Novelty Detection and 3D Shape Retrieval using Superquadrics and Multi-Scale Sampling for Autonomous Mobile Robots

P. Drews Jr, P. Núñez, R. Rocha, M. Campos and J. Dias

Abstract— **In many applications, it is important to detect changes in data models and communicate these changes efficiently. For instance, in some mobile robotics applications (*e.g.* surveillance) the robot needs to detect significant changes in the environment (*e.g.* a layout change) by comparing data provided by its sensors with a previously acquired map of the environment. This feature is often an extremely challenging one because large amounts of data must be compared in real-time. This paper proposes a framework to efficiently detect and segment changes in a data model and represent these changes through a compact model. It comprises: multi-scale sampling to reduce the computation burden; change detection based on Gaussian mixture models; fitting superquadrics to detected changes; and refinement and optimization using the split and merge paradigm. Experimental results in various real and simulated scenarios demonstrate the approach's feasibility and robustness with large data sets.**

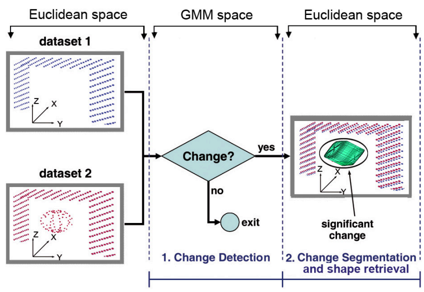

Fig. 1: Change detection and shape retrieval.

I. Introduction

Autonomous mobile robots working in unknown and dynamic environments have to be capable of (1) building a map of the environment based on perceptual data, simultaneously localize with respect to the map (SLAM), and (2) autonomously explore and navigate across the world. This is why extensive work has been devoted for the past decade to techniques that deal with SLAM [1] and the action selection problem (*e.g.* [2]).

In these robotic tasks, changes in the environment that affect the robot's path may be risky situations requiring the activation of some kind of alarms with which the robot should be aware of. Therefore, when the robot revisits some section of the environment, it is worth to compare current perceptual data with previously acquired one, in order to detect novelties in the scene [3]. However, the scope of this problem is not confined to mobile robot navigation; it is certainly important, for instance, in automatic surveillance and security systems [5] or, in general, whenever there is a need to compare signals of the same type with the aim of detecting novelties.

Solving this problem in real-time with large datasets is quite challenging and requires the development of specific techniques, which aim at achieving two inter-related goals (Fig. 1): firstly, to detect whether there is some significant change; secondly, if some significant change exists, to segment the data associated with it – change detection and segmentation – and represent the change through a compact model – shape retrieval.

This paper proposes a framework to efficiently detect, segment and represent changes in a data model. Firstly, the data to be compared is simplified through a multi-scale sampling technique in order to reduce the computation burden of detecting changes. Secondly, a previously developed method by the authors [3] is improved and validated, which is based on Gaussian Mixture Models (GMM). It is used for detecting changes and obtain a segmented point cloud representing those changes. Finally, this point cloud is used to retrieve the shape of the novelties using superquadrics [4].

The rest of the paper is organized as follows. After briefly reviewing the state of art in sec. II, sec. III presents an overview of the proposed solution. The next sections present the different parts of the solution: the novelty detection in sec. IV and the shape retrieval using superquadrics in sec. V. Experimental results are described in section VI. Finally, in sec. VII, the main conclusions and future work are drawn.

II. Related work

The behavior of an autonomous mobile robot working in dynamic environments has been intensively studied for the last decade. The common strategy has been to remove the dynamic objects in order to improve the navigation and localization tasks [7]. However, these changes in the robot's surrounding may actually be relevant depending of the applications. In this sense, Andreasson *et al.* presented a system for autonomous change detection with a security patrol robot [5] using 3D laser range data and images from a color camera.

