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

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Abstract— **There are several applications for which it is important to both detect and communicate changes in data models. For instance, in some mobile robotics applications (*e.g.* surveillance) a robot needs to detect significant changes in the environment (*e.g.* a layout change) which it may achieve by comparing current data provided by its sensors with previously acquired data (*e.g.* map) of the environment. This often constitutes an extremely challenging task due to the large amounts of data that must be compared in real-time. This paper proposes a framework to detect, and represent changes through a compact model. The main steps of the procedure are: 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 datasets.**

I. INTRODUCTION

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

Changes in the environment that may affect a robot's path may be caused by risky situations that will trigger some kind of alarms with the robot should be correctly handle. Therefore, when a robot revisits some place of the environment, it may be worthwhile to compare current perceptual data with previously acquired one, in order to detect novelties in the environment [4]. This problem is not restricted to mobile robot navigation alone; but it is certainly important, for instance, in automatic surveillance and security systems [3] or, whenever need arises 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 involves achieving two interrelated goals (Fig. 1): first, to detect whether there is some significant change; second, if some significant change exists, to segment the data associated with it – *change detection and segmentation* – and to represent the change using a compact model – *shape retrieval*. These two steps could be necessary for *a posteriori* classification and identication of changes.

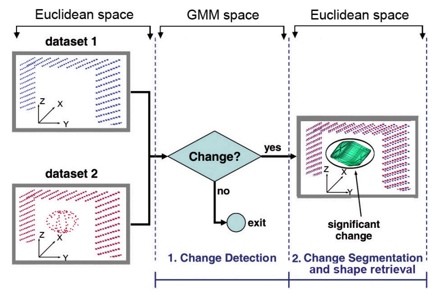

Fig. 1. Change detection and shape retrieval.

This paper proposes a framework to 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 [4] is improved and validated, which is based on Gaussian Mixture Models (GMM). This model is used to detect changes and obtain a segmented point cloud representing those novelties. Finally, this point cloud is used to retrieve the shape of these novelties using superquadrics [5].

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

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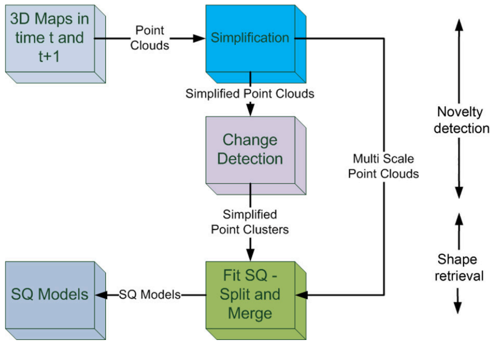

Fig. 2. Overview of the proposed method.

On the other hand, the detection of shapes is a common task in many areas of geometry and computer science. In past years, a vast number of algorithms has been proposed that use different strategies: region growing [8], RANSAC-based shape detection method [6] or superquadrics [5].

Novelty detection based on Gaussian Mixture Models (GMM) and Earth Mover's Distance (EMD) were addressed in the work proposed by Núñez *et al.* [4]. In a first stage, GMM was calculated for clustering 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 [4]: RANSAC [6] in the Euclidean space; and a newly proposed algorithm working directly in the GMM space. In spite of the impressive results attained, the computation time of the proposed techniques were not suitable for large datasets. This paper refines the approach in [4] with the goal of reducing the required computation burden and representing changes through a highly expressive model: superquadrics [5].

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

III. Change Detection and Shape Retrieval

The main steps of our 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 and generating a multi-scale point cloud [11]. Sparse outliers and ground plane removal methods are also used. After this initial stage, the novelty detection algorithm is applied, which is based on the work of Núñez *et al.* [4]. Finally, the shape retrieval problem is solved using the 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 details in the following sections.

