Data Fusion by Uncertain Projective Geometry in 6DoF Visual SLAM

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Abstract. In this paper we face the issue of fusing 3D data from different sensors in a seamless way, using the unifying framework of uncertain projective geometry. Within this framework it is possible to describe, combine, and estimate various types of geometric elements (2D and 3D points, 2D and 3D lines, and 3D planes) taking their uncertainty into account. Because of the size of the data involved in this process, the integration process and thus the SLAM algorithm turns out to be very slow. For this reason, in this work, we propose the use of an R*-Tree data structure to speed up the whole process, managing in an efficent way both the estimated map and the 3D points clouds coming out from the stereo camera. The experimental section shows that the use of uncertain projective geometry and the R*-Tree data structure improves the mapping and the pose estimation.

1 Introduction

Simultaneous Localization and Mapping, SLAM hereafter, is a well-known problem in mobile robotics since many years [1], [2], [3]. A very relevant aspect in SLAM concerns the representation of the entries in the world model and the management of their uncertainty; improper uncertainty management induces errors in robot localization and in mapping world, which therefore suffers of geometric inconsistencies. These prevent practical use of mobile robotics technology whenever an a priori and reliable map is not available.

Marzorati et al. [4] demonstrated that it is possible to provide a general framework for 3D sensor fusion, in vision based SLAM, that takes into account uncertainty in projective geometry, providing a mean for seamless integration of several information sources, e.g. 3D line segments, 3D planes, clouds of 3D points, etc.

The principal problem of the SLAM algorithm proposed in [4] is the lack of an algorithm evaluation based on real data and the velocity of the algorithm ($\sim$ 2000sec to complete a loop of 40m), due to the size of the data involved in the process. In particular, for this last problem, it is possible to identify two bottlenecks: the first is the point-segment association and the second is the map-measurements data association. In literature it is possible to find different kind of solutions, for example, to reduce significantly these computational costs, Nüchter et al. [5, 6] proposed to use different methods, namely point reduction, kd-trees, approximate kd-trees and cached kd-trees. Following

Marzorati D., Matteucci M., Migliore D. and G. Sorrenti D. (2008).
Data Fusion by Uncertain Projective Geometry in 6DoF Visual SLAM.
In *VISAPP-Robotic Perception*, pages 3-12
DOI: 10.5220/0002341600030012

a parallel line, in this paper, we propose to use the R*-Tree taking into account the uncertainty of the data involved in the process while indexing percepts.

2 Uncertain Projective Geometry

Uncertain projective geometry is a framework used to represent geometric entities and their relationship introduced by Heuel [7, 8]. This framework is able to describe, combine, and estimate various types of geometric elements (e.g. 2D and 3D points, 2D and 3D lines, 3D planes) taking uncertainty into account. These elements are represented using homogeneous vectors, allowing the derivation of simple bilinear expressions to represent join and intersection operators. This is obtained using only three matrices (called construction matrix): $\mathbf{S}(\cdot)$ (for 2D points and 2D lines), $\mathbf{O}(\cdot)$ (for 3D lines) and $\mathbf{\Pi}(\cdot)$ (for 3D points and 3D planes). To get a line from two 2D points we can use operator

$$\mathbf{l} = \mathbf{x} \wedge \mathbf{y} = \mathbf{S}(\mathbf{x})\mathbf{y} \tag{1}$$

$$\mathbf{S}(\mathbf{x}) = \frac{\partial \mathbf{x} \wedge \partial \mathbf{y}}{\partial \mathbf{y}} = \begin{pmatrix} 0 & -x_3 & x_2 \\ x_3 & 0 & -x_1 \\ -x_2 & x_1 & 0 \end{pmatrix}, \tag{2}$$

the same holds to join two 3D points into a 3D line:

$$\mathbf{L} = \mathbf{X} \wedge \mathbf{Y} = \mathbf{\Pi}(\mathbf{X})\mathbf{Y}, \tag{3}$$

$$\mathbf{\Pi}(\mathbf{X}) = \frac{\partial \mathbf{X} \wedge \partial \mathbf{Y}}{\partial \mathbf{Y}} = \begin{pmatrix} W_1 & 0 & 0 & X_1 \\ 0 & W_1 & 0 & -Y_1 \\ 0 & 0 & W_1 & -Z_1 \\ 0 & -Z_1 & Y_1 & 0 \\ Z_1 & 0 & -X_1 & 0 \\ -Y_1 & X_1 & 0 & 0 \end{pmatrix}. \tag{4}$$