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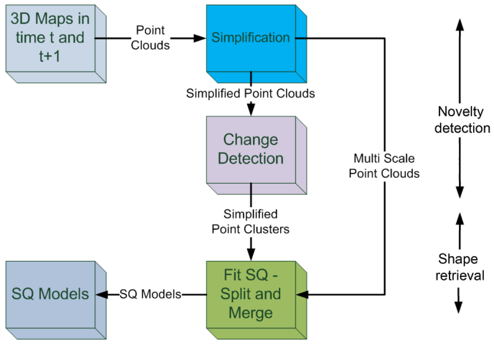

Fig. 2: Overview of the proposed method.

On the other hand, the detection of shapes is a common task in many areas of geometry and computer science. In the last years, a vast number of algorithms have been proposed that use different strategies: region growing [8], RANSAC-based shape detection method [6] or superquadrics [4].

Novelty detection based on Gaussian Mixture Models (GMM) and Earth Mover's Distance (EMD) was addressed in Núñez *et al.* 's work [3]. In a first stage, GMM was calculated to cluster the set of 3D range data. Next, EMD was used to quantify changes in the data. Two different algorithms for the shape retrieval problem were compared in [3]: RANSAC [6] in the Euclidean space; and a newly proposed algorithm running directly in the GMM space. In spite of the impressive results attained, the computation time of the proposed techniques are not suitable to run with large data sets. Being similar in the essence, this paper refines the approach in [3] with the aim of relieving the required computation burden and representing changes through a highly expressive model: superquadrics [4].

Superquadrics are a family of geometric shapes with a fairly simple parameter set. Leonardis *et al.* [9] introduced the standard in segment and shape retrieval using superquadrics. This method was applied to range images in which data is regular and well organized. An important approach in 3D point cloud is proposed in [10], wherein the split and merge principle is used to unstructured 3D data. In spite of the high time consumption, it gets interesting results. A good review of superquadrics can be found in [12].

III. Change detection and shape retrieval

The main steps of the change detection and shape retrieval process (Fig. 1) are outlined in Fig. 2. The simplification stage reduces the number of points in the 3D map using the surface information, generating a multi-scale point cloud [11]. Besides, sparse outliers and ground plane removal methods are used. After this initial stage, the novelty detection algorithm is applied, which is based on Núñez *et al.* 's work [3]. Finally, the shape retrieval problem is solved using a split and merge paradigm [10], as well as an iterative method to best fit superquadric models using this multi-scale information. Novelty detection and shape retrieval stages are explained in more detail in the following sections.

IV. Novelty detection in 3D maps

The novelty detection stage is based on our previous work [3]. In the current work, the 3D laser range data in Euclidean space is transformed to the mathematical space of GMM, so as to achieve data compression and efficient comparison using the EMD-based quantification of novelty [3]. Secondly, we using a new greedy algorithm EMD-based, it allows the system to segment the changes in the maps. The main advantages of this approach are (i) low processing time, due to the simplification and greedy approach, (ii) robust segmentation, due to the outliers removal and GMM method. A description of the method is explained in the next subsections.

A. Pre-processing Functions

The most important part of the pre-processing step is the simplification method due to the high density of points acquired by 3D laser scanner. The method should maintain more points in the corners and less points in plan surfaces, as a mean to reduce the computational time. The approach assumes that the unstructured point cloud acquired by laser scanner is composed locally by surfaces. Using the robust normal estimation, based on covariance analysis, the method computes a multi-scale point cloud using binary space partition. The use of covariance analysis allows compute the surface variation (σ), based on eigenvalues. So, the point cluster P is split if the size of $|P|$ is larger than a value and surface variation is above a maximum threshold σ_{max} [11].

This hierarchical cluster simplification builds a binary tree based on the split of each region. The split plane is defined by the centroid of P and the eigenvector associated to the greater eigenvalue (λ_2). Thereby, the point cloud is always split along the direction of greatest variation. The multi-scale representation is based on the level of restriction imposed to the tree. Considering the tree was created until the cluster be only one point, the scale choice is made setting values to size of $|P|$ and to σ_{max}.

On the other hand, considering a point cloud obtained by a laser scanner, the ground plane is almost always present in the data. In this work, a simple method using RANSAC to fit a ground plane is used [13]. Finally, sparse outliers in the 3D scan laser data are removed based on the technique proposed in [14].

