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Interactive semantics-driven reconstruction methodology from Point Clouds

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Abstract

3D point cloud acquisition has become a common practice in the AEC Industry (Architecture, Engineering and Construction). With the emergence of BIM (Building Information Modeling), more and more industrials are interested in creating an "as-built" CAD model of their facilities. The transition from point cloud to a digital model is currently an extremely tedious task due to the large volume of data and the uniqueness of each scanned environment. Many researches are directed towards an automatic extraction of structural and piping elements of increasing complexity. The result however, is a geometry devoid of meaning, or a semantic classification of specific objects in very limited number.

In this article, we highlight the context and industrial needs for a generic object reconstruction method and we present the state-of-the art of manual and automatic methods. We then propose a semi-automatic reconstruction method combining semantization with 3D digitization of objects.

We review the most recent methods for each operation. Finally, we identify and discuss the technological gaps that need to be addressed in our future research.

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Keywords: As-Built BIM; Semantics-driven; 3D object retrieval; 3D shape decomposition

1. Introduction

3D surveys are accurate, almost exhaustive, and done in a limited time. Most of the time, they are generated using a terrestrial laser scanner (TLS) that rotates to capture the elements in the scene at a rate of several hundred thousand points per second. Point cloud is an excellent information carrier and as a visualization aid, it provides the possibility to examine a location remotely from multiple viewpoints. The points can be manipulated, hidden, colorized, removed - pushing the limits of human perception. Point clouds allows distance and surface flatness measurement [2] even on humanly inaccessible areas - allowing companies to carry out prefabrication operations. Especially in the industrial sector, a lot of resources are wasted when technicians have to go on site to perform control measurements [3].

Still the true potential of 3D surveys is on the information enrichment and the recognition of objects to 3D computer-aided design (CAD) model of the scene [1]. Indeed for the last decade, point clouds acquisition have significantly aided the expansion and democratization of BIM (Building Information Modelling) among professionals of architecture and civil engineering.

1.1. "As-Built" BIM

The BIM is a process based on information transactions and requires collaborative workflows. It works with a digital representation for physical and functional characteristics of buildings. [13] describes "As-Built" BIM as a BIM representation of a building at the moment of the 3D survey. One could use the terms "As-Existing" or "As-Is" instead of "As-built", as a building could suffer from deformations in its life cycle and indeed be different from the time it has been built.

As-built spatial modelling for facilities is the process of capturing the infrastructure spatial data and transforming it into a structured, object-oriented representation. [7] describes this transformation with 3 major steps :

- Geometrical modelling of building elements.
- Integrating semantic information with each element.

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- Establishing relationships between elements.

This representation is suitable for generating useful information valuable to architects, engineers, constructors, owners, inspectors and maintainers. A project's stakeholders can use spatial modelling in order to solve complex problems such as identifying deviations from design, quantity take-off, real-time monitoring of construction progress, project management, and 3D/4D simulation, maintenance, during different phases of a facility's life cycle.

1.2. Problem statement

1.2.1. Business Issues

Building owners or industries usually appoint scanning service providers to scan their facilities and register clouds to form a coherent representation. As the process of conversion to an "As-Built" CAD model is an laborious and manual task [7][15], service providers often call on modelling companies in an abroad country with cheaper labor cost. This 2-stages course of action often results in lost of communication, errors and overmodelling. Bringing modellisation to building stakeholders would grant them flexibility for small and medium-sized project where current "scan to BIM" processes often disregard them [5]. "Scan to BIM" is a term given to the survey process of capture to model. [4] describes this concept as wrongly formulated because the end result is not BIM but a 3D parametric model that assists the BIM process at its current level of development.

1.2.2. Technical Issues

In this paper, we qualify as point cloud, data delivered by terrestrial laser scanner (TLS), not handheld laser scanner nor aerial LiDAR nor CMM oriented laser scanner.