IV. Novelty Detection in 3D Maps

The novelty detection stage is based on our previous work [4]. In the current work, the 3D laser range data is transformed from the Euclidean space into the mathematical space of GMM. The system also achieves data compression and efficient comparison using the EMD-based quantification of novelty [4]. Secondly, a new EMD-based greedy algorithm is used to segment changes in the maps. The main advantages of this approach are (i) low processing time, due to the simplification and greedy approach, and (ii) robust segmentation, due to the outliers removal and GMM method. A description of the method is explained in the next subsections.

A. Preprocessing functions

The central part of the preprocessing step is the simplification method used to reduce the high density of points acquired by 3D laser scanner. The approach presented herein is based on the work proposed by Pauly *et al.* [11]. The method has one important contribution: it reduces the computation time without loosing much geometric information. Moreover, it computes a multi-scale point cloud using binary space partition. The use of covariance analysis enables the method to compute the surface variation (σ) based on eigenvalues. The point cluster P is then split if the size of $|P|$ is larger than a value and surface variation is above a maximum threshold σ_{max}. The value used for σ_{max} is 0.1, and the range of σ is $[0; \frac{1}{3}]$; which was empirically selected for a typical laser data density.

This hierarchical cluster simplification process 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). The point cloud is always split along the direction of greatest variation. The multi-scale representation is based on the restriction level imposed to the tree. The tree grows until the cluster is just one point, where the scale is chosen by setting values to size of $|P|$ and to σ_{max}.

On the other hand, for 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. Gaussian mixture model

A *Gaussian mixture model* (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 satisfies $\sum_{k=1}^{K} p_k = 1$, and by a mean and a covariance matrix.

The GMM provides good models of clusters of points where each cluster corresponds to a Gaussian function. Therefore, given a set of points, it is possible to find the GMM Θ using the well known method called as *Expectation Maximization* (EM). The size of the K is selected using K_{max} and the MDL penalty function [16]. Fig. 3 illustrates this idea. See [4] for further details.

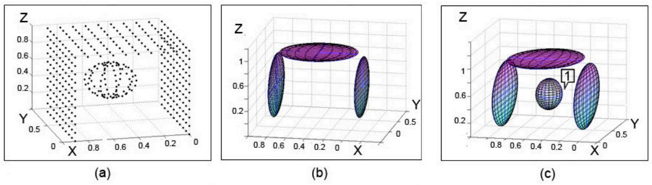

Fig. 3. Novelty detection algorithm: a) ideal 3D corridor where an object was placed inside; b) GMM associated to the corridor map; c) GMM associated to a). The novelty detected by the algorithm has been indicated by the label '1'.

C. Earth Mover's Distance

The *earth mover's distance* (EMD) [15] can be used to compute the distance between two distributions. Let, $\Theta = ((\theta_1, p_1), \dots, (\theta_n, p_n))$ and $\Gamma = ((\gamma_1, q_1), \dots, (\gamma_m, q_m))$, be two Gaussian mixture models associated with two 3D scans, where θ_i and γ_j are Gaussian functions, and p_i and q_j are the weights associated to each Gaussian, respectively. Thus, the distance between GMM is computed by [4]:

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

D. Novelty segmentation to a mixture of Gaussian

Eq. (1) can be used as a quantitative metric to assist in detecting changes in the environment. Typically, the problem of change detection can be tackled by defining an adequate threshold U_{th}, which represents the maximum value beyond which it will be assumed that a novelty exisits in the recently acquired map. However, using a fixed threshold is a shortcoming of this approach. Therefore, we propose a new greedy algorithm that overcomes this limitation by keeping unchanged a decisions that are taken. An example of the application of this technique can be seen in the Fig. 3 where the GMM associated with clusters of 3D points are shown. 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. The method achieves more than just detecting changes since the novelty is segmented and the set of points associated to it is retrieved using posterior probability.