Again we can join a 3D point with a 3D line into a 3D plane:

$$\mathbf{A} = \mathbf{X} \wedge \mathbf{L} = \mathbf{O}(\mathbf{L})\mathbf{X}, \tag{5}$$

$$\mathbf{O}(\mathbf{L}) = \frac{\partial \mathbf{X} \wedge \partial \mathbf{L}}{\partial \mathbf{X}} = \begin{pmatrix} 0 & L_3 & -L_2 & -L_4 \\ -L_3 & 0 & L_1 & -L_5 \\ L_2 & -L_1 & 0 & -L_6 \\ L_4 & L_5 & L_6 & 0 \end{pmatrix}. \tag{6}$$

These construction matrices are useful tools to derive new geometric entities from other ones, e.g. a 3D line from two 3D points, a 3D point from the intersection of two 3D lines, etc.; at the same time, being bilinear equations these operators represent the Jacobian of the very same transformation that could be used for uncertainty propagation in the construction process as well. Moreover, these matrices can be used to express various geometric relations between pair of elements: incidence, identity, parallelism and orthogonality.

Using these relations we can generate probabilistic tests to verify the relationships between entities and to formulate a simple estimation process, to fit an unknown entity β to a set of observations $\tilde{\mathbf{y}}$ constrained by a set of relationship $w(\tilde{\mathbf{y}}, \beta)$. Suppose, in fact, to have a set of observations, described by equation:

$$\tilde{\mathbf{y}}_\mathbf{i} = \mathbf{y}_\mathbf{i} + \mathbf{e}_\mathbf{i}, \tag{7}$$

where $\mathbf{e}_\mathbf{i} \sim N(\mathbf{0}, \mathbf{Q})$. To estimate the unknown entity it is possible to use a simple, two steps, iterative algorithm:

1. Estimate the unknown entity using the relationship between the unknown and the observations $\mathbf{w}(\tilde{\mathbf{y}}, \beta) = \mathbf{0}$ and the homogeneus constraint $\mathbf{h}(\beta) = \mathbf{0}$. This can be obtained by minimizing

$$\begin{aligned} &\mathbf{\Theta}(\tilde{\mathbf{y}}, \beta, \lambda, \mu) = \\ &= \tfrac{\mathbf{1}}{\mathbf{2}}(\mathbf{y} - \tilde{\mathbf{y}})^\mathbf{T}\mathbf{Q}_\mathbf{y}^{-\mathbf{1}}(\mathbf{y} - \tilde{\mathbf{y}}) + \lambda^\mathbf{T}\mathbf{w}(\tilde{\mathbf{y}}, \beta) + \mu^\mathbf{T}\mathbf{h}(\beta), \end{aligned} \tag{8}$$

   where λ and μ are Lagrangian multipliers, respectively for the relationship and the constraints.

2. Re-evaluate the constraints on the observations by another iterative process, updating observations by the use of the relationship, the homogeneus constraint and the new entity estimated.

Being bilinear operators, we can estimate any new entity z, from two entities x and y, with a simple matrix multiplication. In general we have:

$$z = f(x, y) = U(x)y = V(y)x, \tag{9}$$

where $U(x)$ and $V(y)$ are, at the same time, the bilinear operators and the Jacobian of the x and y entity respectively. Assuming entities to be uncertain, the pairs (x, Σ_{xx}), (y, Σ_{yy}) and, possibly, the covariances Σ_{xy} between x and y are required for computing the error propagation using the following simple equation:

$$\begin{aligned} &(z, \Sigma_{zz}) = \\ &\left(U(x)y, [V(y), U(x)] \begin{pmatrix} \Sigma_{xx} & \Sigma_{xy} \\ \Sigma_{xy} & \Sigma_{yy} \end{pmatrix} \begin{bmatrix} V^T(y) \\ U^T(x) \end{bmatrix} \right). \end{aligned} \tag{10}$$

in case of independence between x and y we obtain:

$$(z, \Sigma_{zz}) = \left(U(x)y, U(x)\Sigma_{yy}U^T(x) + V(y)\Sigma_{xx}V^T(y) \right). \tag{11}$$

Since we have estimated uncertainty, to check the geometric relationship between two geometric entities, it is possible to use a statistical test on the distance vector d

