between views is available, a fine registration can then be computed. In coarse registration, the main goal is to compute an initial estimation of the rigid motion between two clouds of 3D points using correspondences between both surfaces.

2.1.1 Pairwise Registration

The point based approach is used to iteratively match two point clouds. (Besl and Mckay,1992) proposed an algorithm capable of registering two sets of three dimensional points (i.e., of computing the rigid transformation that maps the first point set onto the second one).Their algorithm simply minimizes the average distance between the two point sets by iterating over the following steps : first establish correspondences between scene and model features by matching every scene point to model closest to it ,estimate the rigid transformation mapping the scene points onto their matches, and finally apply the computed displacement to the scene. The iterations stop when the change in mean distance between the matched points falls below some preset threshold. In this technique, the ICP algorithm is employed which is included some of the processes as follows:

1) Assume a close initial alignment
2) Compute the closest point
3) Compute the transformation from error metric
4) Apply the transformation
5) Next iteration

This method has some advantages such as slow convergence, finding local minima, well performance with good initialization. It is important to know that initial alignment may come from manual or feature-based registration.

2.1.2 Feature Based Approach

The feature based approach is consists of two stages. First stage is a feature extraction stage and the second one is finding transformation by matching features. This method is involved in point based features as spin images, line based features, DARCES as point groups sliding and bitangent curves matching. Therefore, more errors occur at feature extraction. Finally, feature based approach usually requires point based methods to refine registration.

2.1.3 Multi View Registration

In this approach, we encounter problem of error accumulation, sequential optimization and simultaneous optimization. In sequential optimization, at first a view is added to current registered view sets at each step. In the next, a view is added at each step while satisfying pair-wise constraints. In simultaneous optimization, at the beginning, it must be minimized the composite transformations errors. Then, error is distributed along cycles. In the next, apply robust methods as statistical estimation on point’s true position and M-estimation. Ultimately, force based optimization is used. Multi view registration usually is involved in point based method. It has time consuming and is hard to find optimal solution.

2.1.4 Model Based

Model based registration builds a simplified geometric model from a training set and identifies parameters that control the characteristics of the model. It registers the model to a target image to adapt to a particular patient and also uses the spatial objects framework for representing geometry. Therefore, it is useful because it derives analytical data from the registration process, not just a pixel-to-pixel mapping.

2.2 Recognition and Model Fitting

The goal of recognizing surfaces and primitive objects is the correct performance of fitting. This process executes to fit a model and surface. As you know, the concept of recognition in reconstruction procedure is different from general one in object recognition. The recognition stage of man-made indoor reconstruction for surface’s type determination is separated to: matching piecewise planar surfaces using interpretation trees and matching free form surfaces using spin images.

2.2.1 Matching Piecewise Planar Surfaces Using Interpretation Trees

The recognition algorithms proposed by (Faugeras and Hebert, 1986) is a recursive procedure exploiting rigidity constraints to efficiency search an interpretation tree for the path(s) corresponding to the best sequence(s) of plane matches. The basic procedure is given in pseudo code in this algorithm. To correctly handle occlusions, the algorithm must consider, at every stage of the search, the possibility that a model plane may not match any scene plane. This is done by always incorporating in the list of potential matches of a given plane token null plane.

2.2.2 Matching Free Form Surfaces Using Spin Images

Differential geometry provides a powerful language for describing the shape of a surface locally (i.e., in a small neighborhood of each one of its points). On the other hand, the region growing algorithm is aimed at constructing a globally consistent surface description in terms of planar patches. We introduce in this section a semi local surface representation—the spin image of (Johnson and Hebert, 1999)— that captures the shape of a surface in a relatively large neighborhood of each one of its points. As shown in the rest of this section, the spin image is invariant under rigid transformations, and it affords an efficient algorithm for pointwise surface matching, thus completely bypassing segmentation in the recognition process.

2.3 Segmentation

We use the term segmentation for a wide range of activities because, although techniques may differ, the motivation for all these activities is the same: obtain a compact representation of what is helpful in the image. It is hard to see that could be a comprehensive theory of segmentation, not least because what is interesting and what is not depends on the application.