In each iteration the algorithm selects a Gaussian $x(\mu, \Sigma)$ from Θ with the greatest quantified change d_{GMM}, computed by the function *GreedySelectGMM*. Furthermore, this function returns the d_{GMM} by the winner and the new set Π. It works computing EMD between Γ and the new sets. These new sets are generated by removing one Gaussian at a 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. The algorithm returns a list of sets of points S. Each set represents the segmented region by one Gaussian, using the posterior probabilities computed by the function *ChoosePtsfromGaussian* that has as arguments a point cloud P used for generating the novelty GMM and a Gaussian x. If $S = \{\emptyset\}$ the algorithm assumes that there are no changes in the 3D map. Moreover, the posterior probability allows the system to identify the topological relation between the segmented regions. This will be useful in the superquadrics computation described in Sec. V-B.

Algorithm 1 Novelty Selection algorithm

$d_{GMM} \leftarrow EMDdistance(\Theta, \Gamma)$
$\Pi \leftarrow \emptyset$
repeat
  $d_{GMM_{old}} \leftarrow d_{GMM}$
  $[x(\mu, \Sigma), \Pi, d_{GMM}] \leftarrow GreedySelectGMM(\Theta, \Gamma)$
until $(d_{GMM_{old}} < d_{GMM})$
$\Pi \leftarrow \Pi - x(\mu, \Sigma)$
$S \leftarrow \{\emptyset\}$
for all $x(\mu, \Sigma) \in \Pi$ **do**
  $S \leftarrow S \cup ChoosePtsfromGaussian(P, x(\mu, \Sigma))$
end for
return S

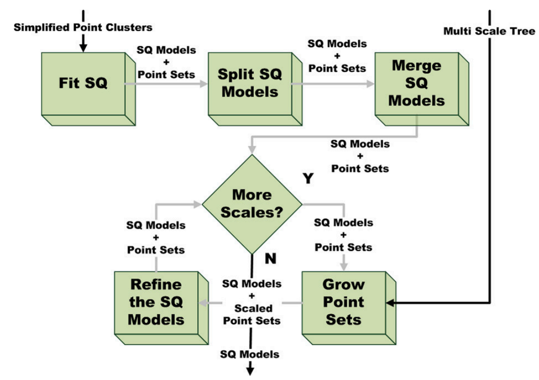

Fig. 4. Data flow of the 3-D shape retrieval using superquadrics. The black arrows represent the input (simplified point clusters and multi-scale tree) and the output (superquadric models).

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 that is related to changes identified in the environment. This set of points associated with the multi-scale tree is the input of our method. The data flow of the method is shown in Fig. 4. It shows the technique used to solve the superquadrics retrieval method. Initially, the three steps are taken with the simplified segmented set of points. Afterwards, the multi-scale tree is used to refine the model.

A. The Superquadric model

Superquadrics are a compact model used to represent shapes. It is defined using two parameters for shape, (ϵ_1, ϵ_2), and three for scale, (a_1,a_2,a_3). The implicit equation of superquadrics is:

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

This equation provides an information about the 3D point position related to the superquadrics surface. Basically, the value of this function is equal to one if the point lies on the surface. If the point is inside, the value is less than one. The point is outside, if this value is larger than one. A superquadric represented on a global coordinate system needs extra six parameters. Therefore, the function can be expressed as $F(x, y, z; \Lambda)$, where the 11 parameters are denoted as $\Lambda = \lambda_1, \ldots, \lambda_{11}$ [12].

B. Multi-scale fitting

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

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

This equation represents a distance metric to compare superquadrics. The constraint $\sqrt{\lambda_1 \lambda_2 \lambda_3}$ is used to enforce the recovery of the smallest superquadric. The exponent ϵ_1 is used to make the error metric independent of the shape of the superquadric [12]. There are other methods to compute this distance, but they are slower [10].

Another important aspect to fit superquadrics is the initial model used. This model determines the local minimum where the method converges as well as the number of iterations. Thus, a good initialization is crucial to the success of the fitting process. So, we use the initial pose based on the matrix M that represents the center of gravity and the central moments. The shape used is an 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 propose a new method for fitting superquadrics based on this refinement. This method computes an initial model using simplified points. After that, it refines the model using as initial solution the model fitted by simplified points, together with more points from the multi-scale tree.

