Dinamic 3D Mapping

Visual Estimation of Independent Motions for 3D Structures in Dynamic Environments

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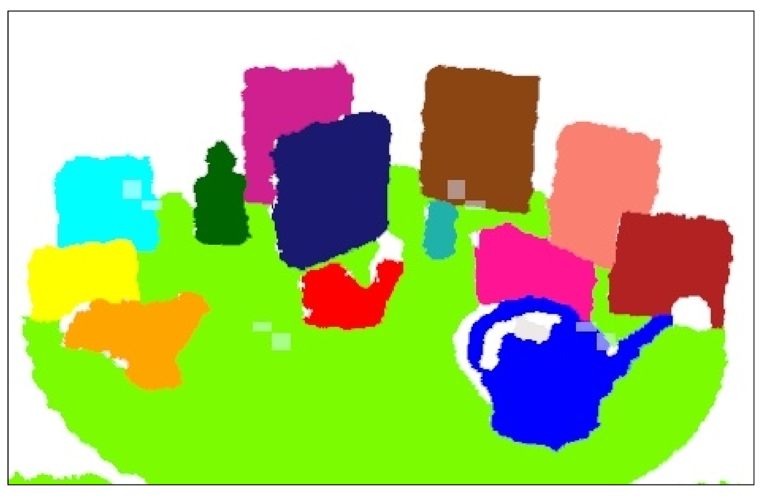
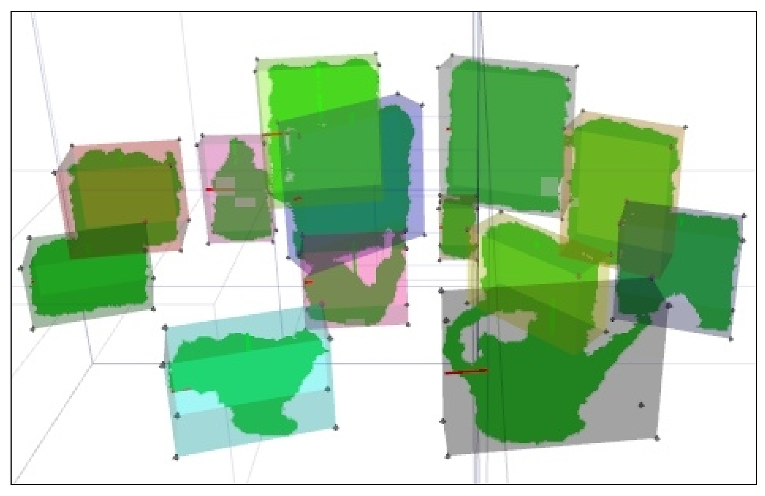
INTRODUCTION

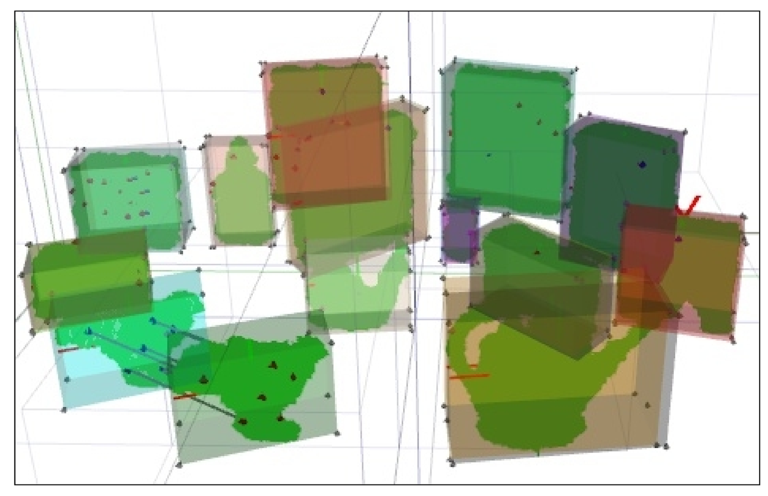
Scene



Tentative object candidates



Encapsulated 3D blobs



Motion estimation

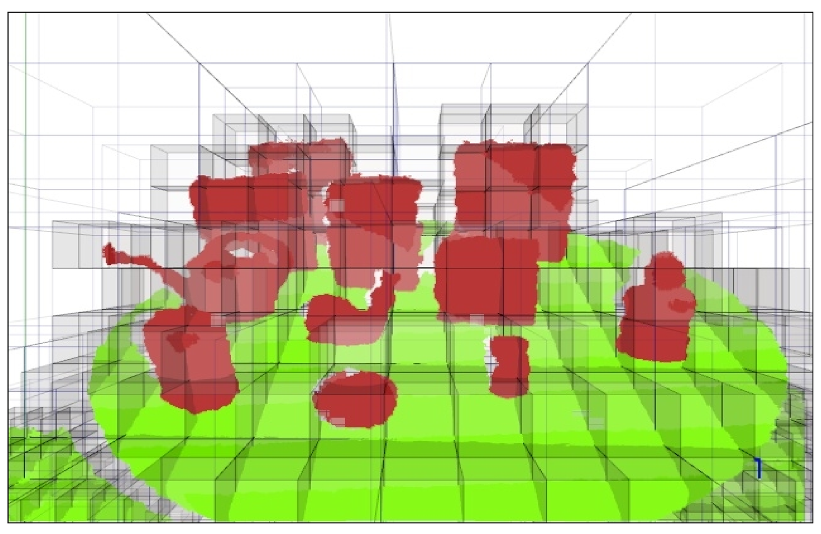
An approach to consistently model and characterize potential object candidates presented in non-static scenes. Three principal procedures support our method:

i) **the segmentation of the captured range images into 3D clusters or blobs, by which we obtain a first gross impression of the spatial structure of the scene,**