Assume that we would like to recognize objects in an image. There are too many pixels to handle each individually. Instead, we should like some form of compact, summary representation. The details of what that representation should be depend on the task, but there are a number of general desirable features. First, there should be relatively few (= not more than later algorithms ca cope with) components in the representation computed for typical pictures. Second, these components should be suggestive. It should be pretty obvious from these components whether the objects we are looking for are present, again for typical pictures.

Three fundamental techniques which are used in segmentation are edge-based, region-based and hybrid. Diversity of these algorithms depends on edge extraction method and type of region extension parameter. To consider the main aim of paper, in a lower level, respective approaches are compared and to more study you can refer to main references.

2.3.1 Edge Based

Edge based approach is used to adapt 2D image processing techniques such as edge masks, residue operators (erosion, dilation, opening and closing) and surface normal clustering. Two kind of its applications are edge linking and edge thinning. This technique as other ones has some limitations for example, fragmented and discontinuous edges, sensitive to noise and not much information for curved surfaces. In spite of that, it is simple to implement, useful for polyhedral objects and an initialized segmentation for later region based.

2.3.2 Region Based

This approach is employed techniques, which are determined particulars of polyhedral surfaces, spheres and cylinders, such as normal decomposition with depth information, normal analysis and scan line clustering. Furthermore, it fits and merges quadratic curve and creates arbitrary shapes by surface model fitting (Besl, P. J. and Jain, R. C., 1985). General steps of this technique are point classification for an initial segmentation, local least square fitting at each pixel and region growing to minimize fitting error, respectively. Benefits of this method are included general solution to surface fitting and providing closed segmented regions, however, it posses high time complexity and cannot provide accurate boundary information.

2.3.3 Hybrid

Hybrid approaches are separated into two parts as follows:

1) Edges first, then regions
2) Regions first, then edges

In the first manner, at the beginning curvature sign map separates regions. Then, edge based method are applied to detect edges and next, edge patches are fitted to certain surface model. In the second manner, using plane fitting and clustering, contour extraction and classification, computing parameters for linear edges, refining step edges based on plane information and finally only polyhedral can extend to curved surfaces.

2.4 Efficiency and Performance

In many practical range image reconstruction projects, we encounter with vast volume of data as creating absolute models for factories and other installations. Such subject is so important that each of the algorithms with respect to efficiency try to employ suitable strategies to prevent problems which are derived from temporal and spatial limits. Different authors in contrast with such problems apply various techniques. These techniques are divided into two strategies. In the first strategy, it has been attempted to optimize algorithm against vast volume of data. In this strategy, typically main algorithms are directed to simpler algorithms which have less power than the main one. In the second strategy, designers try to use powerful approaches, which efficiently handle vast volume of data, as multi resolution analysis. With regard to this analyzing method, it must be said that initial data which are acquired in variant scales. Therefore, it is possible to use powerful and complicated algorithm.

2.5 Noise and Outliers

One of the most sensitive problems in acquiring range data from range scanners, structural lights and other instruments is presence of noise and outliers. Such problem may be derived from, hardware's infirmity, algorithms or conditions that are governed for the stage of data gathering. Presence of noise and outliers can extremely affect whole the reconstruction procedure. Obviously, an algorithm can be applied as a practical reconstruction technique that consider aforementioned problem. Two basic approaches to contrast with noise and outliers are presented as follows:

1) Noise and outlier reduction
2) Robust to noise and outliers

In the first approach, initially in a pre-processing stage, noisy data and outliers are filtered. The positive point of that is its simplicity and the negative one is some information smoothed after removing the noise. In the second approach, as algorithms are designed that are robust to noisy data and outliers.

2.6 Input

Input of the reconstruction algorithm which is based on indoor range data is a set of three dimensional points which forms a point cloud according to desired subjects. The achieved point cloud from diverse instruments as range scanners and structural lights can be categorized into two sets: uniform and non-uniform. The major of adopted equipments try to create a uniform point cloud. In concern about uniformity, different algorithms have limitations with respect to the type of input data that such cases cause subsequent limitations.

The second taxonomy for point cloud data is based on data whether are organized or unorganized. To this purpose, we can mention two viewpoints. In the primary viewpoint, organization as opposed to being unorganized is corresponded with grid data in comparison with random data. Hence, to consider all the equipments acquiring range data which create a random point cloud, as compared to algorithms which use regular data, require a preprocessing stage to convert random data to regular data. Accomplishing such stage cause to create subsequent errors and also interpolation error of this stage is entered to whole the reconstruction procedure and therefore impress it. In the second viewpoint, the purpose of regular data is structural data in contrast with unstructured data. Such structure that is done in a preprocessing stage is used for both random data and grid data.

