Novelty detection and shape retrieval for 3-dimensional maps

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Grupo Ingeniería de Sistemas IntegradoS

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Polo 2 – Universidade de Coimbra (Portugal)

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Introduction

Autonomous mobile robot operation in unknown and dynamic environments relies on

- Building a map of the environment based on perceptual data
- Localizing itself with respect to the map
- Autonomous exploration and navigation

SLAM

Introduction

- Autonomous exploration and navigation

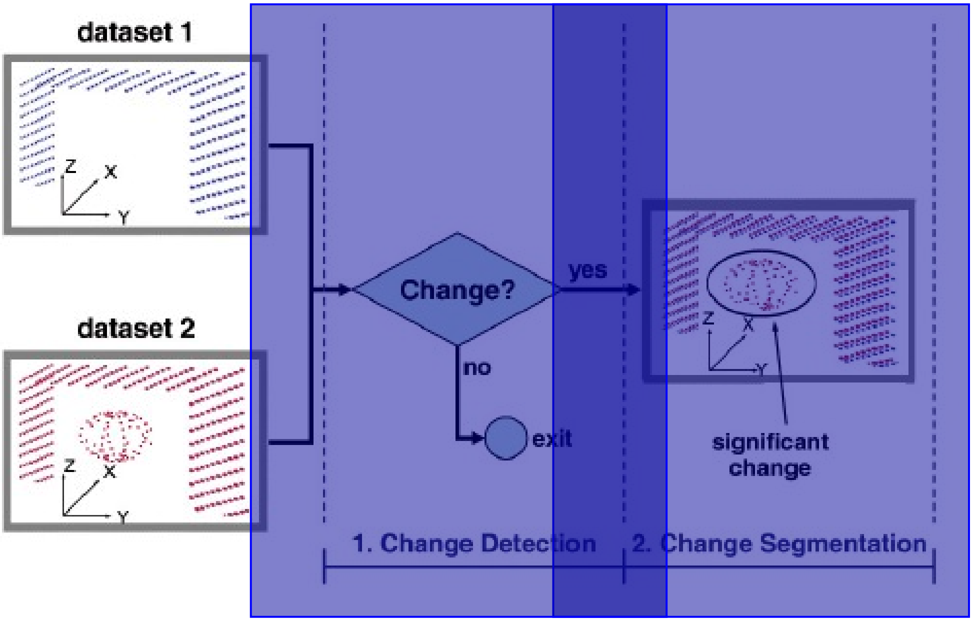
It is important to provide the mobile robot with some kind of alarms that are activated whenever there are important changes in the environment

When the robot revisits some section of the environment, it is worth to compare current perceptual data with previously acquired data, so as to detect significant changes

Novelty detection and shape retrieval
for 3-dimensional maps

Introduction

These techniques aim at achieving two inter-related goals:



Introduction

The extraction of geometric shape using 3D point clouds is an important task to obtain a virtual representation of the novelty detected.

Virtual representation: provides an abstraction of the point data that eliminates much of the redundancy.

Primitive shapes can easily be assembled into higher semantic level models that represent dynamic elements of the environment

Set of primitive shapes: Sphere, Cylinder and Plane

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Novelty detection and shape retrieval
for 3-dimensional maps