C. Split and merge paradigm

The segmentation of changes produced by the GMM-EMD method has an important limitation: it may fail due to local minima. To overcome this problem, an approach based on split and merge is proposed by Chevalier *et al.* [10]. We propose an extension to their method: initialize with the segmented regions and the topological relation given by novelty detection method, proposed in this section. This extension further simplify the method and reduces the processing time.

The first step of the method splits the data so that all points in a subset belong to the same object. Then, this set of points is further divided into two sets using a split plane. This plane is chosen using the inertia axis [10]. Afterwards, superquadrics are adjusted for both new sets. If the distance of each one of the two superquadrics is less than the distance to adjust a superquadric to the original set, then this split operation is validated. This method generates a binary tree that represents the topological relation between the segmented sets. This relation is important because it avoids the recomputation of these relations in the merge step. Finally, the method concludes the merge step. The new subsets generated by the split step are merged in order to reduce the number of superquadrics without increasing the whole distance. This method can be divided into two parts:

1) For each subset of points, the method computes the cost matrix. It represents the cost to merge neighbor subsets. The neighbourhood is based on the topological relation.
2) Choose the pair which minimizes the distance. The subsets are merged if their distance is less than the largest distance of each pair and the size of the newly merged superquadric is smaller than the sum of the size of the two superquadrics.

An important contribution of our merge method is the use of dynamic programming. In this work, we use a matrix where the computed distances are saved. When the sets are merged, the matrix is updated. This allows our method to run faster than the method proposed in [10]. The time to compute the 3D shape retrieval is shown in Table I. This time depends of the number of segmented sets and the characteristics of the changes. The table shows the time only for the simplified data, because the method is adapted to run with the multi-scale tree.

VI. EXPERIMENTAL RESULTS

In this paper, the change detection and shape retrieval stages have been analyzed separately. The proposed methods have been evaluated using simulated and real data. The algorithms were developed in C++ software and the benchmark tests were performed on a PC with a 2.0GHz AMD Turion X2 CPU. The artificial data are composed of a set of 3D points, simulating the readings of a laser scanner in a corridor. A normal random error with zero mean and variance $0.001m^2$ was added to these points.

In order to evaluate the algorithms, objects were introduced in different poses and scales inside the corridor. A total of 30 different simulated datasets have been generated. Real data have been acquired by an Hokuyo laser mounted on a pan-tilt unit. We run experiments in three different environments, and two acquisitions were made in each one of them. Firstly, a 3D map was acquired to obtain a representation of the environment. Afterwards, a novelty was introduced. Finally, in order to obtain statistically significant results, the experiments were repeated ten times for each test area.

A. Novelty detection results

The results of the novelty detection method are shown in Fig. 5. Blue points 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 the person being the novelty, are drawn in the second row (Test Area 1). The results show this person adequately segmented in one cluster, in green. The third row (Test Area 2) illustrates a corridor where the door is opened in the reference map, and half opened afterwards. The results show the door adequately segmented by a Gaussian, in green. Finally, the forth row (Test Area 3) shows an office environment with a closed door. The results show the door represented by a Gaussian, in green. In this case, the scan data do not allow the system to 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 demonstrates the introduced improvement by the simplification stage. The experiments include real data composed by three test area and thirty simulated datasets. Tests with both real and simulated data were repeated ten times; the values in the table show the average values. The ground truth for the change detection stage (sucess rate) was generated manually by selecting the points that represent the changes, and comparing automatically the true positives with the results of the algorithm. As it is shown in Table I, the simplified data shows better results than with complete data, because the set of outliers is reduced by the point cloud simplification step. The processing time gain with simplified data varies between $3\times$ and $6\times$; this difference is caused by the characteristics of the data. The method to simplify data has low computation cost and low information loss. The maximum number of Gaussians (K_{max}) in each GMM used in the experiments is 16. Clearly, the bottleneck in the system is the method to compute the GMM for each 3D map.