Other input data for some reconstruction algorithms are initial information about desired subjects to reach the modeling. These initial information particularly in relation with interactive algorithms or neural network ones are categorized as information based on human knowledge for selecting model are located into the one set and information based on learning algorithms are located into another set.

2.7 Output

An output model based only on the measured points will usually consist of surface boundaries that are irregular and overlapping and need some assumption to be corrected using for example planes and plane intersections. For large structures and scenes, since the technique may require a large number of images, the creation of the model requires a significant human interaction even if image registration and a large number of 3D points were computed fully automatically. The degree of modeling automation increases when certain assumptions about the object, such as architectures, can be made. A large number of algorithms have been developed and the dense output is generally used for view synthesis, image based rendering or modeling of complete regions (Remondino. F. and El-Hakim. S., 2006).

The method that we use in this paper is based on a taxonomy summarized as follows:

1) Continuous
    a. Combinatorial
        I. Topological set
        II. Memberships
    b. Functional
        I. Parametric
        II. Implicit
2) Discrete

In this taxonomy has been attempted to distinguish algorithms via a continuity comparison. Thereby, if output model possesses a continuous model, but it is a combination of some models and it belongs to combinatorial models. Combinatorial models, depending on their shape and scale, are topological sets or memberships. On the other hand, if output model possesses an absolute continuous model, it is a functional model. Such models with respect to type of its function will be parametric models or implicit ones. Finally, if a model includes no aforementioned cases, it will be a discrete model.

3. A SUMMARY FOR RECONSTRUCTION ALGORITHMS

An alternative robust approach for the estimation of parameters based on random sampling and called Random Sample Consensus (RANSAC) has been presented by (Fischler and Bolles, 1981, 1987). The execution time is considered approximately 1 sec for each camera position. The methods have been proposed to fit cylinders to point clouds can be divided into two main categories: those requiring a prior segmentation and those processing raw point clouds without segmentation. The methods belonging to the second category try to avoid these problems by processing raw point clouds by using robust fitting methods like RANSAC (Bolles and Fischler, 1981; Chaperon and Goulette, 2001). For example in (Chaperon and Goulette, 2001) RANSAC is used for cylinder detection and fitting. This algorithm has two kind of output classification (see Table.1).

There has been a lot of work, mainly in the Computer Graphics community, on using the zero set of the signed distance field for the recovery of a smooth manifold from a given point cloud (Curless and Levoy, 1996; Hoppe et al., 1992). Such a manifold is essentially a free-form surface, and thus cannot be easily represented by a CAD model. Moreover, the surface should be completely covered with the point cloud of uniform density. Because of these requirements combined with the types of models produced, these methods are not useful for industrial reconstruction.

An approach that has been proposed by (Borges, D. L., 1995) presents a complete solution to the problem of recognizing 3D objects, using shape information extracted from range images, and parameterized volumetric models. It has developed an integrated approach that addresses representation, feature extraction and interpretation in the context of the above mentioned domain of objects.

A general purpose algorithm for reliable integration of sets of surface measurements into a single 3D model has been introduced by (Hilton, A., Stoddart, A.J., Illingworth, J. and Windeatt, T, 1997). This new algorithm constructs a single continuous implicit surface representation which is the zero-set of a scalar field function.

The method which has been proposed by (Leonardis, A., Jaklic, A. and Solina, F., 1997; Krivic, J.andSolina, F., 2004) is a novel approach to recovery of part-descriptions in terms of superquadric models from range data. The approach is based on the recover-and select paradigm. The recover-and-select paradigm consists of two intertwined stages: model-recovery and model-selection. Procedures which are applied in recover-: seed selection, superquadric fitting, decision making regarding models, search for new compatible points (growing) and model selection.