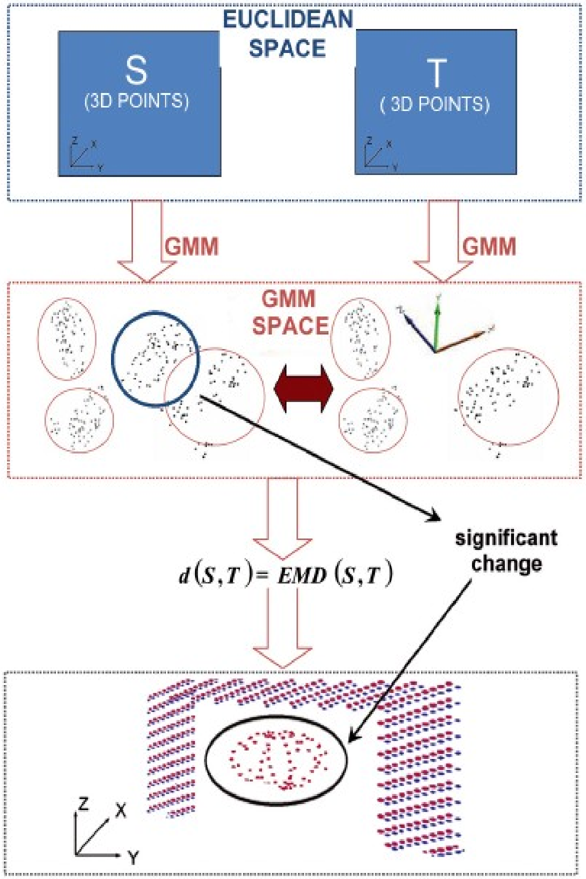
Novelty detection algorithm

• 3D data acquired by the sensors

• Data in Euclidean space is transformed to the mathematical space of GMM

• Efficient comparison using the EMD-based quantification of novelty

• Data associated with novelty is segmented
•in GMM space and back-propagated to the
•Euclidean space using the retrieval algorithm



Novelty detection algorithm

Previous work (Amorim *et al [1]*)

GMM
gaussian mixture models

PCA
promcipal comp. analisis

PE
plane extraction

$$d : P \times P \longrightarrow \Re_0^+$$

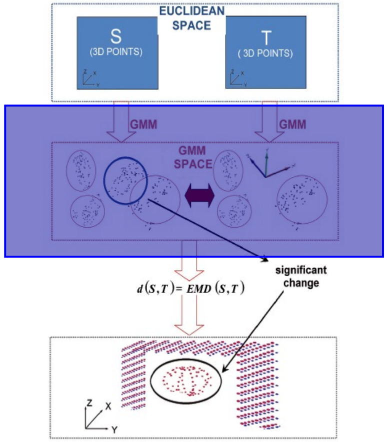
Dataset 1 (first P), Dataset 2 (second P)

GMM presented the most consistent behavior.

Lower standard deviation.

[1] I. Amorim, R. Rocha, and J. Dias. "Mobile Robotic Surveillance Systems: Detecting and Evaluating Changes in 3D Mapped Environments". In *Proc. of 2nd Israeli Conference on Robotics* (ICR2008), Herzlia, Israel, Nov. 19-20, 2008.

Novelty detection algorithm



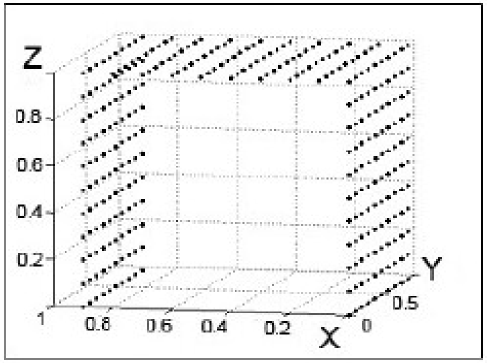
Gaussian mixture model

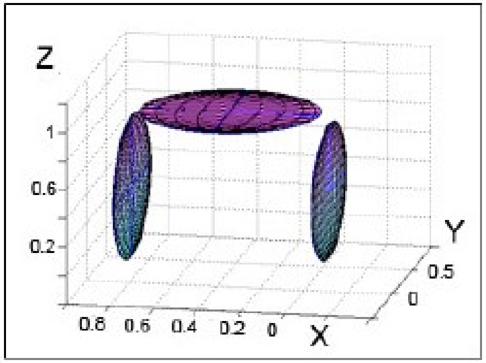
$$f(\mathrm{x}, \Theta) = \sum_{k=1}^{K} p_k \, g(\mathrm{x}; \mu_k, \Sigma_k) \quad (\mathrm{x} \in \mathbb{R}^N)$$

Mixtures of Gaussian functions provide good models of clusters of points: each cluster corresponding to a Gaussian

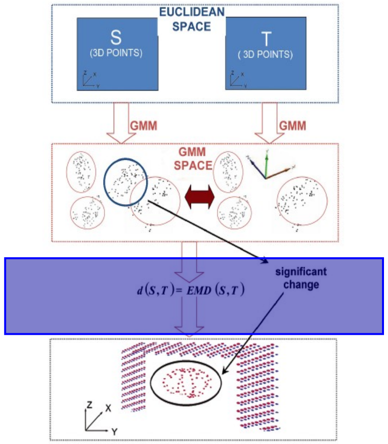
$$\Theta = ((\theta_1, p_1), \ldots, (\theta_K, p_K))$$