(being this an entity defined as the previous bilinear equation as well). In particular such relationship can be assumed to hold if the hypothesis

$$H_0 : d = U(x)y = V(y)x = 0 \tag{12}$$

cannot be rejected. Notice that the hypothesis H_0 can be rejected with a significance level of α when

$$T = d^T \Sigma_{dd}^{-1} d > \varepsilon_H = \chi^2_{1-\alpha;n}, \tag{13}$$

Obtaining the covariance matrix Σ_{dd} of d by first order error propagation as

$$\Sigma_{dd} = U(x)\Sigma_{yy}U^T(x) + V(y)\Sigma_{xx}V^T(y).$$

In the general case Σ_{dd} may be singular; this happens if d is a n x 1 vector, r is is the degree of freedom of the relation R and $r < n$. The singularity causes a problem, as we have to invert the covariance matrix, but, at least for projective relations, it can be guaranteed that the rank of Σ_{dd} is not less than r (see Heuel [7, 8]).

3 6DoF Visual SLAM

Our interest in the framework described in the previous section comes from the issue of integrating 3D points, sensed by a stereo camera like the one in [9], with the 3D segments used in a previously developed algorithm for 6DoF hierarchical SLAM, sensed basing on trinocular stereo vision, like in [10]. The algorithm uses hierarchical map decomposition, uncertainty modeling for trinocular 3D data, and 6DoF pose representation.

In [11] we discussed in details some algorithms for data association and the importance of using a proper criterion to match features in the view with features in the map. Usually the point-to-point distance is considered as an appropriate criterion for single segment matching and much of the effort is devoted in finding a good association strategy for dealing with the exponential complexity of finding the best match for the whole view. In that paper we showed how a better criterion for 3D segment matching results in a better data association almost independently from the algorithm for interpretation tree traversal (i.e., data association algorithm).

The approach we proposed is based on a multi-criteria evaluation, for associating segments in the view with map segments. The reason for discarding the point-to-point criterion is mainly due to the problem of the moving-field-of-view in the sensing system, which turns in a moving window on the world feature(s). More precisely, the segment extrema are induced by the reduced field of view and are not always related to real extrema of feature in the world; when the sensing system moves it senses new extrema, which could result in new segments, at each step; this can easily become a problem for the classical point-to-point distance[3].

[3] Our proposal is of interest also for 2D-3DoF SLAM systems which groups 2D data points into 2D lines, because this moving-field-of-view issue applies there too.

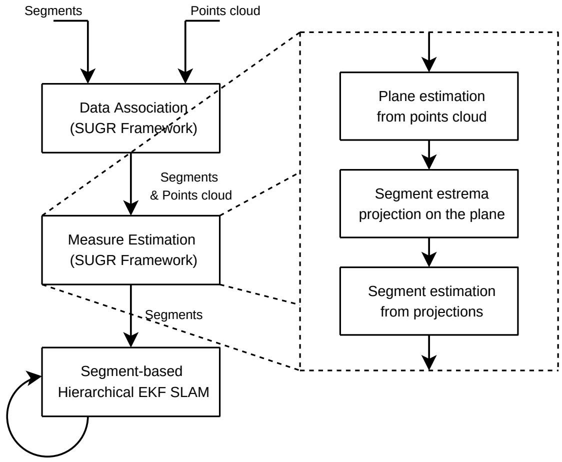


Fig. 1. The sensor fusion mechanism.

By using the uncertain projective geometry framework we are able to extend the original system by integrating the 3D segments coming from the feature-based trinocular stereo with the 3D points detected by the correlation-based stereo camera. Our idea is to improve our original SLAM algorithm by integrating segments and points into 3D segments; this is done by using the math introduced in Section 2, before introducing this more reliable data in the EKF-based state filter. In this way we can reuse the original filter, since we still base on segments to perform the SLAM. Moreover, being uncertain projective geometry a probabilistic framework, we can also take into account uncertainties in percepts, so to have a consistent estimate of the measurement uncertainties in the filter.

3.1 Sensor Fusion Mechanism

Sensor fusion is performed before the measure of each segment is passed to the SLAM algorithm; we say the fusion is performed “outside of the filter”. Following the flowchart in Figure 1, we perform hypothesis test to assign a sets of points to each segment by using the Statistically Uncertain Geometric Reasoning (SUGR) framework. In this data association phase, we identify three sets of points for each segment, using three hypothesis tests: two tests, one for each extrema, are devoted to check if there are points to be fused with the segment extrema, ehile the third test aims at searching points incident to the support line in between the two extrema. It is important to notice that the SUGR framework allows us to estimate, in a simple way, the 3D support line passing trough the two extrema and its uncertainty as well. It is therefore possible to identify points incident to the line by taking into account also the uncertainty in line estimation.