Source	Computing	Segmentation	Registration	Recognition and Model Fitting	Noise and Outliers	Input	Output	Efficiency and Performance
Bolles, R.C., 1981	Conventional	RB	No	No	Noise and outliers reduction (Filter out gross errors by RASNAC technique)	Point Cloud/ Non-uniform	Continuous/ Functional/ Parametric/ Ellipse and line	Efficient to time (The execution time is approximately 1 sec for each camera position)
Hoppe, H., 1992	Conventional	No	No	No	Robust to noise (Controlling noise by using a noise threshold)	Range image/ Non-uniform	Continuous/ Functional/ Parametric/ Simple Surface	Efficient to time (Reduce time complexity by a favor of n)
Borges, D. L., 1995	Soft	H1	No	Matching free form surfaces using spin images	Sensitive to noise	Range image/ Uniform	Continuous/ Functional/ Parametric/ Shape parameters	Unknown
Curless, B., 1996	Conventional	No	MB	No	Noise and outlier reduction (Reduce sensor noise by utilization all range data)/ Robust to outliers	Range image/ Uniform	Continuous/ Functional/ Parametric/ Complex model	Efficient to space (Employing a run-length encoding of the volume)/ Efficient to time
Hilton, A., 1997	Conventional	No	No	No	Robust to noise	2.5D range image	Continuous/ Functional/ Implicit/ Single surface	Partly efficient to time
Leonardis, A., 1997	Conventional	RB	No	No	Robust to noise and outliers	Unsegmented range image	Continuous/ Functional/ Parametric/ Generalized cylinder and superquadric model	Efficient to time/No presegmentation
Luca Foresti,G, 1998	Soft /Neural trees	H2	No	Matching free form surfaces using spin images	Robust to noise	Range image	Continuous/ Functional/ Parametric/ Surface	Inefficient to time
Lukacs, G., 1998	Conventional	RB	No	No	Robust to noise and outliers	Range image/ Uniform and non-uniform	Continuous/ Functional/ Parametric/ sphere, cylinder,cone and tori	Efficient to time/ Efficient to space/ Iterative(e.g. Gauss-Newton or Levenberg-Marquardt method)/ Need to initialization

Table 1. Range image reconstruction approaches. Legend for all tables is as follows: RB=Region based, H1=Hybrid (first edge then region), H2=Hybrid (edge and region), EB=Edge based, MB=Model based, PB=Point based, FB=Feature based, MV=Multi view

Tang, C.-K., 1999	Conventional	No	No	Matching free form surfaces using spin images	Robust to Outliers	Range image	Continuous/ Functional/ Parametric/ Surface, curve and junction	Stable to partial derivative computation/ non-iterative/ No initialization
Ermes,P., 1999	Conventional	No	No	No	Noise and outliers reduction	Range image/ Uniform	(Continuous/ Combinatorial/Topological set/Triangulated mesh) and (Continuous/ Functional/ Parametric/ Quadric surface and spline)	Partly efficient to time
Heuvel, F. A. v. d., 1999	Conventional	No	No	No	Sensitive To Noise	Range image	Continuous/ Functional/ Parametric / Surface	Unknown
Reed, M.K., 1999	Conventional	No	MB	Matching free form surfaces using spin images	robust to outliers	range image	Continuous/ Combinatoria/ Membership/ Solid	Unknown
Vosselman, G., 1999	Conventional	EB	MB	Matching free form surfaces using spin images	Noise reduction/ Robust to outliers	laser altimetry data/ Uniform (High Density)	Discrete/ Voxel	Unknown
Werghi, N., 1999a	Conventional	RB	No	Matching free form surfaces using spin images	Noise reduction	Range image/Unifom	Continuous/ Functional/ Implicit/ Algebraic/ Quadric Surface	Inefficient to time/ Inefficient to space
Boughorbel, F., 2000	Soft/Neural network/ Genetic algorithm	No	MB	No	Unknown	Range and intensity image/ Uniform and non-uniform	Continuous/ Functional/ Parametric/ Triangular mesh with texture	Partly efficient to time/ Inefficient to space/ Need to operator intervention/ No need to initialization
Chaperon ,T., 2001	Conventional	No	No	No	Robust to noise and outliers	Range image/ Uniform	(Continuous/ Functional/ Parametric/ Sphere, cylinder, cone and tori) and (Discrete/ Voxel)	Unknown