There are several challenges going along 3D Reconstruction from point clouds such as:

- The high variation of point density [6]
- The inaccuracy of the input data [29] (digital noise from the scanner or scanned environment) due to the presence of :
 - specular surfaces [9],
 - moving objects [11],
 - registration errors [8]
 - the type of material of scanned surface [10]
- Occlusion and clutters which inherently implies to deal with partial data [12].
- The diversity of elements present in industrial environments.
- Distinguishing elements that have similar shape. One can take the example of a wall and a partition wall, both elements are flat and vertical surfaces with a close texture. Nevertheless for a building professional making a distinction between these two elements is paramount.

1.3. Aim and structure

In section 2, a review of the current 3D reconstruction methods, manual, semi-automatic and automatic, to BIM object is drawn. Section 3, describes a semi-automatic reconstruction method combining semantization with 3D digitization of objects. We sub-divide the process into four steps:

- A semantic enrichment by a Tag from the user.
- Corresponding the semantic entity to a constrained graphs describing the topological relations of the primitive forms.
- Modelling of geometric primitives.
- Adjustment of the CAD object.

2. Related Work

In this section, we review the different forms of representation to describe an object. We then assess reconstruction method per their level of automation, manual, automatic and semi-automatic.

2.1. Representing the shape of objects

Similar to the work presented in [7] and in [13], in the context of "As-Built" BIM, shape description of object can be separated in three aspects: parametric or non-parametric, global or local, explicit or implicit.

- Parametric vs. non-parametric representation With a parametric representation, the shape is described with a small number of parameters. [7] gives as an example, a cylinder represented non-parametrically with a triangle mesh. In the heritage sector, meshes are used to directly convert cloud of points to CAD Design [20]. Indeed ornaments or deterioration over time on a structure, with sometimes a significant geometric complexity, makes it hard to model with a parametric representation, even though HBIM process (Historic Building Information Modelling) introduced in [21], proposed a library of parametric architectural objects.
- Local vs. Global representation

Local representation describes a portion of an object which parametric representations are often associated. Intensive researches has been done on local surface feature based methods for 3D object recognition [24][26][25][23][27][28]. These methods generally consist of three phases :

 - 3D keypoint detection [25] are points of a shape that are prominent according to a particular definition to recognize or classify point clouds at different scales.
 - local surface feature description which consist of encoding geometric information on a point or within its neighborhood.

- surface matching which contains three steps, i.e., feature matching, hypothesis generation and verification [24].

For global representations, the area of interest includes the object as a whole, this has the consequence of having a detection sensitive to occlusions. Generally methods adopting global descriptors expect to have properly segmented and complete objects, which is certainly not the case in an industrial environment.

- **Explicit vs. implicit representation**
Explicit representation is a direct encoding of the shape of the object (i.e. polygon mesh, bezier surfaces, NURBS, B-Rep, CSG).
Implicit representation allows an indirect encoding for the shape of the object, using an intermediate representation.

In industrial environments, we assumed that most objects under consideration can be well represented by a set of primitive shapes (planes, spheres, cylinders, cones and tori). [61]

2.2. Manual Reconstruction Methods

As of today, the digital modelling of building and MEP (Mechanical Electrical and Plumbing) is a manual task and considered a particularly time-consuming, subjective [43], laborious one requiring skilled operators. [16] [8] It needs important expertise for an operator to interpret the scene, as well as enriching the model with semantic informations. Even with training, results can differ from 2 operators.

Take for example the modelling of walls, since tracing the points in a 3D space is difficult, the process consists of drawing 2D sketches, then extruding, using an orthophoto of a trimmed point cloud as a guide. Usually this work is done using Autodesk Revit Architecture.

Another process of manual reviewed in [14], consist in an operator stitching 3D surface with some algorithm help following with identifying the object which is fitted after a proper search in a database of standardized object. Then, as-built attributes can be assigned manually.