B. Mixture of Gaussian functions

A *mixture of Gaussian functions* (GMM) is a probability density function described by a convex linear combination of Gaussian density functions. Each Gaussian is defined by a coefficient $p_k \geq 0$, which satisfy $\sum_{k=1}^{K} p_k = 1$, and by mean and covariance matrix.

Mixtures of Gaussian functions provide good models of clusters of points: each cluster corresponding to a Gaussian function. Thereby, given a set of points, one can try to find the mixture of Gaussian functions Θ using a method known as *Expectation Maximization*). More details in [3]. The Fig. 3 illustrates this idea.

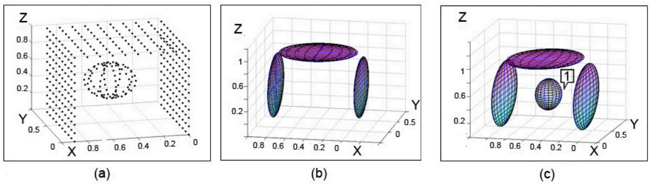

Fig. 3: Novelty detection algorithm: a) ideal 3-dimensional corridor with an object has been moved inside the corridor; b)GMM associated to the corridor map; c) GMM associated to a). The novelty detected by the algorithm has been indicated by the label '1'.

C. Earth Mover's Distance

The *earth mover's distance* (EMD) [15] can be used to compute the distance between two distributions. The EMD distance between two GMM, Θ and Γ, let $\Theta = ((\theta_1, p_1), \ldots, (\theta_n, p_n))$ and $\Gamma = ((\gamma_1, q_1), \ldots, (\gamma_m, q_m))$, being two mixture of Gaussian functions, associated with two 3D scan data, where θ_i and γ_j Gaussian functions, and p_i and q_j are the weights associated to each Gaussian, respectively. Thus, the distance between GMM is calculated as [3]:

$$d_{GMM}\left(\mathbf{\Theta}, \mathbf{\Gamma}\right) = \text{EMD}\left(\mathbf{\Theta}, \mathbf{\Gamma}\right). \tag{1}$$

D. Novelty segmentation to a mixture of Gaussian

Eq. (1) can be used as a quantitative metric to assist the detection of changes in the environment. Normally, the problem of change detection can be reduced to the definition of an optimal threshold U_{th}, which represents the maximum value in order to consider that there is a novelty between two maps. This fixed threshold value is a limitation. We proposed a new greedy algorithm to overcome this limitation. Our algorithm detect changes based on the principle that after it takes a decision, it never changes it. Fig. 3 illustrates the GMM associated with clusters of 3D points. After applying the proposed algorithm to these two sets of Gaussians, a novelty is detected in the maps (marked as 1 in Fig. 3c). The overall structure of the method is outlined in pseudo-code in algorithm 1. It allows more than detecting changes: it segments the novelty and retrieval the point sets that represents the changes using the posteriori probabilities.

In each iteration, the algorithm selects a Gaussian $x(\mu, \Sigma)$ from Θ with the greatest quantified change, computed by the *GreedySelectionfromGMM* function,as the d_{GMM} by the winner and the new set Π. It is made computing the EMD of Γ to new sets build removing one Gaussian by time from Θ. The best Gaussian is removed from the initial mixture Θ and is also included in the new Gaussian mixture model Π. The distance d_{GMM} is compared iteratively with the previous EMD distance. A threshold U_{th} is used to limit the number of iteration and precision. The algorithm returns a set K composed by a set of points. Each set represents the segmented region by one Gaussian, using the posteriori probabilities computed by the function *ChoosePtfromGaussian* that have as argument a point cloud P used to generate the novelty GMM and a Gaussian x. If $K = \{\emptyset\}$, there is no changes in the 3-dimensional map. Moreover, the posteriori probability allows the system to identify topological relation between the segmented regions. It will be useful in the superquadrics computation.