Table 2. Continued

Olson, C .F., 2001a	Conventional	RB	No	Matching free form surfaces using spin images	Noise and outliers reduction	Range Image/ Uniform	(Continuous/ Combinatoria/ Topological set/ Mesh subdivision) and (Continuous/ Functional/ Parametric/ Surface)	Efficient to time/ Efficient to space
Yu,Y., 2001	Conventional	RB	PB	Matching free form surfaces using spin images	Unknown	Range Image/ Uniform	Continuous/ Combinatoria/ Topological set/Mesh subdivision	Efficient to time
Xiyu, L., 2002	Soft/Neural network/ Genetic algorithm/Back propagation	No	No	No	Unknown	Range image	Continuous/ Functional/ Parametric/ Polynomials-trigonometrical function	Efficient to time (parallel computing) / Need to initialization
Jeong W.-K., 2003	Soft /Neural Network and the statistical analysis of its learning process	No	No	No	Robust to noise	Point cloud	Continuous/ Functional/ Parametric/ Surface	Efficient to time/ Efficient to space
Liu, Y., 2003	Conventional	No	PB	No	Robust to noise and outliers	Range Image	Continuous/ functional/ parametric/ Free form surface	Inefficient to time / Iterative
Tubic, D., 2003	Conventional	No	FB	No	Robust to noise and outliers	Range image	Continuous/ Functional/ Parametric/ Surface	Efficient to time reducing (the execution time by parallelization)
Benlamri, R., 2004	Conventional	H2	MB	Matching free form surfaces using spin images	Sensitive to noise	Registered range and intensity image	Continuous/ Functional/ Implicit/ Algebraic surfaces/ Free form object	Need to preregistration
Ivrissimtzis, I., 2004	Soft /Neural network	No	No	No	Noise reduction	Point cloud	Continuous/ Functional/ Parametric/ Surface	Inefficient to time / Inefficient to space/Need to initialization
Krivic ,J ., 2004	Conventional	RB	No	Matching piecewise planar surfaces using interpretation trees	Unknown	Raw Data/ Range Image/ Uniform and non-uniform	Continuous/ Functional/ Parametric/ Superquadric	Unknown

Table 3. Continued

O'Leary, P., 2004	Conventional	No	No	No	Robust to noise	Point cloud/ Non-uniform	Continuous/ Functional/ Implicit/ Algebraic	Efficient to time
Park, S.-Y., 2004	Conventional	No	PB/ MV	No	Noise reduction (Using height threshold constraint)	Range and intensity image	Continuous/ Functional/ Parametric/ Surface	Efficient to time
Vosselma n,G. , 2004	Conventional	RB	No	Matching free form surfaces using spin images	Robust to noise /Sensitive to outliers	Range Image/U niform	Continuous/ Functional/ Parametric/ Surface	Partly efficient to time
Wang, W., 2004	Conventional	No	No	No	Robust to noise	Raw Data/ Point Cloud/ Non-uniform	Continuous/ Functional/ Parametric/ B-Spline	Efficient to time/Need to initialization
Chen, H., 2007	Conventional	No	No	Matching free form surfaces using spin images	Robust to noise and outliers	Range image	Continuous/ Functional/ Parametric/ Surface	Efficient to time

Table 4. Continued

In approach that has been used by (Luca Foresti,G. and Pieroni,G., 1998), a new neural tree architecture whose nodes are generalized perceptrons without hidden layers is applied to segment range images into surface patches, according to the six models of differential geometry, e.g., peak, ridge, valley, saddle, pit and flat. A new learning scheme which improves upon the standard neural tree algorithms in terms of convergence is proposed.

The particular contributions of the method have been proposed by (Luk´acs, G., Martin, R. and Marshall, D., 1998) are methods for the least-squares fitting of spheres, cylinders, cones and tori to three-dimensional data. This method has the particular advantage of being robust in the sense that as the principal curvatures of the surfaces being fitted decrease (or become more equal), the results which are returned naturally become closer and closer to the surfaces of "simpler type", *i.e.* planes, cylinders, or cones (or spheres) which best describe the data, unlike other methods which may diverge as various parameters or their combination become infinite.