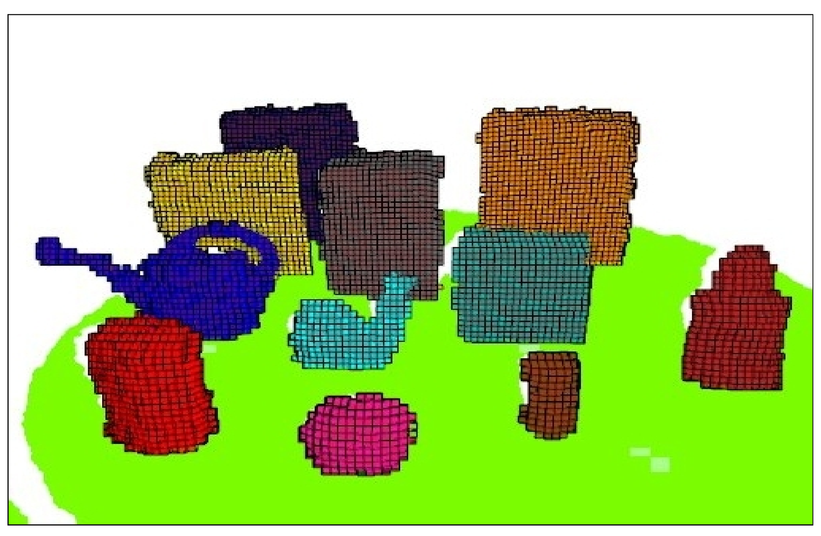
ii) **the maintenance and reliability of the map, which are obtained through the fusion of the captured and mapped data to which we assign a degree of existence (confidence value),**

iii) **the visual motion estimation of potential object candidates, through the combination of the texture and 3D-spatial information, allows not only to update the state of the actors and perceive their changes in a scene, but also to maintain and refine their individual 3D structures over time.**

3D-MAPPING FRAMEWORK



Plane detection and octree



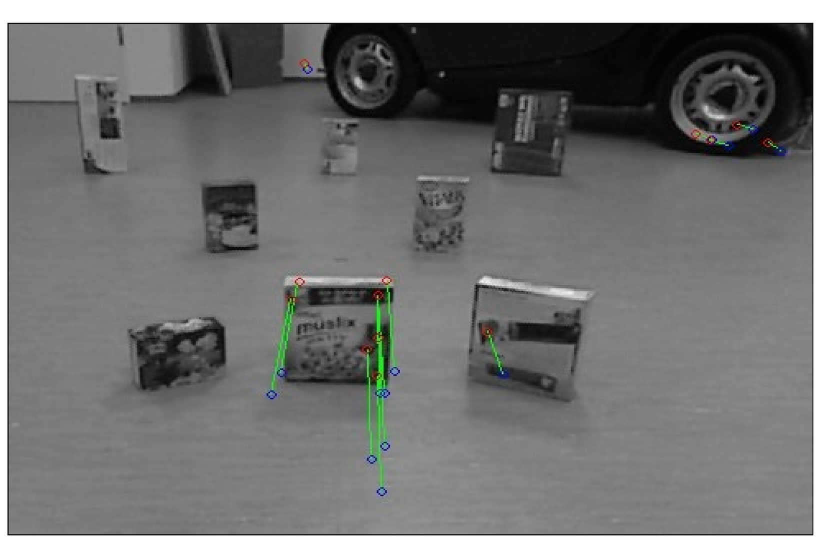
Blob detection, clustering

3D-Blob Detection

After the supporting-plane detection, the 3D rigid registration is stored in an octree. In order to find the spatial relations among the 3D points a Depth-First-Search (DFS) is performed by transversing the leaves inside the octree and finally identifying and clustering the connected points.