Algorithm 1 Novelty Selection algorithm

$d_{GMM} \leftarrow EMDdistance(\Theta, \Gamma)$
$\Pi \leftarrow \emptyset$
repeat
  $d_{GMM_{old}} \leftarrow d_{GMM}$
  $[x(\Sigma, \mu), \Pi, d_GMM] \leftarrow GreedySelectionfromGMM(\Theta, \Gamma)$
until $(d_{GMM_{old}} \geq d_{GMM}) \wedge (d_{GMM} \geq U_{th})$
$K \leftarrow \{\emptyset\}$
for all $x(\Sigma, \mu) \in \Pi$ **do**
  $K \leftarrow K \cup ChoosePtfromGaussian(P, x(\Sigma, \mu))$
end for
return K

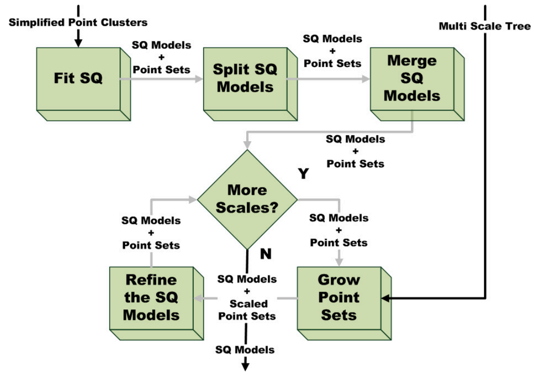

Fig. 4: Data Flow of the 3-dimensional Shape Retrieval Using Superquadrics. The black arrows represent the input (Simplified Point Clusters and Multi Scale Tree) and output (Superquadric Models).

V. Shape Retrieval Using Superquadrics

This section introduces the 3D shape retrieval algorithm used to obtain a superquadrics-based model of the detected novelties. The previous stage obtains a set of points related to change detection, which is related to changes identified in the environment. It is the input of our method, beyond the multi-scale tree. The data flow of the method is shown in the Figure 4. It shows the technique used to solve the superquadrics retrieval. Basically, the initial three steps are made with the simplified segmented set of points, and after it a multi-scale data is used to refine the model.

A. The Superquadrics Model

The superquadrics are an extension of the quadric surfaces and can be distinguished in four kind of models: supertoroid, superhyperboloid with one or two sheets, and superellipsoid. In this work, we focus on the superellipsoid which is useful to fit shapes, because they are compact in shape and have a closed surface. In this paper, the term superquadrics is used to superellipsoid. A superquadrics is defined using two parameters for shape (ϵ_1, ϵ_2) and three to scaling factors (a_1,a_2,a_3). The implicit equation of superquadrics is:

$$F(x,y,z) = \left(\left(\frac{x}{a_1} \right)^{\frac{2}{\epsilon_2}} + \left(\frac{y}{a_2} \right)^{\frac{2}{\epsilon_2}} \right)^{\frac{\epsilon_2}{\epsilon_1}} + \left(\frac{z}{a_3} \right)^{\frac{2}{\epsilon_1}} \quad (2)$$

This equation provides an information on the position of a 3D point related to the superquadrics surface. Basically, the value of this function is:

1) F(x,y,z) = 1 , Point lies on the surface;
2) F(x,y,z) > 1 , Point is outside;
3) F(x,y,z) < 1 , Point is inside.

We must represent it in a global coordinate system to model or to recover superquadrics from point cloud. It requires more 6 parameters for expressing the rotation and translation. In this work, we use Euler angles (ϕ,θ,ψ) and p_x,p_y,p_z to express it. The function can be expressed as $F(x, y, z; \Lambda)$, where the 11 parameters are called by $\Lambda = \lambda_1, \ldots, \lambda_{11}$.