Having performed such tests, we are able to integrate each set of points with the corresponding segment, updating both the position and the uncertainty of its extrema. This activity is also performed “outside of the filter” and aims at generating a new measure for the perceived 3D segments.

To have a more robust segment estimation, we decided to perform the integration by following the three steps procedure outlined herefter. This is mainly due to the presence of points that satisfy the test because of their large uncertainty: they usually belong to the plane incident with the segment, but not necessary to the segment itself. For each segment we:

1. Estimate a 3D plane incident to each point in the subset matching the incidence hypothesis test.
2. Estimate the new extrema of the segment, estimating the two points incident to the plane and equal to the old extrema, i.e., the point sets that passed the first two tests.
3. Estimate the new segment by using these two projected extrema.

Now it is possible to pass the segments as new improved measures for the EKF in the segment-based Hierachical SLAM algorithm described in [12, 11].

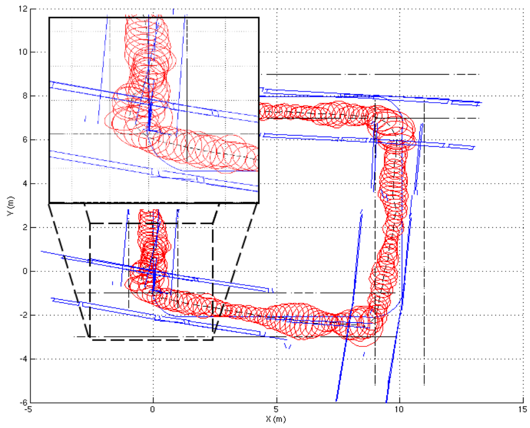
3.2 Using R*-Tree to Speed Up Slam Process

One of the problem of the SLAM process described in the previous sections is its computational complexity. This is due to the huge size of 3D points clouds involved (i.e., a single acquisition with a correlation based sensor consists of $\sim$ 100K points). For this purpose we decided to improve the algorithm by using an optimized data structure, speeding up data association and segment-point fusion processes.

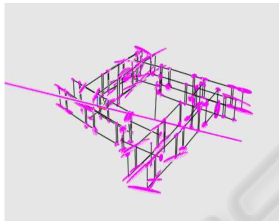
We propose the use of R*-Tree [13], a tree data structure that keeps data spatially sorted and allows searches, insertions, and deletions in logarithmic amortized time. Usually it is used in spatial access methods (i.e., for indexing spatial information like the one in geographical information systems) and, in this case, we use it to index points clouds acquired with che correlation based sensor, and the maps of segments as well.

The R*-Tree data structure splits space with hierarchically nested, and possibly overlapping, minimum bounding rectangles (MBR); we have modified the original algorithm to take into account the uncertainty of the data in the size of the MBR. Each node of this tree has a variable number of entries (up to some pre-defined maximum) and each entry within a non-leaf node stores two pieces of data: the identifier of a child node, and the bounding box of all entries within this child node.

The insertion and deletion algorithms use the bounding boxes from the nodes to ensure that elements close in space are placed in the same leaf node (in particular, a new element will go into the leaf node that requires the least enlargement in its bounding box). Each entry within a leaf node stores again two pieces of information: the indentifier of actual data element (which, alternatively, may be placed directly in the node) and the bounding box of the data element. Similarly, the searching algorithm, in this case a K-Nearest Neighbor, uses the bounding boxes to decide whether or not to search inside a child node. Most of the nodes in the tree are never "touched" during a search. The R*-Tree attempts to reduce both coverage and overlap to improve further on the performance, using a combination of a revised node split algorithm and the concept of forced reinsertion at node overflow. This is based on the observation that tree structures are highly susceptible to the order in which their entries are inserted, so an insertion-built (rather than bulk-loaded) structure is likely to be sub-optimal. Deletion and reinsertion of entries allows them to "find" a place in the tree that may be more appropriate than their original location.