One common problem faced by all range segmentation algorithms is the estimation of local surface properties like gradient, surface normal, principal curvatures and higher-order derivatives from the noisy data. Robust estimation techniques must be used to counter the effects of outliers and noise (Tang and Medioni, 1999).
As most modeling procedures consist of two separate processes of surface fitting and conversion to CAD model, it is difficult to simultaneously enforce the geometric constraints. Compared to B-rep, CSG provides a powerful, though less general, method to specify both the surface geometry and associated constraints in one package. Based on this observation, techniques for fitting CSG models with constraints to images have been developed by (Ermes et al., 1999). This algorithm has two kind of output classification (see Table.2).

In industrial environments many objects consist of one or more planar faces that can be used for registration. Describing a plane by the normal vector $n = (n_x\ n_y\ n_z)^T$ and the perpendicular distance from the origin provides a singularity free representation (Heuvel, 1999). This representation is also known as Hesse form of the plane.

A method for automatically constructing a solid (in the CAD sense) model of an unknown object from range images is (Reed, M.K. and Allen, P.K., 1999). A solid representation is derived from a mesh surface that models the range data from each view, which is then merged with the model built from previous sensing operations. This modeling system has the benefit of constructing a solid model at each phase of the acquisition process, and is able to model parts that are difficult or impossible using other methods, such as extremely thin parts or those with deep through-holes.

An approach that has been presented by (Vosselman, G., 1999) is based on the detection and outlining of planar faces in dense height data. To avoid loss of information due to interpolation, all operations are performed on the Delaunay triangulation of the original height points. The planes of the faces are determined by clustering of the points. The outlines of the faces are determined by a connected component analysis on the triangles of the Delaunay triangulation. Only a limited amount of generic knowledge is used in the reconstruction.

Some techniques for recovering quadric surface based models by using constraints have been presented by (Werghi et al., 1999a). They first extract planar and quadric patches from the segmented range data, analyze them to infer the geometrical constraints like perpendicularity, equality of radius etc. These constraints are then used to improve the fitting results.

Boughorbel, F., Page,D. and Abidi,M., (2000) present a statistical technique for multi modal image registration. This approach requires the use of a robust optimization scheme for the maximization of the similarity measure. To achieve accurate results, they investigated the use of heuristics such as genetic algorithms. The retrieved pose parameters are used to generate a texture map from the color image, and the occluded areas in this image are determined and labeled. Finally the 3D scene is rendered as a triangular mesh with texture.

A hybrid approach for object-recognition, that combines both generate-and-test and Hough-transform-based methods, is reported by (Olson, 2001a). The first stage generates possible hypotheses using distinguished-features but the final testing stage uses randomized Hough transform. This method is called RUDR (Recognition Using Decomposition and Randomization). Another technique similar to the Hough Transform is template matching, its main limitations being the computational complexity and the sensitivity to noise and occlusions. This algorithm has two kind of output classification (see Table.3).

A range segmentation algorithm based on graph partitioning using normalized cut framework has been presented by (Yu et al., 2001) that first detects connected clusters in the range image, and then uses average position, surface normal and average intensity of these clusters to group them together using normalized cuts. This algorithm results in over-segmentation which needs to be corrected by manual editing and merging.

A new surface reconstruction method based on complex form functions, genetic algorithms and neural networks has been presented by (Xiyu, L., Mingxi, T. and Hamilton Frazer. J., 2002). Surfaces can be reconstructed in an analytical representation format. This representation is optimal in the sense of least-square fitting by predefined subsets of data points. The surface representations are achieved by evolution via repetitive application of crossover and mutation operations together with a back-propagation algorithm until a termination condition is met.

Jeong W.-K., Ivrissimtzis I. and Seidel H.-P., (2003) present a method for the adaptive reconstruction of a surface directly from an unorganized point cloud. The algorithm is based on an incrementally expanding Neural Network and the statistical analysis of its Learning process. In particular, they make use of the simple observation that during the Learning process the normal of a vertex near a sharp edge or a high curvature area of the target space, statistically, will vary more than the normal of a vertex near a flat area.

A novel practical algorithm for automatic free-form surface matching has been proposed by (Liu, Y., 2003). This method directly manipulates the possible point matches established by the traditional ICP criterion based on both the collinearity and closeness constraints without any feature extraction, image pre-processing, or motion estimation from outliers which are corrupted data.

A new approach to surface recovery from range images has been presented by (Tubic´,D., He´bert, P. and Laurendeau, D., 2003). While the reconstructed surface is described in its implicit form as a signed distance field within a volume, registration information for matching partial surfaces is encoded in the same volume as the gradient of the distance field.