2.3. Automated Reconstruction Methods

The focus of academic research has mainly been oriented on algorithms aiming at automatic segmentation, modelling of geometry and labeling of 3D LiDAR point clouds. Due to the large size of collected point clouds, automatic algorithms is said to be preferable to reduce the necessity of expensive and slow human processing.

Their is a division of research between geometry detection, which primarily focus on point cloud segmentation, and understanding, which primarily focus on object detection then leading on to model construction [4]. Researches are still on going to join those two approaches into a multistage method for geometry reconstruction.

2.3.1. Indoor Modelling

Work reported from the literature can be classified into two broad categories. One focus on the modeling of spaces [62] and the other on the modelling of elements composing the building [31], i.e., walls and slabs [32]. [33], [17] and [58] use Conditional Random Field (CRF) model that exploit contextual information to classify extracted planar patches to reconstruct a semantic 3D models of indoor environments. Their approach differs from other that rely on hard-coded rules represented by a semantic network, such as strict orthogonal constraints between walls and floors [44].

[59] developed an automatic indoor reconstruction methodology focusing on common rooms in modern construction. With successive operations of ground plan detection, occlusion labelling, opening detection and classification, the output of the developed method consists of a set of labelled planar patches (walls, ceiling, and floor), their connections with adjacency maps and a set of openings detected within each planar surfaces.

2.3.2. MEP Modelling

There has been a growing demand for the 3D reconstruction of MEP (Mechanical Electrical Plumbing) elements, with historically a focus on pipes and elbows.

The 3D reconstruction process of as-built pipelines has been on manual interaction and interpretation which is difficult, requiring skilled personnel with an high level of knowledge to identify each pieces of pipeline only with their appearance in the unstructured 3D point clouds (e.g., valves, pumps, heaters, exchangers)[35].

There have been efforts over the last decade to automate this process, [39] gives a review of automated as-built modeling methods

2.4. Semi-automatic reconstruction

Work on interactive tools for point cloud focus on segmentation and labeling. [55] proposes an approach where the user can correct a segmentation performed by an automatic algorithm using strokes. After the segmentation is completed, each region is used to retrieve a matching 3D model from a database.

[54] presents a semi-automated method for shape detection with a user-controlled segmentation. The lasso interaction is improved by performing selection on points that suits a detected shape.

[60] proposes a system allowing users to quickly and interactively label the environment using a RGB-D camera in real-time and through voice commands. Then a volumetric fusion algorithm reconstructs the scene in 3D with additional color data.

3. Our contribution

In 2.3, we reported that current 3D "As-built" reconstruction of building elements or MEP often lean towards automation with little or even no user intervention. In softwares, like EdgeWise (Trimble), that offers automatic geometry retrieval,

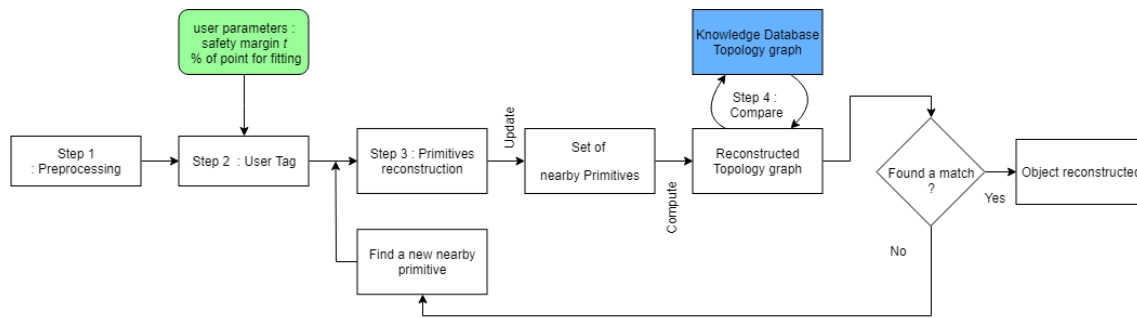


Fig. 1. Our method of an interactive semantic enrichment process

it goes as far as condemning skilled operators to an important and dull backchecking task of errors committed by the machine. The goal is ultimately to transform a point cloud directly to a BIM-ready semantically-enriched CAD model.