B. Multi-Scale Fitting

Considering a set of 3D data points, the first objective is estimate the parameters of superquadric model. The gradient least-square minimization based on Levenberg-Marquard are solve this problem [12]. Basically, this method tries to minimize the following expression:

$$\min_{\Lambda} \sum_{i=1}^{n} (\sqrt{\lambda_1 \lambda_2 \lambda_3}(F^{\epsilon_1}(x_i, y_i, z_i; \Lambda) - 1))^2. \quad (3)$$

This equation represents a distance metric that allows compare superquadrics. The constraint $\sqrt{\lambda_1 \lambda_2 \lambda_3}$ is to enforce the recovery the smallest superquadric. The power ϵ_1 made the error metric independent from the shape of the superquadric [12]. Although, there are other methods to compute the distance between superquadrics, like the radial Euclidean distance, but it is method is slower [10].

Other important aspect to fit superquadrics is an initial model. It will determine which local minimum the method will converge, as well as the number of iteration. Thus, a good initialization is crucial to the success of the fit method. So, we use the initial pose based on the matrix M that represents the center of gravity and the central moments. The shape is a ellipsoid, *i.e.* , $\epsilon_1, \epsilon_2 = 1$. The scale factors are based on the eigenvalues (λ) of the inertia matrix M.

Using the multi-scale approach, we proposed a new method to fit superquadrics based on this refinement. The idea of the method is computed a initial model, using simplified points. After that, it refines the model using as initialization the model fitted by simplified points, together with more points from the multi-scale tree. An approach to overcome problems with the estimation based on simplified points, it estimates two superquadrics, one using the method above and other using the initial estimation using inertial matrix, and choose the best one.

C. Split-and-Merge Paradigm

The changes segmentation generated by GMM-EMD method has a important limitation. It could fall due the local minimum. The approach based on split and merge are proposed by Chevalier *et al.* to overcome this problem [10]. We proposed an extension, initialize with the segmented regions and the topological relation given by novelty detection method, proposed in this paper. It improve the simplicity of the method, as well as reduce time processing.

The first step is split the data so that all points in a subset belong to the same object. At the end of this step, a new set of segmented points is generated. We limited by number of points to control the split method. Before it limitation, we fit superquadric for both new sets. If the distance of each two new set is less than the distance of the original set, then the data are split. This method generate a binary tree, it represents the topological relation between the segmented set. This relation is important because it avoid the merge method recompute the topological relation between the sets, an expensive operation. The splitting plane is chosen using the inertia axis [10].

The last step is the merge, it considers solved the problem of one subset with data of two distinct objects. Now, the subsets will be merged, in order to reduce the number of descriptors without increase the whole distortion. This method can be divided in two parts:

1) For each subset of points, based on the topological relation, compute the matrix of costs to merge each neighbor subsets.
2) Choose the couple which minimizes the distance. Thus, merge it if the distance is less than biggest distance of each couple and the size of the new merged superquadrics is less than sum of the size of the two superquadrics.

An important contribution of our merge method is the use of memoization. It is an optimization technique used to speed up by avoid repeating the calculation of results for the same data. In this work, we use a matrix where the computed distances are saved. When the sets are merge, the matrix is updated. It allows this method work faster than the method proposed by [10].

VI. Experimental Results

In this paper, change detection and shape retrieval stages have been analyzed separately. The proposed methods have been evaluated using simulated and real data. The algorithms were develop in C++ software, and the benchmark tests were performed on a PC with a 2.0GHz AMD Turion X2 CPU. The artificial data is formed by a set of 3D space, simulating the readings of a laser scanner in a corridor. A normal random error, with zero mean and variance 0.001, was added to these points.

In order to evaluate the algorithms, objects are introduced in different poses and scale inside the corridor. A total of 30 different simulated data have been generated. On the other hand, the real data has been acquired by an Hokuyo laser mounted on a pan-tilt unit. Three different data acquisition areas were used with two captures for each test area. First, a 3D map was acquired to obtain a representation of the environment. Afterwards, a novelty was introduced. Finally, in order to obtain statistical results, the experiments were repeated ten times for each test area.