$$\theta_k = (\mu_k, \Sigma_k)$$





Novelty detection algorithm



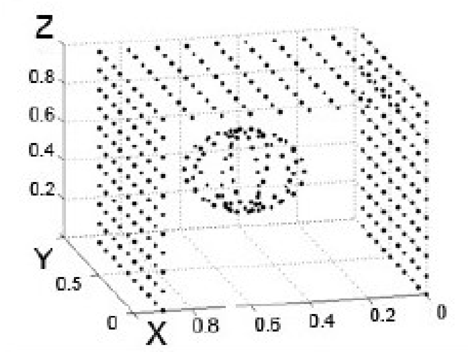
Earth mover's distance

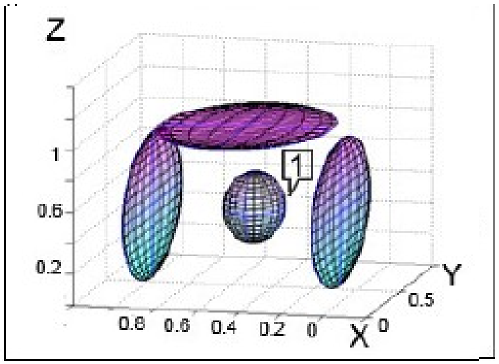
$$\mathrm{EMD}(A,B) = \min_{F \in \mathcal{F}(A,B)} \frac{\sum_{i=1}^{m} \sum_{j=1}^{n} f_{ij} d_{ij}}{\min\{W, U\}}$$

Earth mover's distance is a measurement between two distributions of points in the space for which a distance between points is given.

$$d_{GMM}(\Theta, \Gamma) = \mathrm{EMD}(\{(\theta_{1\ldots n}, p_{1\ldots n})\})$$

$$d_{GMM} \geq U_{th}$$





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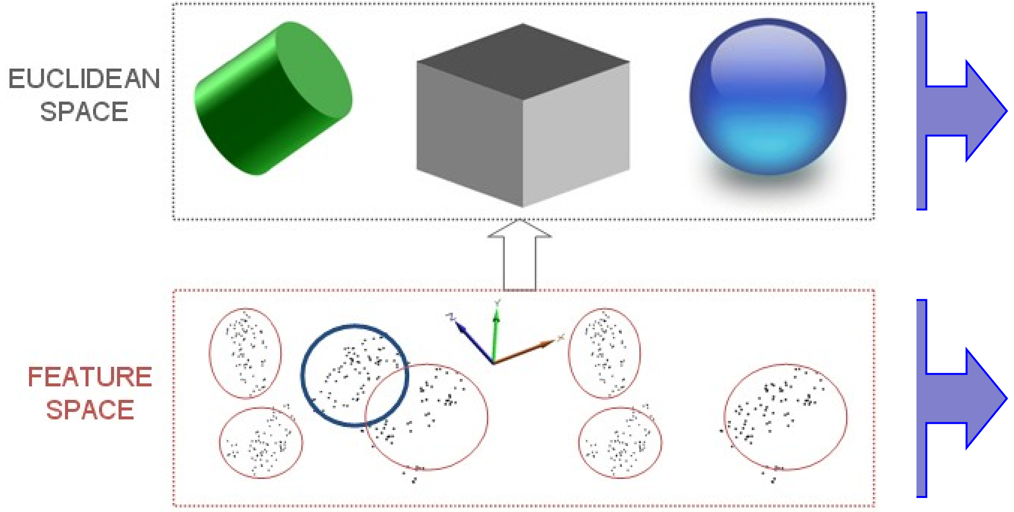
Shape retrieval algorithm



EuclideanShapeRetrieval (*G_n*)

FeatureShapeRetrieval (*G_n*)

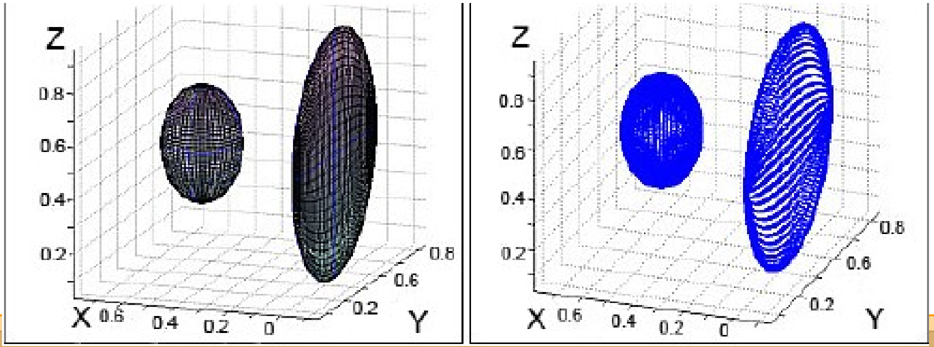
Comparative study_between these two techniques