However, due to the high complexity of industrial scenes and the limitation of 3D scanners, manual intervention cannot be avoided [56]. [52] addresses this problem as an interface problem, stating "if a machine cannot meet the required accuracy and needs continuous guidance and interaction with the user, as valuable as it is to continue improving the learning component of the system, it is important to make the existing algorithms efficiently interact with the currently inevitable human presence in the loop".

In this aspect, we raise the need of a more interactive semantic enrichment process. We present here our semi-automatique reconstruction method combining semantization with 3D digitization of objects fig.1.

The process starts once a user selects a point in the cloud, a precision parameter and a safety margin parameter, he can label it as an object, e.g a wall. The wall is an object defined in a knowledge database and is symbolized by a topological graph of two parallel planes. From the selected point, a region of points is grown from which a model fitting algorithm determines the best fitting plane. It is then added to a set of primitives from which we compute a topological graph that is compare to the knowledge database topological graph. Until a match is found, we search for new primitives nearby and update our graph.

We subdivide the process into four steps:

- Step 1 : Preprocessing
- Step 2 : Semantic enrichment by a Tag from the user.
- Step 3 : Multiple primitives reconstruction
 - Step 3.1 Point cloud Segmentation.
 - Step 3.2 Modelling of geometric primitives.
- Step 4 : From primitives to object using a knowledge database

3.1. Step 1 : Preprocessing

The preprocessing consists in partitionning the unstructured cloud using an octree structure [41]. In his work, Wimmer presents an algorithm capable of displaying enormous

unprocessed point clouds at interactive rates by making use of nested octrees and memory optimized sequential point trees(MOSPT). MOSPT is an improved version of sequential point trees(SPT)[50] which is a data structure that allows adaptive rendering of point clouds completely on the graphics card, the point tree's nodes are rearranged into a list, sorted by depth. It allows access to different level of detail using indices of array fig.2, i.e, gradually display points depending on the distance between camera and the object.

In this octree form, all nodes are recursively split into eight identical children, resulting in all nodes at the same depth being the same size. We qualify as voxel, the cubic volume of deepest nodes in octree. The voxel grid because of its spatial structure allows rapid and easy searching for adjoining voxels.

Similar to the work of [40], which consists in an octree-based region growing segmentation, we estimate three features derived from the point distribution in each voxel, a normal vector, a barycentre and a residual value. We apply a Principal Component Analysis to compute those features by first fitting a plane characterized by its barycentre and its normal vector, then evaluate the residual. The residual value has been introduced with the work of [42] and is a scalar representation of the surface curvature thus impacted by the noise data.

3.2. Step 2 : Semantic enrichment by a tag

We define as a tag, an annotation designating an object to be reconstruct, and linked to a point on the cloud. Each tag is unique and has hierarchical structure according to a system decomposition, e.g. a radiator is a component which is part of a branch which is part of the heat network, that runs through all the buildings. Similar to the object hierarchy utilized in Revit, object are decomposed into family, type, instance.

3.3. Step 3 : Multiple primitive reconstruction

For primitive reconstruction, we refer to Ahn's book [38], that presents algorithms for least squares orthogonal distance fitting (ODF) of curves and surfaces. Orthogonal distance is defined as the shortest geometric distance between the model feature and the measurement points, it is use as the error measure to be minimized. Our approach to geometrical primitive fitting is similar to Ahn's object recognition procedure called