A. Novelty Detection

The results of novelty detection method are showed in Fig. 5. Blue points in Fig. 5 represent the 3D data acquired by the robot, and the ellipses are the Gaussians associated to the segmentation. The first row in Fig. 5 illustrates the results using simulated data. The results using a real corridor with a person representing the novelty are drawn in the second row. The results shows this person perfectly segmented in one cluster, in green. The third row illustrates a corridor where the door is open in the reference map, and after is half opened. The results shows the door very well segmented by a Gaussian, in green. Finally, the forth row draws an office environment with a closed door. The results shows the door represented by a Gaussian, in green. In this case, the scan data does not allow identify the closed door. However, due to the smooth salience in the door, the combination GMM-EMD is able to detect the novelty.

Table I illustrates the performance of the proposed novelty detection algorithm with simulated and real data, and testing the introduced improvement by the simplification stage. The experiments are composed of three data sets for real data, and thirty different simulated. Both, real and simulated test, have been repeated ten times. Ground truth for the change detection stage has been generated manually and the values of the table show the average of the values. As is shown in the Table I, the simplification shows better results working in real data than the complete data, due to the set of outliers is reduced by the point cloud simplification. In the real data the gain are 4,85x, while the gain in simulated data are 9,62x. This difference is caused by the limitation imposed to the GMM method to compute at the maximum a limited number of Gaussian, it limits the computation cost of the method.

B. 3D Shape Retrieval Results

The Fig. 6 illustrates the different steps of the Fig. 4 for fitting superquadrics to the novelties detected. First, the simulated data are used to test the shape retrieval algorithm in Fig. 6-a. In Fig. 6-a-1 draws two initial superquadrics associated to the changes. The original shape of the yellow superquadrics is a sphere, but due to the high noise applied to the data, the best fit is a smooth cube. In Fig.6a-2 results of split method is drawn, showing the cut plane based on the highest eigenvalue. Next, Figs. 6a-3,4 illustrate the results of merge and refine method. It shows the quality of the simplifier method. The gain using the multi-scale approach is not visible. Although, the shapes are less smooth due the greater number of points with noise in this case.

Next, the shape retrieval algorithm has been tested in real data. Fig. 6b-c shows the results of two datasets, which are associated to the novelties illustrated in Figs.5 in rows 2-3. Figs.5-b,c shows the fit superquadric result of the door, after split and merge method (from left to right image: initial superquadric fitting, split and merge-refine method, respectively). As is shown in this figure, due to the good segmentation by the novelty detection, the initial fit is enough to obtain a good result. Fig.6-b draws the superquadrics fitting results associated to the person (i.e. novelty) inside the corridor. After the split method, the person is divided in a set of superquadrics, and the merge and refine stage segments the initial superquadric in six superquadrics. In the right image, the yellow color represents the head, the green the trunk of the person. Due to the person in the scanner is with one arm near the truck, it was segmented in green. The other arm are showed by superquadric in blue. The two legs are showed by superquadrics in gray and cyan. Finally, the two foots are showed by pink and red superquadrics. The fit method has a little difficult to segment this 3D laser data because is near a plane, and the variance in depth is short.

VII. Conclusions and Future Works

The presented approach has described an efficient method to detect and retrieve the shape of the changes in a 3D real environment for robot navigation. Real data acquired by the laser range finder is pre-process in order to reduce the size of the point clouds. Next, $Gaussian\ Mixture\ Models$ has been used to obtain a new representation of theses point clouds and $Earth\ Mover's\ Distance$ is employed to quantify the existence of a novelty in the scene. Changes detected in the environment are modeled using $Superquadrics$. Results of the proposed algorithm demonstrate the reliability and efficiency of the method. Besides, the presented shape retrieval approach has been compared with our previous work in terms of computational time, robustness and accuracy.

Future work will focus on the extension of the novelty detector method to work iteratively, when the data are captured by the robot. One possible approach is use iterative GMM method. The final goal of the work is obtain a complete system capable of detecting and representing virtual objects in the robot's world which is capable to discriminate various objects. Thus, a classification method to the superquadrics shapes are being studied.