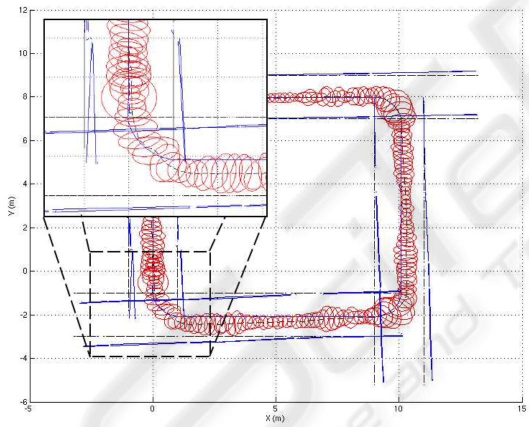


(a) Comparison with ground truth for trinocular

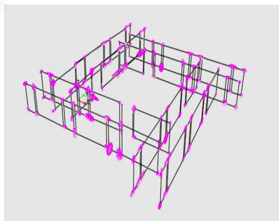


(b) 3D map from trinocular based on simulated data

Fig. 2. Map estimated taking in input simulated data, in particular the input is just the segments from the trinocular data.



(a) Comparison with ground truth for sensor fusion

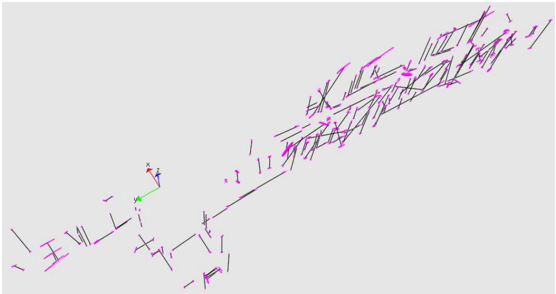


(b) 3D map from sensor fusion based on simulated data

Fig. 3. Map estimated taking in input simulated data, in particular the input is the data fused (segments+points) by using the uncertain geometry framework proposed.

4 Experimental Validation

In this section we show the capabilities of the framework presented in this paper, using simulated and real data. Given a map of segments and the robot trajectory, we simulated the image formation process on the two devices, as well as the uncertain measurements of the world. The reason for using a simulated environment, to test the proposed method,



(a) 3D map from trinocular based on real data

(b) 3D map from sensor fusion based on real data

Fig. 4. Comparison between the same SLAM system, which takes in input different real data. Top: the input is just the set of segments from the trinocular system. Bottom: the input is the set of fused data (i.e., segments + points) obtained by using the framework proposed (only the segments with at least ten associated points were used).

is to have access to the ground truth and perform, in this way, a numerical comparison about the consistence of the EKF.

The two algorithm, i.e. the one with and the one without sensor fusion, have been compared on the very same data. We expect that the differences between the two will increase even more with real data.

In Figure 2 and Figure 3 it is possible to compare the results of the approach proposed in this paper with our previous work on the trinocular based SLAM algorithm. The plots refer to a circular trajectory of 40m and the SLAM algorithm has been stopped before loop closure to underline the relevance of the approach. In Figures 2(a) and 3(a), we plotted the $\pm 3\sigma$ confidence ellipse around the estimated robot pose. It can be noticed how the estimate of robot pose with the trinocular based system eventually becomes inconsistent; on the other hand, using sensor fusion helps in maintaining it consistent.

Figures 2(b) and 3(b) allow mapping comparison. Notice that by using trinocular data and SVS points we are able to reduce the uncertainty in the segment extrema (ellipses in the plots) and to improve the overall accuracy.

In Figure 4 it is possible to compare the results based on real data acquired in a corridor. The measured segments and points, in this case, are more noisy than simulated ones and it is common to obtain, before the fusion step, "spurious" segments. To reduce this undesired effect, we decided to filter the segments using a simple criterion: use only the segments with at least ten points associated. This allows to estimate a map with less ”spurious” segments than that obtained using only trinocular segments. Figure 4 demonstrates the quality that can be reached with the proposed approach, which allows to combine non-homogeneous features of the scene, i.e., 3D segments and 3D points, into a single representation, segment-based in our case

5 Conclusions and Future Works

This paper presents a 6DoF SLAM algorithm that exploits the uncertain projective geometry framework to perform sensor fusion of 3D data coming from different sensors. The framework allows to represent 3D segments and 3D points with their associate uncertainty. Although the algorithm presented in this paper deal with vision data, it is straightforward to include other source of 3D information in the framework. For instance, laser scans could be integrated either using single measures as points, extracting 3D lines, or computing 3D planes, when dealing with 3D laser scans.