- Computational load
- Accuracy of the shape retrieval algorithm

Shape retrieval algorithm

Euclidean Space shape retrieval

$$P(k,x) = \frac{g(\mathbf{x};\mu_k,\Sigma_k)\cdot p_k}{f(x,\theta)}$$



Mixtures of Gaussian is a generative model: it is useful to consider the process of describing a synthetic 3D region using the samples generated from the Gaussian functions.

RANSAC paradigm is a well-known strategy to extract shapes from 3D cloud of points by randomly drawing minimal sets from the data.

Shape retrieval algorithm

Gaussian Space shape retrieval

The shape retrieval algorithm finds the shape that better approximate to an ideal basic shape: new shape retrieval algorithm based on the covariance matrices matching.

$$d(\Sigma_1, \Sigma_2) = \sqrt{\sum_{i=1}^{N} ln^2 \lambda_i(\Sigma_1, \Sigma_2)}$$

$$\Sigma_i = T \Sigma_j T^T = (R \cdot L) \Sigma_j (R \cdot L)^T$$

Minimize using a Least squares minimization method based on Levenberg-Marquardt algorithm, which modifies the rotation and scaling matrices in each iteration.

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Experimental results

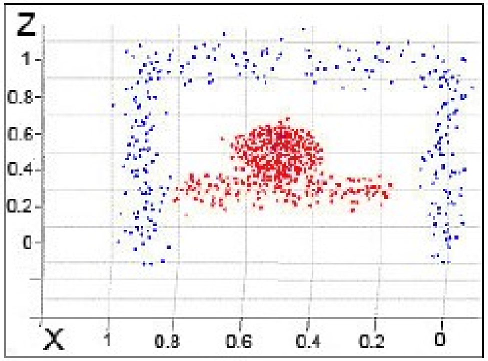
Simulated data

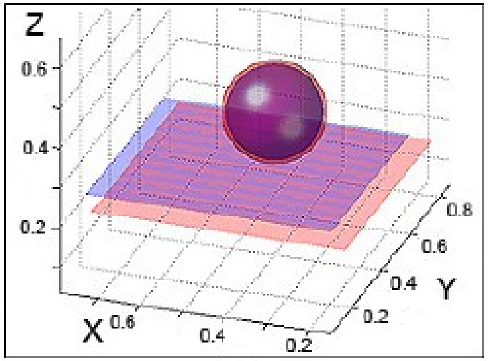
• The artificial data is formed by a set of 400 points in 3-dimensional space, simulating the readings of a perfect laser range finder in a corridor
• A random error, normally distributed with zero mean and variance 0.001, was added

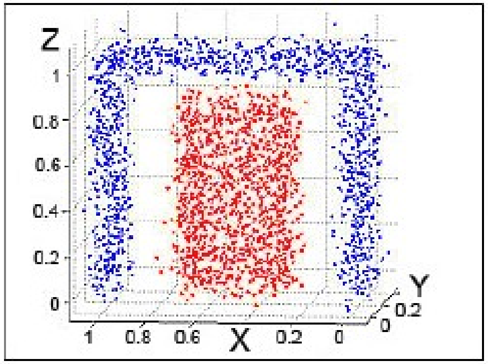
Algorithm	Euclidean Space	Feature Space
Execution time (sec)	0.3491	0.07425
TruePos	0.8330	0.9367
FalsePos	0.1467	0.0400
$\sigma_{\Delta S(S_x, S_y, S_z)}$ [cm]	(12.13, 11.01, 8.09)	(9.11, 7.998, 7.11)
$\sigma_{\Delta R(\psi, \vartheta, \varphi)}$ [deg]	(2.01, 1.12, 3.22)	(1.32, 1.99, 2.88)