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TABLE I: Comparative study of the novelty detection with simplification

	Simulated Data			Real Data		
	Number Points	Time Consumption(s)	Success Rate(%)	Number Points	Time Consumption(s)	Success Rate(%)
Simplified	342	0.21	92.3%	8575	91.83	91.5%
Complete	2960	2.02	93.4%	31786	445.67	89.7%

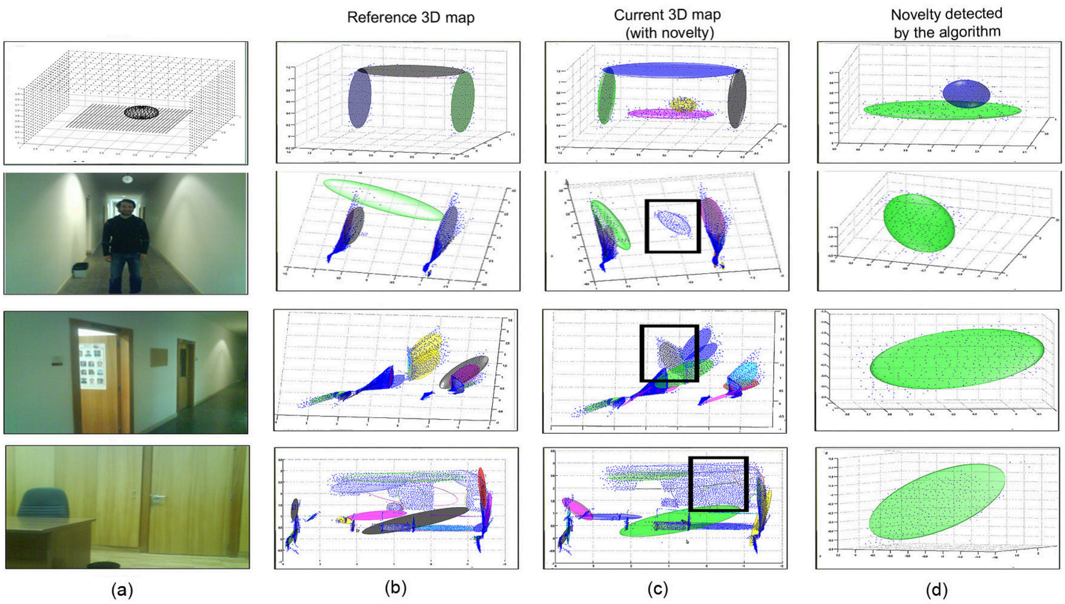

Fig. 5: Testing the change detection algorithms: a) Test sites image; b) Reference 3D map; c) the current 3D map including the novelty (black boxes); d) the changes detected. The first rows represents simulated data, the others are real data.

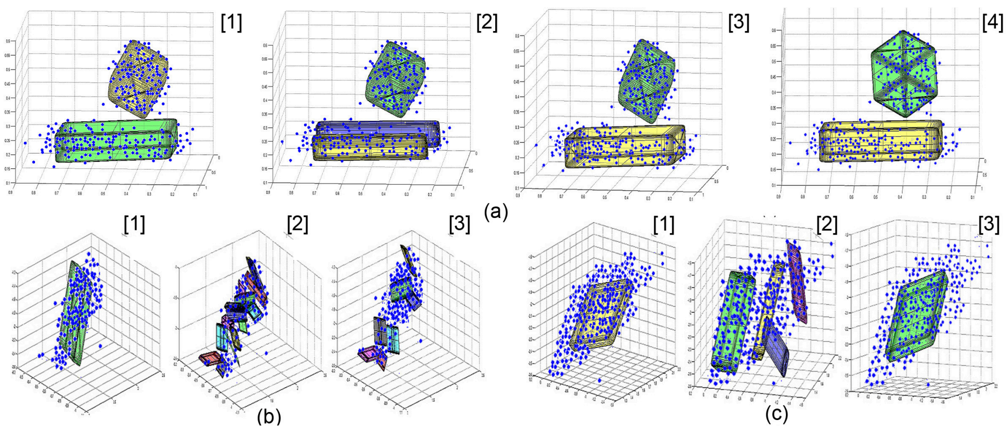

Fig. 6: Testing the shape retrieval algorithms using simulated Data(a) and real Data(b-c).

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