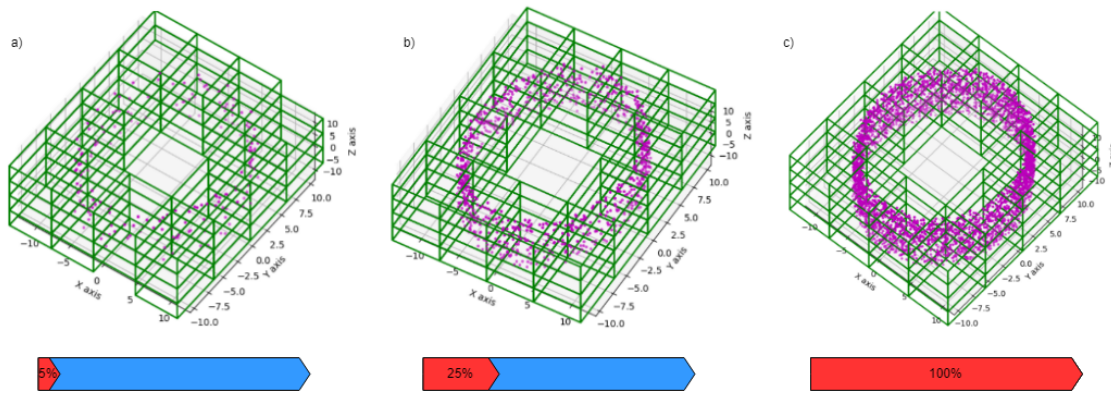


Fig. 2. Representation of a cylinder with different level of detail with MOSPT ; a) 200 points = 5 per/cent total points ; b) 1000 points = 25 per/cent total points c) 4000 points = 100 per/cent total points

'Click & Clear'. It is an interactive process aiming at building a parametric model of geometric primitives, by a iterative refining scheme combining segmentation (Step 3.1) and model fitting (Step 3.2). The model fitting is also preceded by an outlier operation and followed by an assessment of its parameters. The model parameters obtained, define the form and the orientation of the geometric primitives in space. The outlier detection consist in excluding outliers from model fitting and focus on calculating orthogonal distance with inliers as this calculation is the time-consuming step in the procedure. Inliers are determined by testing if they belong inside a domain volume defined around the model feature with a safety margin t , e.g, a sphere has four parameters, position X_c, Y_c, Z_c of the center c and radius r of the sphere, the domain volume is defined between two spheres of center c and radius $r - t$ and $r + t$ fig.3 .

The safety margin t is set by the user, it is intuitive by users with a mechanical background. Indeed many segmentation or model fitting methods employ a large number of parameters, that are often not clear to the unexperienced user, and it needs several attempts to find the best set of parameters [42]. Compare to algorithms such as Random Sample Consensus [63] and its extension(MLESAC, etc...), that are overwhelmingly recognized as one of the fastest reconstruction algorithm, often used in real time application, Ahn's procedure has more analytical and computation difficulties. However, because of its iterative scheme of fitting parametric model, low-level model feature (such as plane) are employed for parameter initialization, enabling a stable and robust convergence fig. 4. As a result of this model hierarchy, the primitive reconstruction can be greatly automated, leaving the seed selection to the user. Detection is launch without specifically naming the type of primitive to be fitted.

Ray tracing algorithm [45] is used to estimate which is the closest point from where a user clicked. From this seed point, an octree-based K-Nearest Neighbor algorithm [51] is launched to create a small patch of points. It serves initializing the model parameters through ODF algorithms, and the searching domain volume.

In the iterative refining scheme, we exploit the octree spatial decomposition to apply outlier detection and model fitting to

points inside the seed point voxel and its neighbors. To speed up the process, we can grow a region of voxels by comparing their features to the original seed point voxel and testing whether or not their barycentre is inside the domain volume. When the region can no longer be grown and the model fitting has been reassess we reconsider boundary voxels as new seed voxel for a new step of segmentation.

The number of points is certainly affecting the duration of every operations of model fitting. In addition, detecting a high variety of objects with different sizes is very challenging, even more because of our interactive procedure and expectation of performance as close to realtime as possible. In this aspect, we propose to let the user specify the level of detail as a parameter, i.e, the pourcentage of points for the fitting step by exploiting MOSPT linear memory structure.