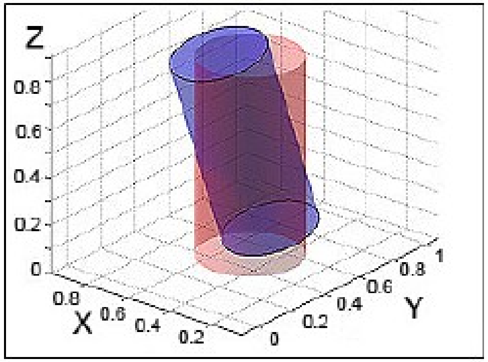
Experimental results

Simulated data









Experimental results

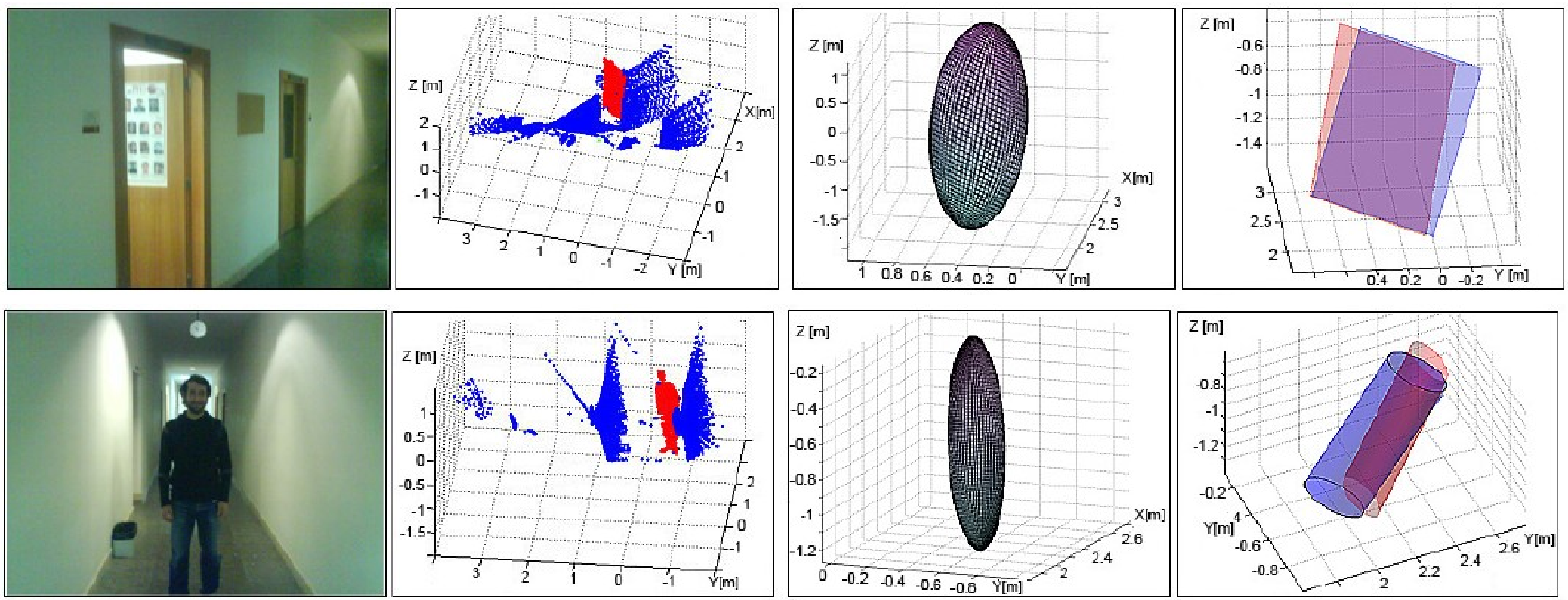
Real data

• Real data has been acquired by an Hokuyo laser range finder which is mounted on a Directed Perception pan-tilt unit.

Algorithm	Euclidean Space	Feature Space
Execution time (sec)	0.3231	0.3156
TruePos	0.8667	0.9000
FalsePos	0.0667	0.0667
$\sigma_{\Delta S(S_x, S_y, S_z)}$ [cm]	(16.21, 13.24, 10.55)	(12.12, 6.22, 8.19)
$\sigma_{\Delta R(\psi, \vartheta, \varphi)}$ [deg]	(4.21, 3.98, 5.12)	(3.12, 2.01, 3.02)

Experimental results

Real data



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Discussion and future work

• New method to directly detect changes in the environment of a robot using a 3-D laser range finder and retrieve its shapes using two different methods

• geometric primitives (e.g. cones or boxes) or more complex structures.

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- **Thanks for your attention!!**

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- **Any questions/advise?**

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