We faced sensor fusion by exploiting uncertain projective geometry, outside the SLAM EKF state filter, to provide a new “virtual” sensor with the purpose of reducing measurement errors and improving the results obtained with the SLAM algorithm. The described framework could be used within the SLAM algorithm as well, for data association, trough hypothesis test, and filter update.

Moreover we demonstrated that it is possible to use this algorithm also with real data, using points not only to improve the estimated map, but also to remove erroneous measurements from data.

In the last years many researchers have demonstrated that it is possible to use pictorial features from a monocular camera to perform SLAM as well. Notable examples are the works of Lacroix et al.[14], Davison et al.[15] and Lowe et al.[16]. The key idea, in this kind of approaches, is to use interest points as features, trying to fulfill the data association task by the use of image descriptors or correlation based methods. Usually, to have significant landmarks, these descriptors are chosen to be invariant to image scale, rotation, and partially invariant (i.e. robust) to changing viewpoints, or illumination. From a SLAM point of view this is very useful not only for the data association but also because it allows the robot to identify possible loop closures.

We are presently working on the integration of these pictorial feature in the framework proposed by this paper. Manipulating uncertain geometric entities, we are able to treat interest points as delimited portions of uncertain planes, enriched by an appearance information represented by the image patch located around the point on the image plane. Performing the data association among frames, we could estimate the most probable plane where the feature lies and, at the same time, update the appearance information depending on its position relative to the camera orientation.

Acknowledgements

This work has partially been supported by the European Commission, Sixth Framework Programme, Information Society Technologies: Contract Number FP6-045144 (RAWSEEDS), and by Italian Istitute of Tecnologogy (IIT) grant.

References

1. Durrant-Whyte, H.F.: Integration, coordination and control of multi-sensor robot systems. Kluwer Academic (1987)
2. Lu, F., Milios, E.: Globally consistent range scan alignment for environment mapping. Autonomous Robots **4** (1997) 333–349
3. Tardós, J.D., Castellanos, J.A.: Mobile robot localization and map building: a multisensor fusion approach. Kluwer Academic (1999)
4. Marzorati, D., Matteucci, M., D. Migliore, D.G.S.: Integration of 3d lines and points in 6dof visual slam by uncertain projective geometry. European Conference on Mobile Robotics (2007) 96 – 101
5. Nüchter, A., Lingemann, K., Hertzberg, J.: 6D SLAM with Cached kd-tree Search. Number 06421 in Dagstuhl Seminar Proceedings. Internationales Begegnungs- und Forschungszentrum für Informatik (IBFI), Schloss Dagstuhl, Germany, Dagstuhl, Germany (2007)
6. Nüchter, A., Lingemann, K., Hertzberg, J., Surmann, H.: 6d slam with approximate data association. 12th International Conference on Advanced Robotics, 2005. ICAR '05. Proceedings (2005) 242–249
7. Heuel, S.: Points, Lines and Planes and their Optimal Estimation. Number 2191 in LNCS. Springer (2001)
8. Heuel, S.: Uncertain Projective Geometry: Statistical Reasoning for Polyhedral Object Reconstruction. Springer (2004)
9. Konolige, K.: Small vision system. hardware and implementation. In: ISRR, Hayama, Japan (1997)
10. Ayache, N., Lustman, F.: Trinocular stereo vision for robotics. IEEE Trans. on PAMI **12** (1991)
11. Marzorati, D., Sorrenti, D.G., Matteucci, M.: Multi-criteria data association in 3d-6dof hierarchical slam with 3d segments. In: Proc. of ASER06 Conf. (2006)
12. Marzorati, D., Sorrenti, D.G., Matteucci, M.: 3d-6dof hierarchical slam with trinocular vision. In: Proc. of ECMR. (2005)
13. Beckmann, N., Kriegel, H.P., Schneider, R., Seeger, B.: The r*-tree: An efficient and robust access method for points and rectangles. SIGMOD Conference (1990) 322–331
14. Lemaire, T., Lacroix, S., Sola, J.: A practical 3d bearing-only slam algorithm. In: Proc. of IROS. (2005)
15. Davison, A.: Real-Time Simultaneous Localisation and Mapping with a Single Camera. In: Proc. of ICCV. (2003) 1403–1410
16. Se, S., Lowe, D., Little, J.: Global localization using distinctive visual features. In: Proc. of IROS, Lausanne, Switzerland (2002)