3.4. Step 4 : From primitives to object using a knowledge database

Our motivation for a generic reconstruction procedure of semantically enriched object relies on a priori geometric information embedded in tags. This information characterizes the geometric knowledge of an object and it's congregate in an knowledge database, e.g, I-shaped beam can be decomposed in a set of planes with topological relationship between those primitives.

In 2.1, we stated that a local implicit parametric shape representation is best suited for our objects. We then derive it to a topology graph similar to [61] describing the relations between primitives shapes. For each primitive a vertex is inserted into the graph, and are connected with an edge. Detection of an object is reduced to a graph matching problem. For matching a tagged object to its analogue in the object collection we try to match subgraphs. Unlike [61] which defined their graph once all shapes in the cloud are determined, our approach is interactive, and all possible set of primitives shapes are not necessarily established, therefore we need to construct our topology graph in real-time. We need constant interactions between the knowledge database and topology graph to assert matching between the set of primitives.

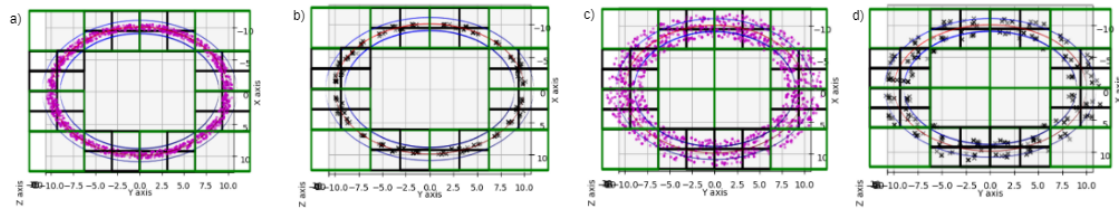


Fig. 3. Representation of a cylinder in a octree structure. purple dot : points black cross : barycenter of each voxels red circle : estimated cylinder model of radius r blue circles : associated search domains $r \pm t$

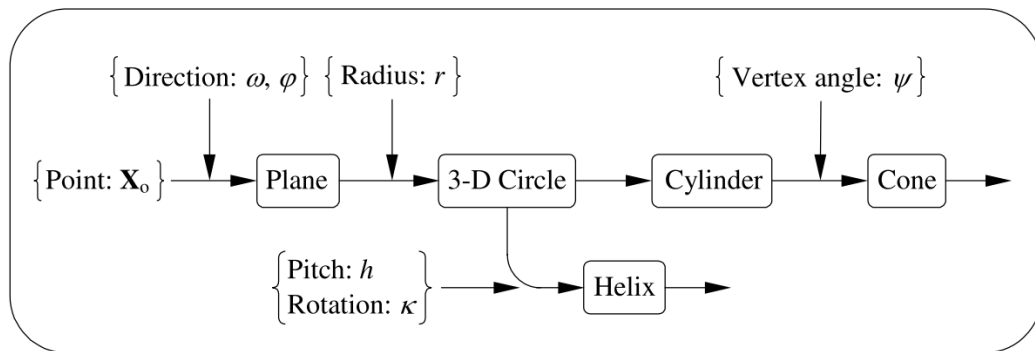


Fig. 4. Evolution of model feature from plane to cone or helix [38]

4. Conclusions

The reconstruction of objects by semantic enrichment is still a developing field of research. As of today, current automatic methods is used for specific tasks of indoor modelling or classification with a limited number of distinct objects. It is conceivable that our approach may facilitate futur creation of labeled datasets hence opening doors for artificial intelligence experts to improve or create new models.

In this article, we have presented a methodology of object reconstruction launched by a user annotation on point cloud. We undeniably try to put forth the user with mechanical and/or structural and/or piping and/or managerial background in the center of industrial modelling. We oriented our approach to be on par with needs of industrials and to overcome challenges with laser data of their environment.

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