The approach, that has been proposed by (Benlamri, R. and Al-Marzooqi, Y., 2004), combines edge and region information to derive a surface description using algebraic implicit surfaces. This is done by propagating and blending piecewise Hermite interpolation surfaces. The proposed technique, not only reduces the number of used patches, but also preserves surface-depth and orientation continuity. It can also be used to generate partial surface models for CAD-based vision and object recognition purposes. Realistic partial models are obtained by mapping texture extracted from a registered color image onto the generated surfaces.

A new surface reconstruction algorithm based on an incrementally expanding neural network known as Growing Cell Structure has been proposed by (Ivrissimtzis, I., Jeong,W.-K., Lee, S., Lee, Y. and Seidel, H.-P., 2004). The neural network learns a probability space, which represents the surface for reconstruction, through a competitive learning process. The topology is learned through statistics based operations which create boundaries and merge them to create handles.

A new method to fit specific types of conics to scattered data points is introduced by (O'Leary, P. and Zsombor-Murray, P., 2004). Direct, specific fitting of ellipses and hyperbolae is achieved by imposing a quadratic constraint on the conic coefficients, whereby an improved partitioning of the design matrix is devised so as to improve computational efficiency and numerical stability by eliminating redundant aspects of the fitting procedure.

The technique that is used by (Park, S.-Y. and Subbarao, M., 2004) is based on novel approaches to pose estimation and integration. Two different poses of an object are used because a single pose often hides some surfaces from a range sensor. A second pose is used to expose such surfaces to the sensor. Two partial 3D models are reconstructed for two different poses of the object using a multi-view 3D modeling technique. The two 3D models are then registered in two steps: coarse registration, and its refinement.

The scans were segmented and planes and cylinders were semiautomatically recovered using methods presented in (Vosselman et al., 2004). The number of recovered objects in scan 1–4 was 28, 44, 46 and 19 respectively. After modeling the scans were registered pair-wise using the indirect method. As pointed out earlier, this is a quick way to get approximate values for the second step of the direct registration.

An approach that has been presented by (Wang,W., Pottmann,H. and Liu,Y., 2004) is a novel and efficient method, called squared distance minimization (SDM), for computing a planar B-spline curve, closed or open, to approximate a target shape defined by a point cloud, i.e., a set of unorganized, possibly noisy data points. It shows that SDM outperforms significantly other optimization methods used currently in common practice of curve fitting. In SDM a B-spline curve starts from some properly specified initial shape and converges towards the target shape through iterative quadratic minimization of the fitting error.

An integrated local surface descriptor for surface representation and 3D object recognition has been introduced by (Chen, H. and Bhanu, B., 2007). A local surface descriptor is characterized by its centroid, its local surface type and a 2D histogram. The 2D histogram shows the frequency of occurrence of shape index values vs. the angles between the normal of reference feature point and that of its neighbours. Instead of calculating local surface descriptors for all the 3D surface points, they are calculated only for feature points that are in areas with large shape variation.

4. CONCLUSIONS

This work reviews some of the most important algorithms that have been developed during the past 26 years to acquire reconstruction products. The evolution of some key technologies used to build 3-D models, showing the trends and progress accomplished during the past two decades. Because prototype development usually takes five to ten years from the initial research laboratory to commercialization, and incremental innovations are implemented more quickly, such approaches are a good indicative of past and current trends in this field. The work describes the most important range image reconstruction methods that are now commercially available.

Current industrial trends and research applications show that 3-D shape alone is not sufficient for a large variety of applications and also shape must be complemented with 2-D texture maps as well as with other types of sensory data. In this review we have addressed different aspects of 3d reconstruction using range and intensity images. By restricting our focus to only industrial installations we were able to exploit the domain specific constraints and apriori information for formulating automatic and semiautomatic methods for segmentation, recognition, registration and model fitting.

In this review, we cannot introduce which of the algorithms is the best one because each of the algorithms has some advantages and different applications. However, we have helped readers to choose the best algorithm according to their occupations, by indicating properties that is determinative for an algorithm, comparing them with other algorithms and representing their products. This could be a subject for future work to incorporate range image reconstruction with various systems.

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