B. 3D Shape retrieval results

Fig. 6 illustrates the different steps of Fig. 4 for fitting superquadrics to the detected novelties. Firstly, in Fig. 6-a the simulated data are used to test the shape retrieval algorithm. In Fig. 6a-1 draws two initial superquadrics associated with 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. Results of the split method are depicted in Fig. 6a-2, showing the cut plane based on the highest eigenvalue. Next, Figs. 6a-3,4 illustrate the results of the merge and refine method. They show the quality of the simplification method. The gain of using the multi-scale approach is not noticeable. Nevertheless, the shapes are less smooth due to the larger number of noisy points in this case.

Afterwards, the shape retrieval algorithm was tested with real data. Figs. 6b-c show the results of two datasets, which are associated to the novelties illustrated in Fig. 5 in rows 2-3. Fig. 6b draws the superquadrics fitting results associated to the person (*i.e.* novelty) inside the corridor. After executing the split method, the person is divided into a set of superquadrics, and the merge and refine stages segment the initial superquadric into six superquadrics. In the right image, the yellow and green colors represent the head and the trunk of the person, respectively. Since the scanned person has his arm near the trunk, it was segmented in green. The other arm is shown by the superquadric in blue. The two legs are represented by superquadrics in gray and cyan. Finally, the two feet are represented by pink and red superquadrics. Fig. 6c show the result of superquadric fit of the door, after using the split and merge method (from left to right: initial superquadric fitting, split and merge-refine method, respectively). As it is shown in this figure, due to the good segmentation provided by the novelty detection, the initial fit is sufficient to obtain a good result.

VII. Conclusions and Future Works

This paper described a method to detect and retrieve shape of changes in a 3D real environment for robot navigation. Real data acquired by the laser scanner is preprocessed in order to reduce the size of the point clouds. Next, *Gaussian Mixture Models* were used to obtain a new representation of the point clouds and the *Earth Mover's Distance*, together with a novel greedy algorithm, are 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 of the method. Furthermore, the presented shape retrieval approach was compared with our previous work in terms of computational time, robustness and accuracy. Moreover, the method may also be used to detect things removed from the scene. This can be attained simply by putting the current map in the reference input.

Future work will focus on the extension of the novelty detection method to work iteratively, with the data being captured online by the robot. One possible approach is to use the GMM method with online learning. The final goal of the work is to obtain a complete system capable of detecting and representing virtual objects in the robot's world, which is capable of discriminating various objects. For that, classification method to the superquadrics shapes is being studied. Another important improvement is to include a registration module in the system. It will allow the system to deal with overfitting volumes, and to avoid the need for having tmaps expressed in the same coordinate system.

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TABLE I

COMPARATIVE STUDY OF THE NOVELTY DETECTION WITH SIMPLIFICATION.

		Number of Points		Time Elapsed (s)						
		Reference Map	Current Map	Simpl. Ref. Map	Simpl. Cur. Map	GMM Ref. Map	GMM Cur. Map	EMD	Superquadrics	Success Rate(%)
Simulated Data	Simplified	80	912	0.0001	0.01	0.02	1.21	0.03	3.24	92,3%
	Complete	300	2960	-	-	0.21	5.29	0.05	-	93,4%
Real Data - Test Area 1	Simplified	9611	9805	0.19	0.21	39.84	55.09	0.50	12.6	92,6%
	Complete	33187	33937	-	-	206.62	225.94	0.79	-	91,5%
Real Data - Test Area 2	Simplified	9030	9411	0.17	0.17	23.3	31.72	0.18	6.45	93,6%
	Complete	31448	32785	-	-	102.0	113.8	0.20	-	91,4%
Real Data - Test Area 3	Simplified	8510	8046	0.17	0.16	33.76	27.69	0.53	7.27	88,3%
	Complete	30028	28421	-	-	158.66	150.44	0.61	-	86,2%