VISUAL MOTION ESTIMATION

Inliers, ego-motion



Outliers, independent-motion

Cost function:

$$\Sigma^2=\sum_{l=1}^{L}\left\|p_{2,l}-\left({}^{ego}R\cdot p_{1,l}+{}^{ego}t\right)\right\|$$

The scoring is based on the similarity of matching points:

$$p'_{1,j}={}^{hyp}R\cdot p_{1,j}+{}^{hyp}t$$

$$v_{jj}=p_{2,j}-p'_{1,j}$$

$$\chi_j^2=v_{jj}S_j^{-1}v_{jj}^T<\chi_\alpha^2$$

$$S_j=P_{1,j}+P_{2,j}$$

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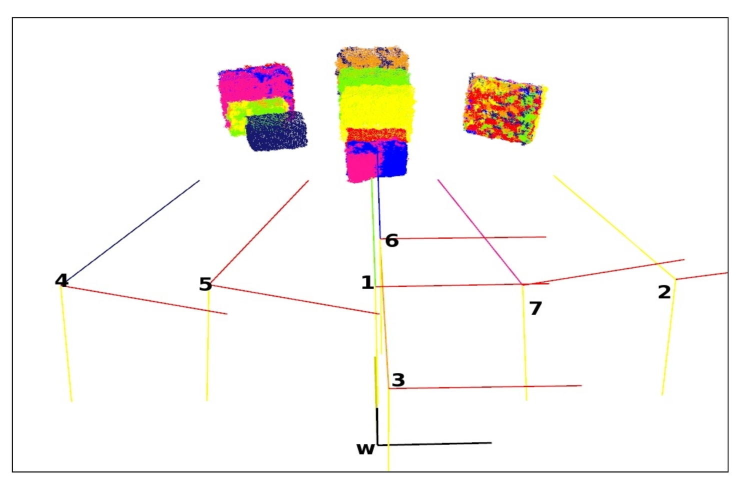
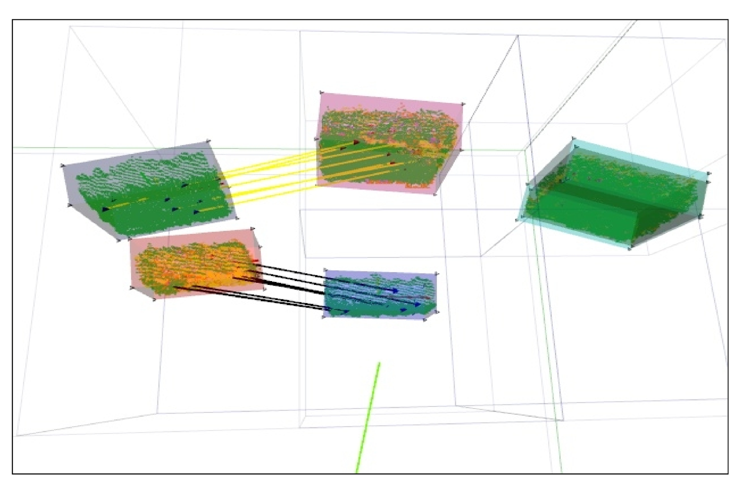
EXPERIMENTS AND RESULTS

On a wheeled robot:

3D textured image



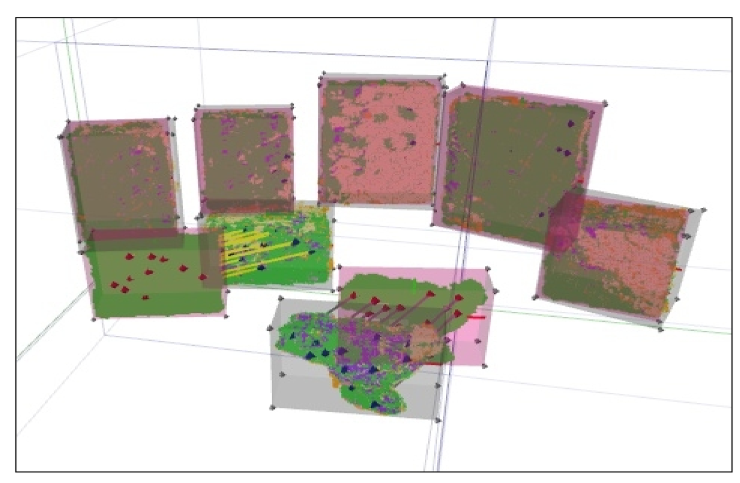
Static registrations and ego-motion detection



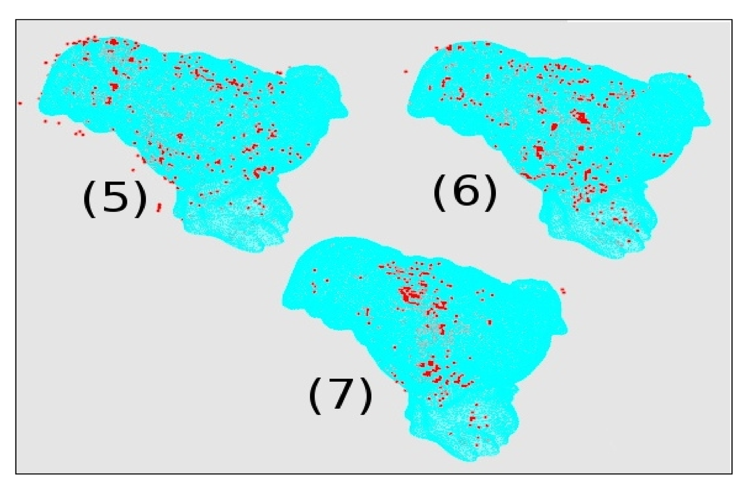
Object-motion detection in the map

In a table scene:

Scene



Object- and ego-motion detection



Confidence value points (red) and object model

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