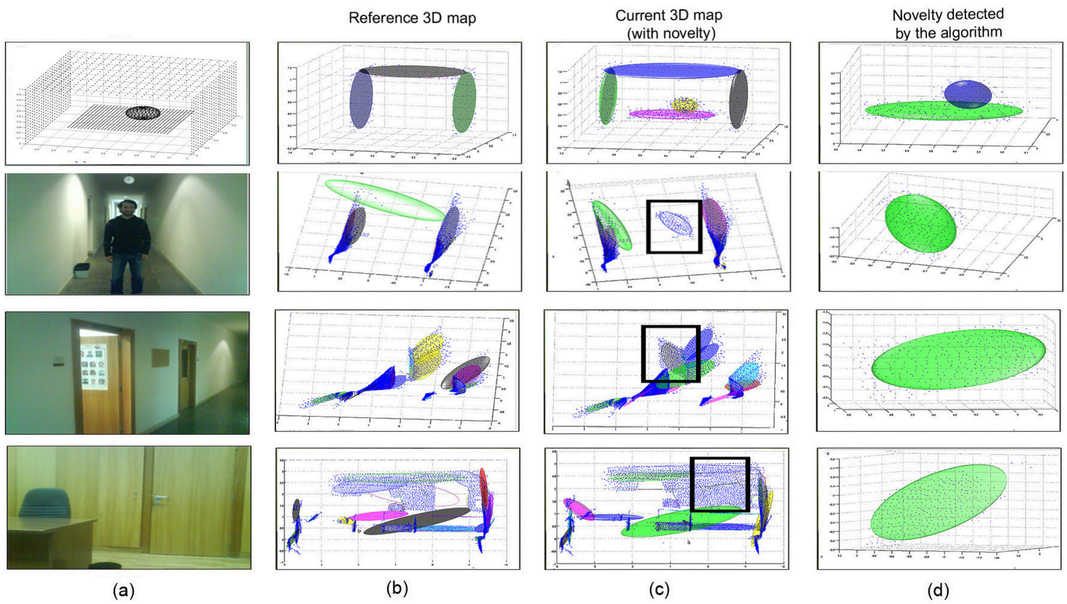

Fig. 5. Testing the change detection algorithms, where the first row represents simulated data, the others are real data. a) Photos of the testing sites with novelties; b) reference 3D map; c) the current 3D map including the novelty (black boxes); d) detected changes, with ”zoom” in the novelty.

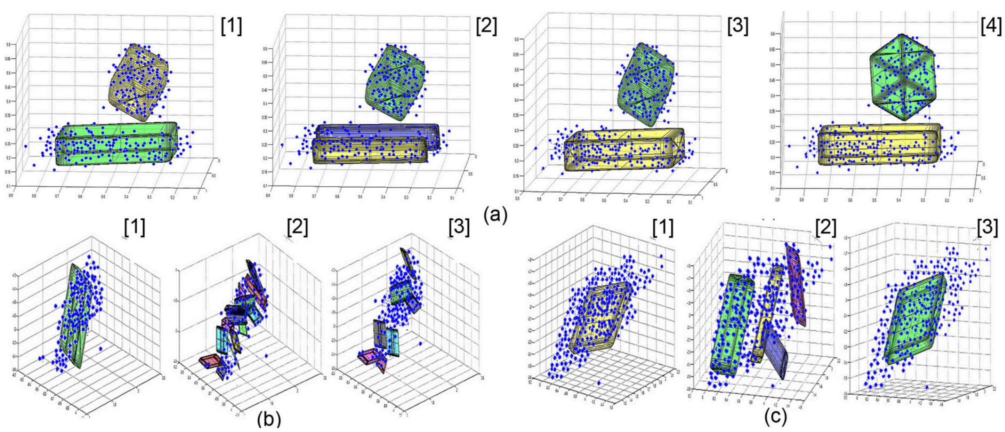

Fig. 6. Testing the 3D shape retrieval algorithms using superquadrics with simulated data (a) and real data (b-c).

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